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

Running head: Land cover and forest fragmentation in Liberia

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LF: Project administration, Resources, Supervision, Writing – review & editing;

CN: Project administration, Resources, Supervision, Writing – review & editing;

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AS: Formal analysis (GEDI data processing);

KG, WT, MW, ZEW, JGY, ETO, JG: Writing – review & editing;

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Running Title (max 45 characters): *Land cover and forest fragmentation in Liberia*

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 was used to map and quantify land cover change and forest fragmentation in Liberia between 2000-2018. In addition, LiDAR data from the Global Ecosystem Dynamics Investigation Mission (GEDI) was applied to assess the integrity of forest remnants. Between 2000-2018, 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: Google Earth Engine, time series, land cover change, forest fragmentation, GEDI.

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, Mittermeier, da Fonseca and Kent, 2000; Oates, Bergl and Linder, 2005) supporting a remarkable diversity of endemic species of plants and animals (Mittermeier et al., 2005; Oates and Nash, 2005), 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 and Klop, 2013 Liu, Wimberly and Dwomoh, 2017; Penman et al., 2003 and 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 of 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 106M 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 of forest cover combined with forest degradation and fragmentation, leads to the release of significant amounts of greenhouse gases emission which are detrimental towards 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, Asner and Lambin, 2017): more than half of world’s exports of cocoa originate from this region (Ruf, Schroth and Doffangui, 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 to 4% of GDP (US$ 31-41 million p.a.) (World Bank, 2020). Charcoal production activities make additional contribution of similar magnitude, with 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 population since the early 1950's (Herrmann, Brandt, Rasmussen and Fensholt, 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, Keculah, Atedhor and Osewole, 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, Santini, Hayman and D'Odorico, 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, Adekokun and Olarinmoye, 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 and Belward, 2005; Bontemps et al. 2011; Friedl et al., 2010; Fritz et al., 2003; Hansen et al., 2013 and Loveland et al., 2000), or from land-use land-cover 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, Bartholomé, Fritz and Belward, 2004; Vittek, Brink, Donnay, Simonetti and Desclée, 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 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. Forest structure (canopy height and canopy cover) was analyzed using waveform LiDAR data obtained from the Global Ecosystem Dynamics Investigation mission (GEDI).

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 non-parametric regressions to evaluate the changes in annual fragmentation is shown in Figure 1.

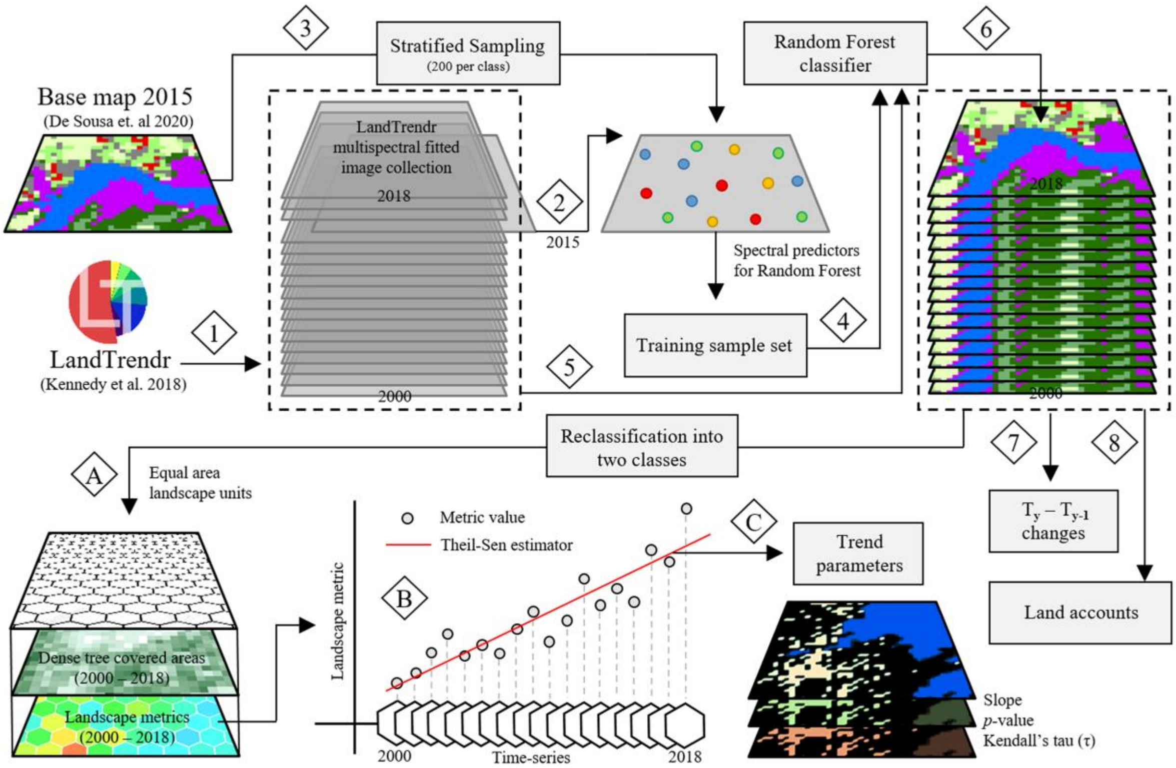


Figure 1 | Schematic overview of the methodology. Numbers represent each step in the land cover classification and change analysis whereas letters represent the order of each process in the forest fragmentation analysis: (1) Annual temporal consistent composites using *LandTrendr*. (2) 2015 fitted image 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 Random Forest model. (6) Land cover maps (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 non-parametric regression was used to evaluate the changes in annual fragmentation for each metric. (C) Spatial distribution of trend-parameters for each landscape metric.

Reference satellite imagery and land cover data

The acquisition of current and thematically comprehensive baseline land-use land-cover products at 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 towards 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 ten classes, including both non-vegetated (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 multi-temporal 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 2000-2018 were created with all scenes for a given year using the multi-dimensional median method (Flood, 2013).

Mapping land cover extent and change

The multi-temporal land-cover classification approach was based on spectral trajectory segmentation using *LandTrendr* (Landsat-based Detection of Trends in Disturbance and Recovery) (Kennedy, Yang and Cohen, 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 land use land cover maps (Yin, et al., 2018). *LandTrendr* was applied over Landsat images from 1985 to 2018. Image data from 1985 to 1999 was 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 9 user-defined parameters to define how the spectral-temporal trajectory segmentation is performed (See Cohen, Yang and Kennedy (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 index (TCW) (Crist, 1985). Tasseled Cap indices have been shown to more accurately separate closed canopy forest from other LULC classes (Dymond, Mladenoff and Radeloff, 2002 and 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 and 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), 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), Non-vegetation Fraction (NV_NDFI).

Change in tropical forests is best shown by spectral metrics (Schultz et al. 2016). A Random Forest (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 to 2018 annual composites were then classified with the trained Random Forest 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 (Supplemental Materials Figure 3). Changes in land cover extent (in km^2) across the 2000-2018 in Liberia was calculated based on the Random Forest classification outputs.

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 x 0.1 km to 10 x 10 km at 100-meter increments. Shannon's diversity index *H* (Shannon, 1948 and Spellerberg and Fedor, 2003) was then calculated for each grid size at each location using the base map as reference (see Supplemental Material Figure 1 for more information on the theoretical background). The final landscape unit size (3 x 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 values curve (Supplemental Material Figure 1b).

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 seen in De Sousa et. al., 2020, included 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, Oom and Beecham, 2007). Avoiding metrics that are redundant and statistically correlated, two key parsimonious fragmentation metrics were computed for each landscape analysis unit across Liberia: number of forest patches and 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 (McGarical and Marks, 1995). Average patch size is the average size of the forest patches within the landscape unit. In this case, smaller average sizes indicate more fragmentation (McGarical and Marks, 1995).

Theil-Sen non-parametric regression (Sean, 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 and 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).

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 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 (100^{th} percentile of beam return height in meters relative to the ground) and total canopy cover (percent) gridded to the Landsat 30-meter pixel. Average height and percent canopy cover was calculated for the three forest classes to derive statistics on the two structural characteristics.

Essential natural napital 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' (Supplemental material Figure 2) 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

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) (Supplemental Materials Figure 3). We found that 96.74% (93,517.97 ± 96.14 km²) of the Liberian territory is covered by the three classes of forests (dense, open, and sparse/degraded forests) while the remaining 3.26% (3,165 ± 82.7 km²) are divided among the other land-use land-cover 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 is 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 to 2006, 2006 to 2012 and 2012 to 2018 shown in Figure 2a), larger extents of dense forest transitioned to the open forest, i.e., 5,012 km², 7,119 km² and 10,034 km², respectively. Similarly, larger extents of open forests transitioned to the sparse/degraded forest class, i.e., 2,289 km², 3,373 km² and 6,649 km², respectively. In contrast to this trend, smaller areas of open forests transitioned to the dense forest class throughout these intervals, i.e., 5,598 km², 2,557 km² and 2,081 km², respectively. The same pattern was observed for sparse/degraded transitioning into the open forest class, i.e., 5,886 km², 4,582 km² and 4,178 km². The transitions from denser to more open canopy classes occurred primarily towards the end of the period while the transitions from sparser to denser forests are more evident in the early years (Figure 2b).

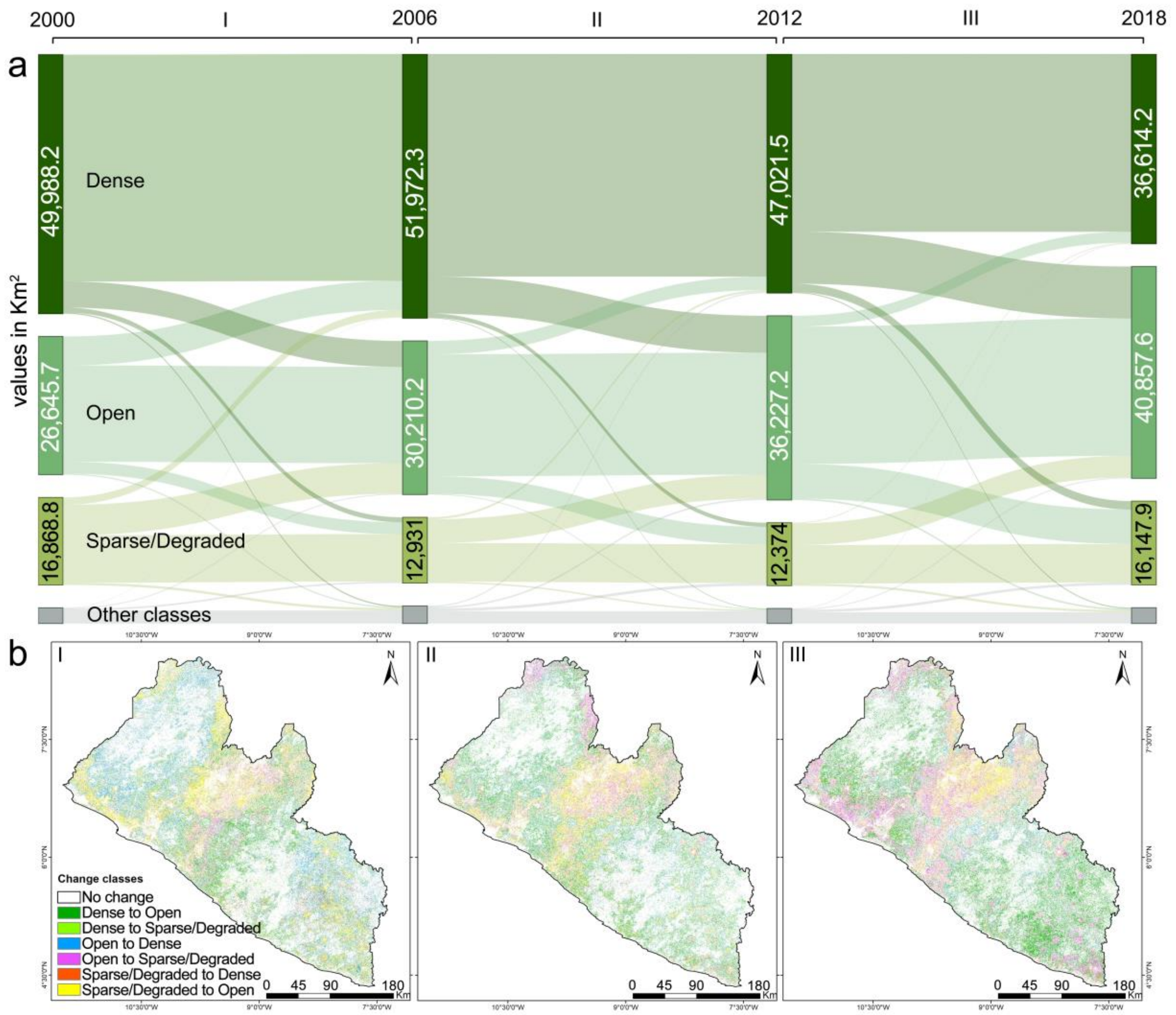


Figure 2 | Land cover extent and change in Liberia, 2000-2018. (**a**) Land cover and forest extent change where columns represent stable extent and the width of the bands between columns is proportional to the area gained and lost between classes during periods I, II and III. (**b**) Spatial distribution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

Other land cover classes have shown significant changes during the 19-year period (Supplemental Materials Figure 4 and 5). We observed an overall increase in non-vegetative classes, namely the 123% increase (196.5 km² in 2000 to 439 km² in 2018) of artificial surfaces and urban areas across the country, followed by 83% increase (229 km² in 2000 to 419 km² in 2018) in bare areas, which correspond mainly with the decrease of grasslands and woody crops (Supplemental Materials Figure 6). Mangroves and wetlands have shown a decreasing trend from 2005 onwards, with a total change of -26% in 2018 from its original extent in 2000.

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 km² landscape unit (Figure 3 and Supplemental Materials Figure 7 and 8). We found a strong increasing 19-year trend of number of dense forest patches across Liberia (Supplemental Materials Figure 5 and 8). This increasing trend (i.e., the process of 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).

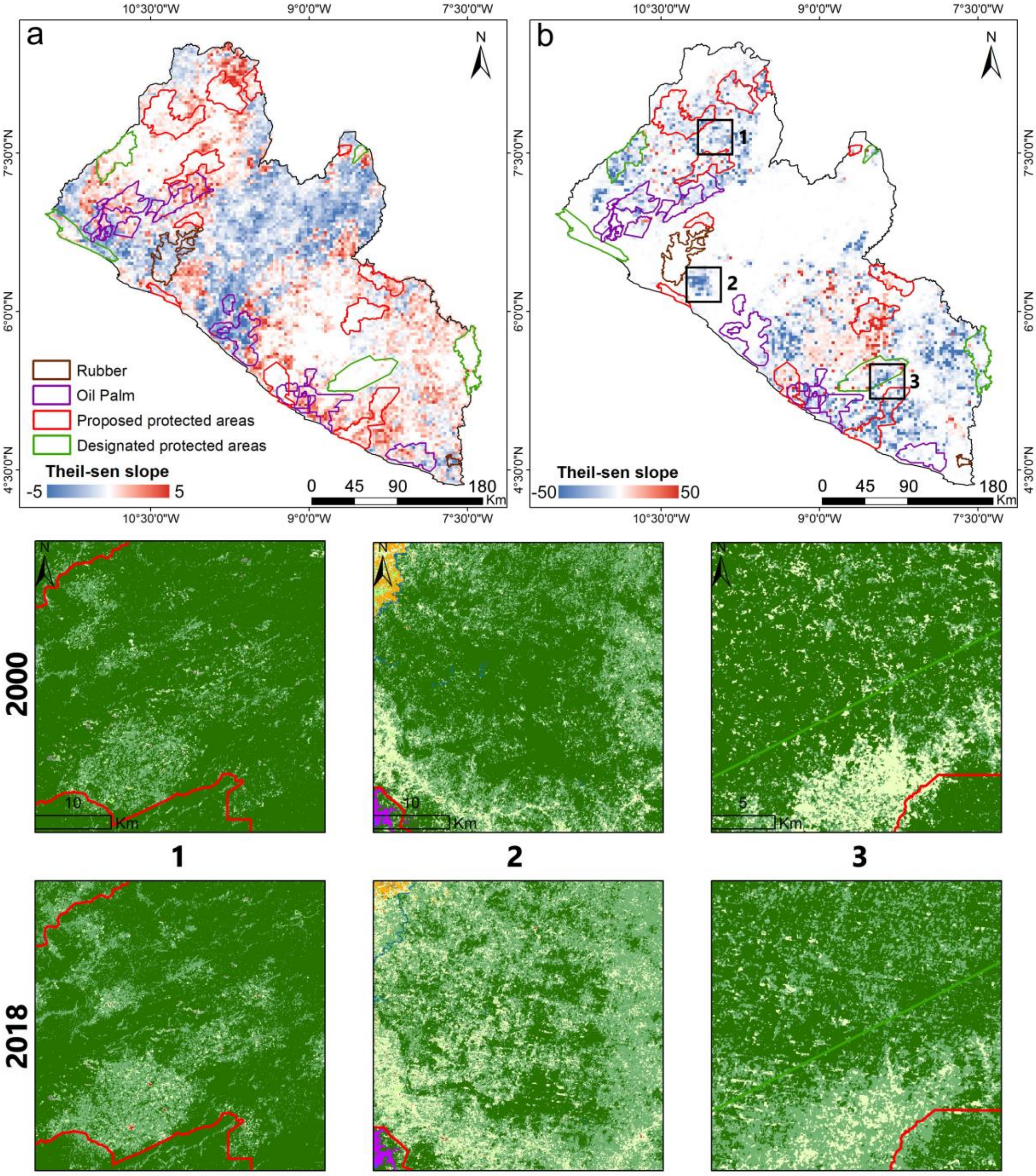


Figure 3 | Theil-sen estimator slope values showing mature dense forest fragmentation trends in Liberia from 2000-2018 at each 9 km² landscape unit. (**a**) The trends in the number of patches within each landscape unit. Positive slope values (red hues) represent an increasing trend in the number of 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 average size. Areas of rubber and oil palm concessions as well as designated and proposed protected areas were included for reference.

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 Supplemental Materials Figure 8).

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 3x3 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 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 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 average patch size but no associated increase in the number of patches.

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 km² of the dense forests have been degraded (i.e., converted into more open canopy classes) in Liberia in the period between 2000-2018 (Figure 2 & Supplemental Materials Figure 6). Approximately 31% of this loss (4,137.3 km²) 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 2,795.5 km² (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 1,292.8 km² (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 km² in the 19-year period. The designated protected areas in Liberia currently encompass 7.87% (2,881.2 km²) 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% % (5,534.2 km²). Overlaying the map of essential natural capital with our dense forest extent map for the year 2018 (i.e., 36,614.2 km²) revealed that 67.5% (24,731 km²) of this area is essential to at least one natural capital, with only 10.2% (2,523.51 km²) 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% (1,931 km²), totaling 18% of Liberia's essential natural capital.

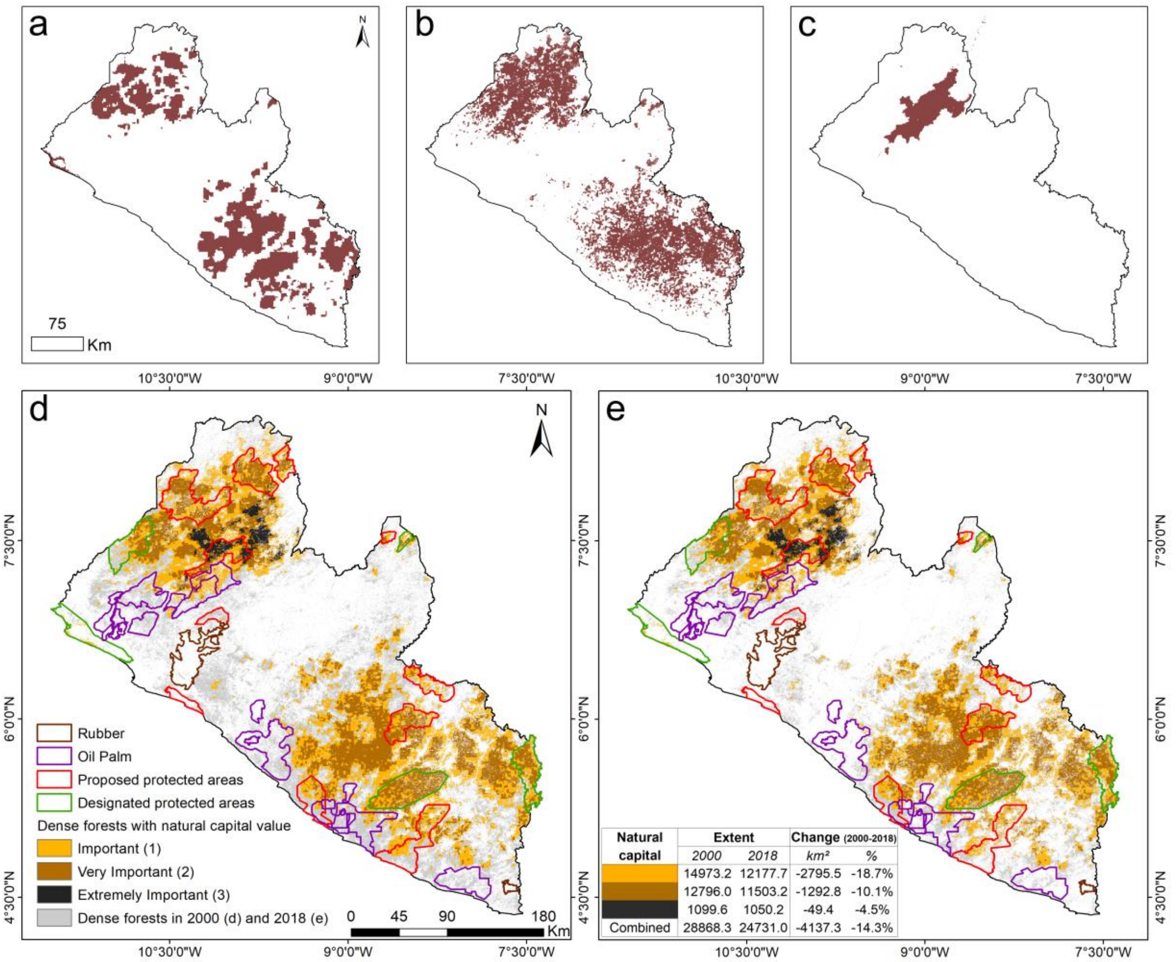
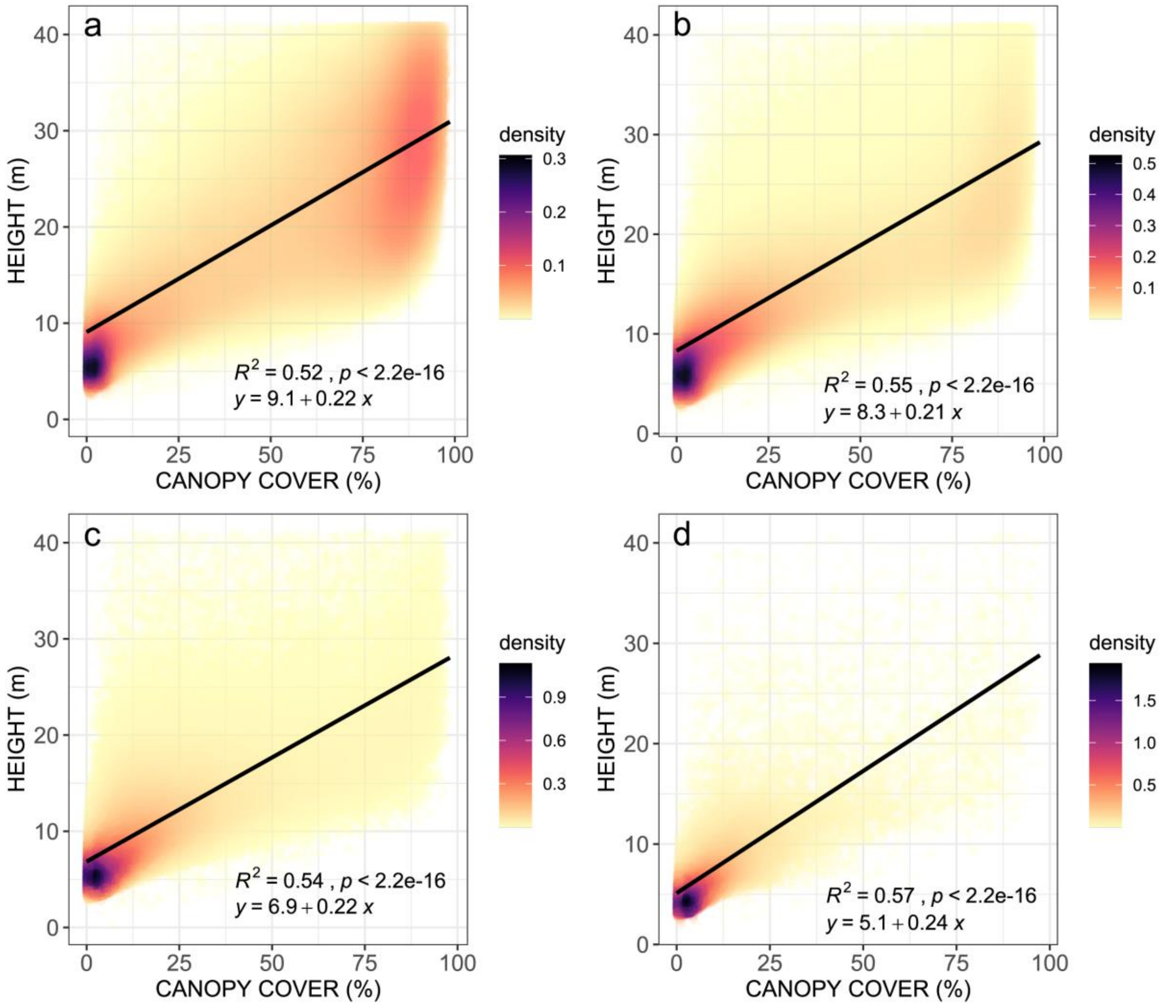


Figure 4 | Essential natural capital of forests in Liberia. An additive 'importance index' (ranging from 1 to 3, where 3 equals to extremely important) was created by combining the areas identified as essential for biodiversity (**a**), forest carbon, (**b**) and freshwater ecosystem services (**c**) 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.

GEDI-based vegetation structure analysis.

The relative height metric RH100 (in meters) and total canopy cover (percent) at each GEDI footprint (Supplemental Materials Figure 9) 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 ± 0.02m (mean ± 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 ± 0.01m tall with a 36 ± 0.05% canopy cover while sparse/degraded forests areas had an average height of 11 ± 0.02 m and 22 ± 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 and height, as dense forests are steadily transitioning into more open-canopy areas (see Figure 2).



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; SE = standard error of the mean).

4. Discussion

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 multi-temporal 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 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 (Supplemental Materials Figure 3). 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.

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, Steininger, Juhn and Peal, 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 Supplemental Materials Figure 5 and 8). Assessing forest fragmentation is dependent on the scale of analysis and there are many metrics that can be applied. 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 (Supplemental Materials Figure 10). It is plausible that some of the observed increase was driven by artifacts found in several of the classified landcover maps. These artifacts, appearing as misclassified areas within the dense forest class, were most likely caused by malfunction of the 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 non-affected scenes (Storey, Scaramuzza and Schmidt, 2005). However, it appears that in regions where there is not a sufficiently large number of non-affected 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 deforest areas (Rosa, Purves, Souza and Ewers, 2013 and Rosa, Purves, Carreiras and Ewers, 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.

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 Lauring 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, Dubayah, Knox, Clark and Blair, 2002 and 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.

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 non-renewable resources such as minerals – has been increasingly recognized as critically important for achieving sustainable development goals, and was one of 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 towards 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 and 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 towards 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 towards 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.

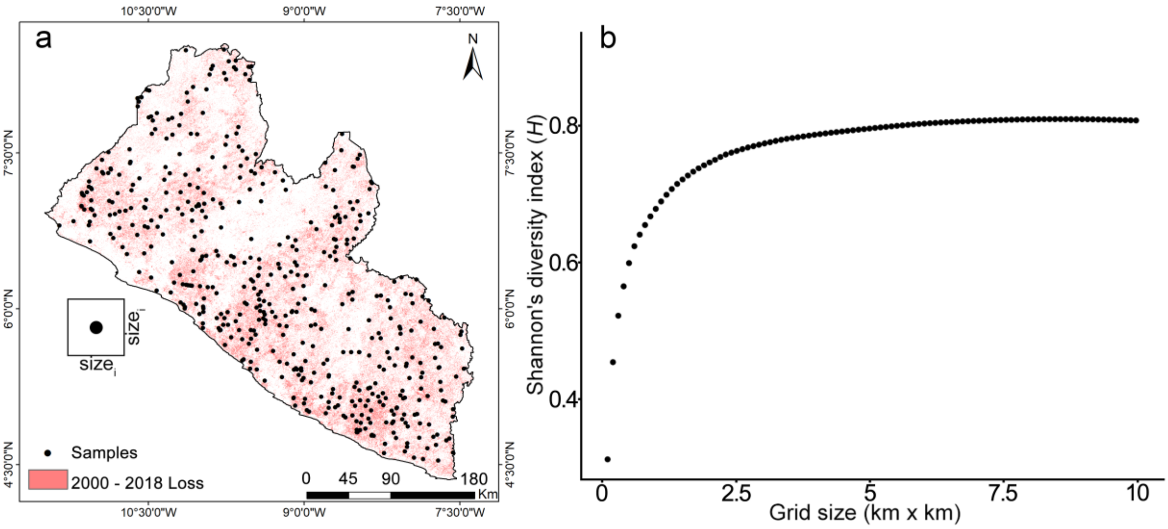
LandTrendr's spectral trajectory segmentation algorithm is a powerful tool that is capable of overcoming a problem of missing observations caused by prevailing cloud coverage common for tropical countries such as Liberia. The implementation of this algorithm in Liberia has been mostly successful with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

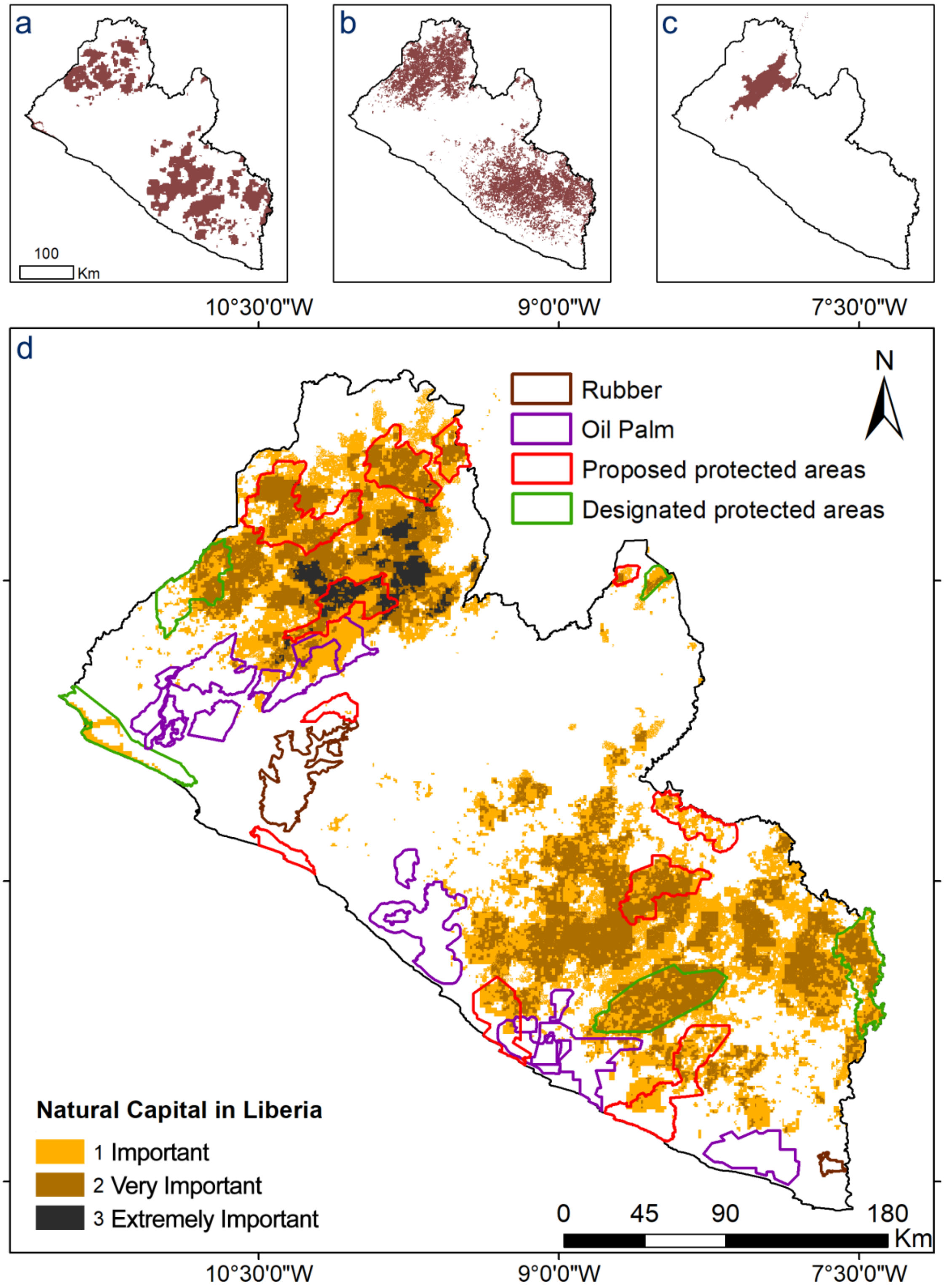
The GEDI analysis of forest structure showed the remaining of dense forests maintained average canopy height that agrees with field-measured canopy height found on the literature. Transitions from the mature dense forest class to secondary open and sparse forest classes were also reflected in the forest 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.

Supplemental Materials



Supplemental Materials Figure 1 | Landscape unit size selection. Theoretically, there is no single scale at which ecological patterns should be studied (Levin, 1992). The choice of a biologically relevant landscape unit size (i.e. resolution) can have profound impacts on model results, yet the optimal scale is not always clear (Turner, Neill, Gardner and Milne, 1989 and Zarnetske, 2019). Any ecological phenomena should be studied at their 'characteristic scale', which is the spatial and/or temporal scale at which the phenomenon principally operates (Wu, 2015). However, identifying characteristic scales, while critical, can be quite difficult. When the characteristic scale is not apparent, it can be useful to compare patterns at several points along a scale spectrum (Wiens, 1989). In this way, it is possible to identify domains of scale over which relationships do not change, or change monotonically (Wiens, 1989). Building on this theoretical background, we performed a preliminary analysis at multiple observational scales and relied on a diversity index (i.e. Shannon's diversity index (Shannon, 1948)) to provide information on where scale breaks/domains were occurring that would be empirically appropriate for assessing forest fragmentation. Shannon's index *H* accounts for both *abundance* and *evenness* of a species in a given area. In the context of this study, *abundance* is the total number of land cover classes in the landscape unit whereas *evenness* is a measure of the relative area of land cover classes within the landscape unit. The proportion of land cover class *i* relative to the total number of land cover classes (p_i) is calculated, and then multiplied by the natural logarithm of this proportion ($\ln p_i$). Finally, the resulting product is summed across land cover classes, and multiplied by -1. **a,** Stratified random sampling in Liberia where 100 grid sizes were tested at each location. **b**, Shannon's diversity index at each grid scale for the 500 locations. Final landscape unit size was selected at the inflection point or slope decrease in the *H* values curve.



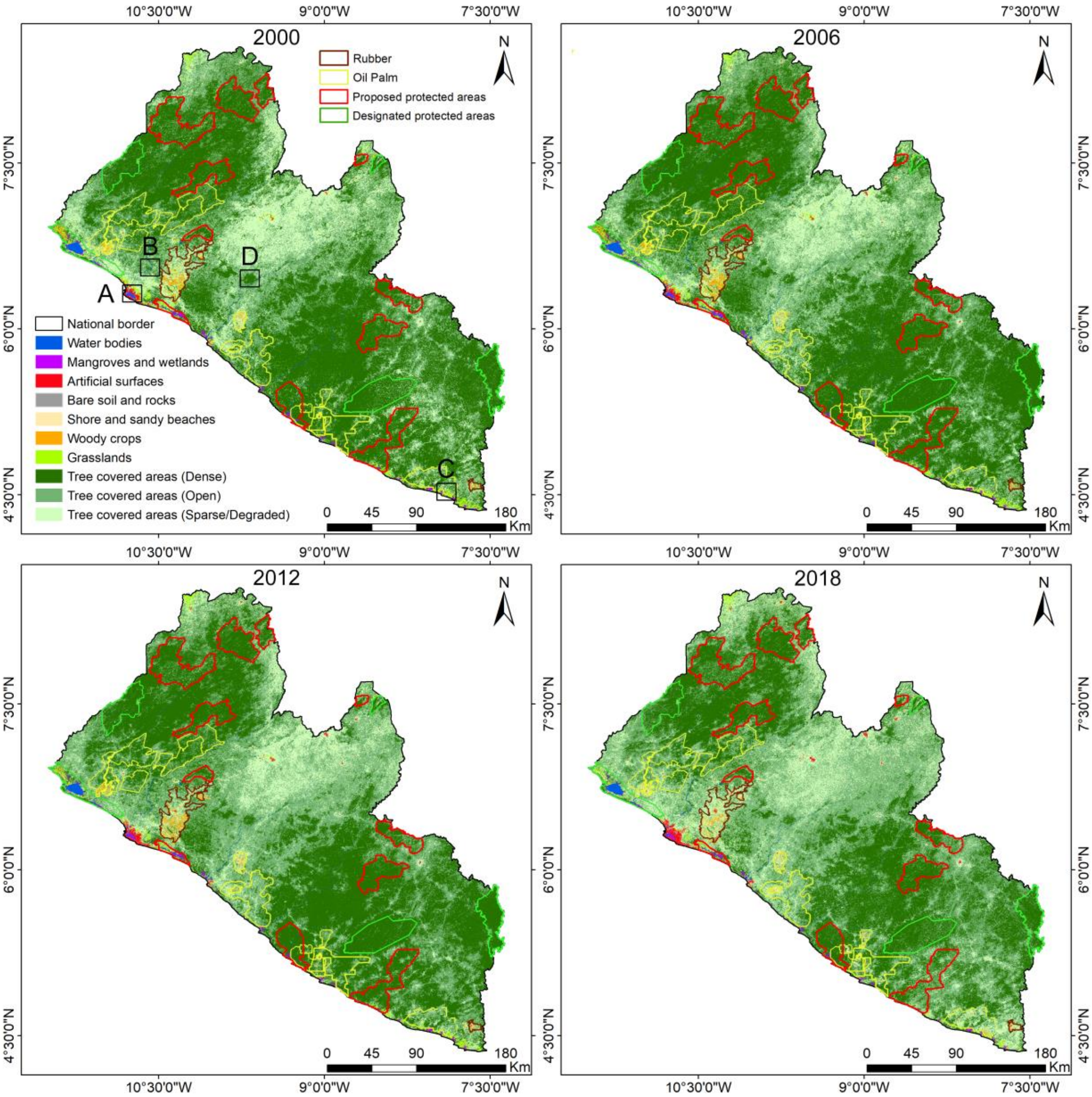
Supplemental Materials Figure 2 | The essential natural capital of forests in Liberia in 2017. The areas identified as essential for biodiversity (a), forest carbon (b) and freshwater ecosystem services (c) (Source: [35]) were overlaid (d) to highlight areas that are essential for one, two or three natural capital assets. Areas of rubber and oil palm concessions as well as designated and proposed protected areas were included for reference.

		User Interpretations											
		A	B	C	D	E	F	G	H	I	J	**Total**	UA[2]
Dataset	Water Bodies (A)	**48**	2	0	0	0	0	0	0	0	0	50	96%
	Mangroves and Wetlands (B)	5	**38**	0	0	0	0	3	4	0	0	50	76%
	Artificial Surfaces (C)	0	0	**41**	3	0	0	3	1	0	2	50	82%
	Bare soil and rock (D)	0	0	5	**25**	0	3	7	0	0	10	50	50%
	Shore and sandy beaches (E)	3	0	0	0	**46**	0	0	1	0	0	50	92%
	Woody crops (F)	0	0	1	0	0	**37**	4	4	2	2	50	74%
	Grasslands (G)	0	0	1	6	0	1	**27**	3	3	9	50	54%
	Tree Covered Areas - Dense (H)	0	3	0	0	0	0	0	**46**	1	0	50	92%
	Tree Covered Areas - Open (I)	0	0	0	1	0	0	0	1	**48**	0	50	96%
	TCA[1] (Sparse/Degraded) (J)	0	0	0	1	0	1	4	2	4	**38**	50	76%
	Column Total	56	43	48	36	46	42	48	62	58	61	**500**	
	Producer Accuracy	86.2%	100.0%	85.4%	71.8%	100.0%	88.9%	71.4%	80.3%	82.8%	67.7%		

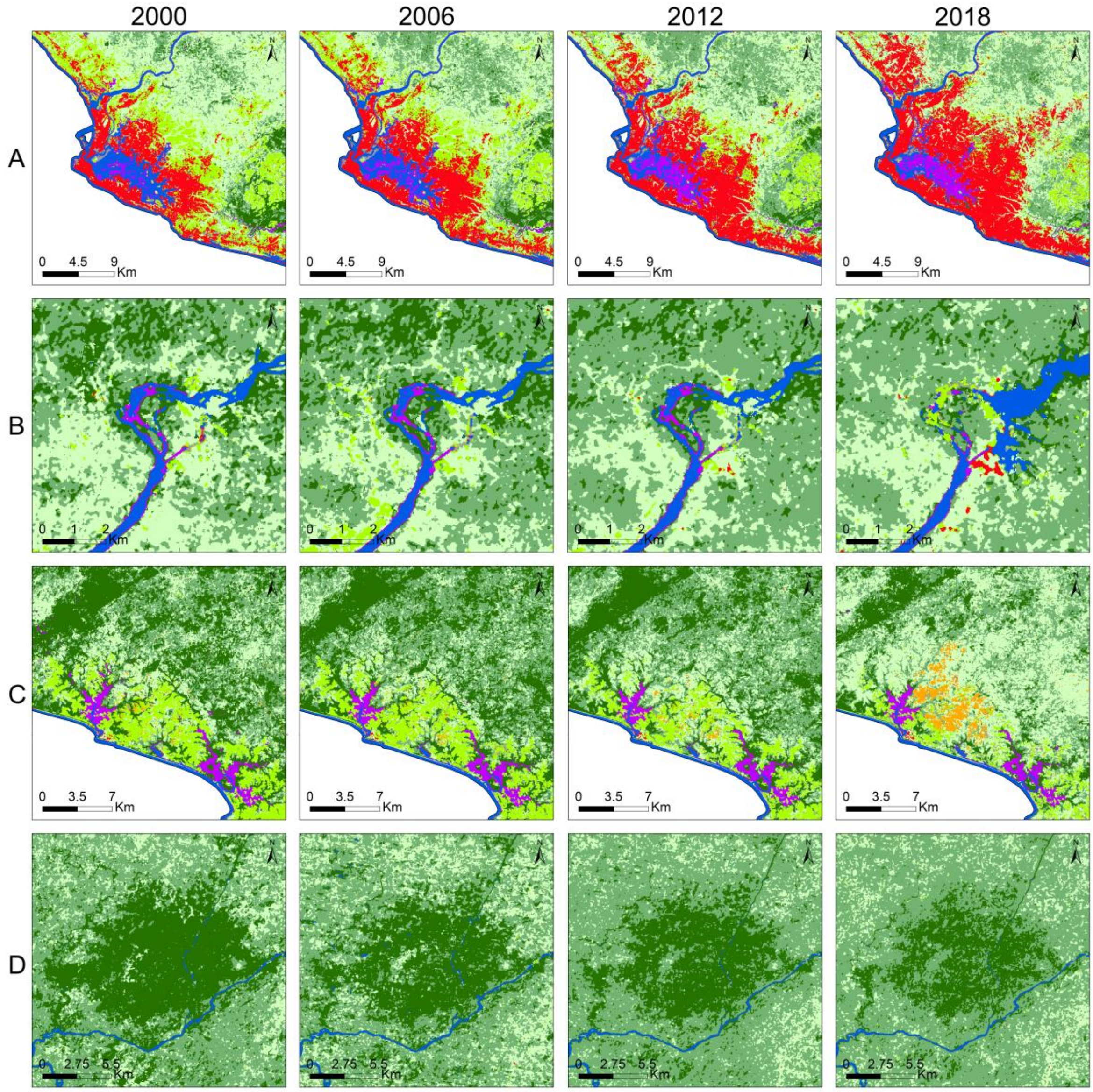
Overall Accuracy	**0.788**

[1] Tree-covered areas [2] User accuracy

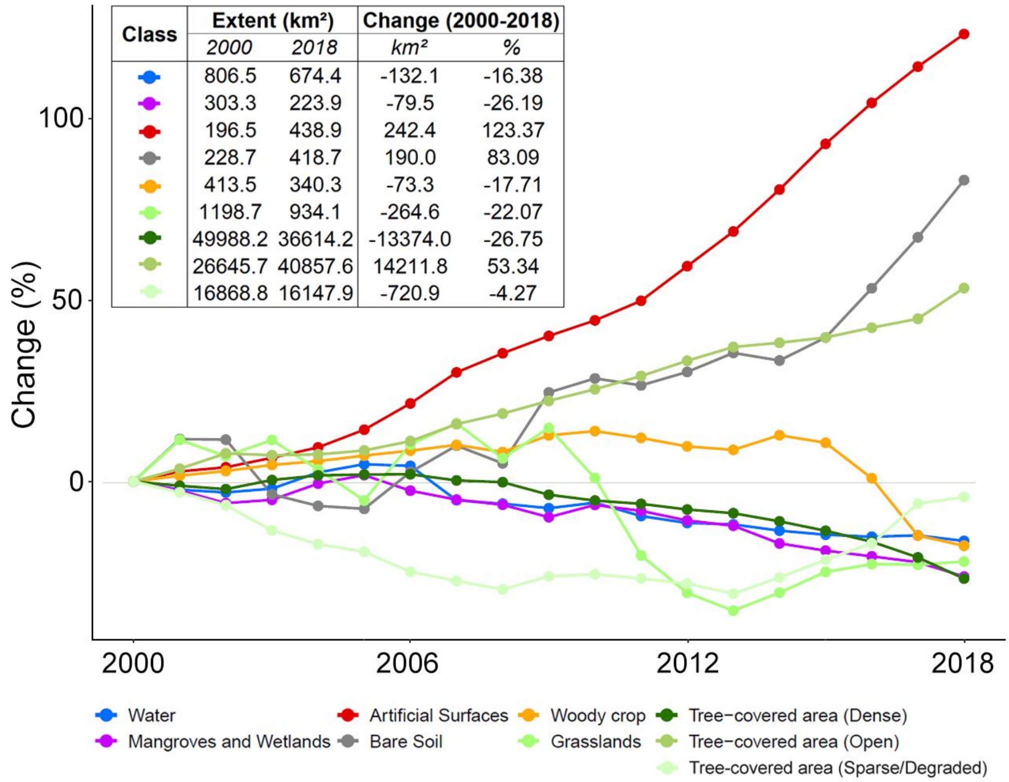
Supplemental Materials Figure 3 | Error matrix for the latest (2018) land cover map in the time series. Dense and Open forest classes, along with water bodies and shore had the highest user's accuracy among all classes.



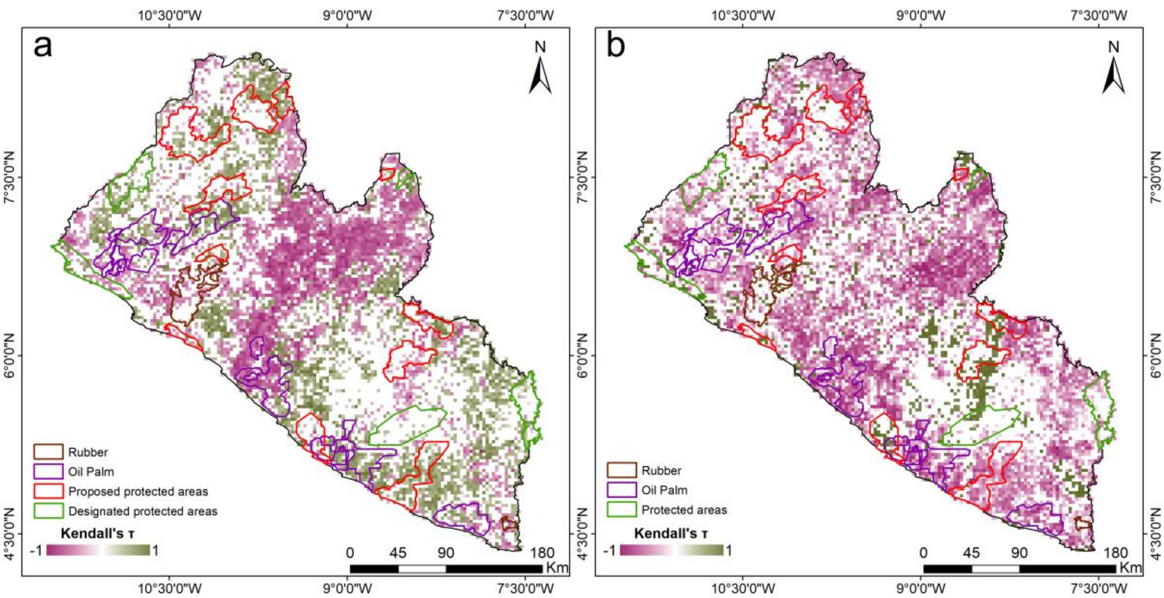
Supplemental Materials Figure 4 | Examples of LULC extent maps for the years of 2000, 2006, 2012 and 2018. Areas of rubber and oil palm concessions as well as designated and proposed protected areas were included for reference. The transition of mature dense forests to more open canopy forest classes is evident. Small scale subsets (locations A, B, C and D) with close up details are shown in Supplemental Materials Figure 5.



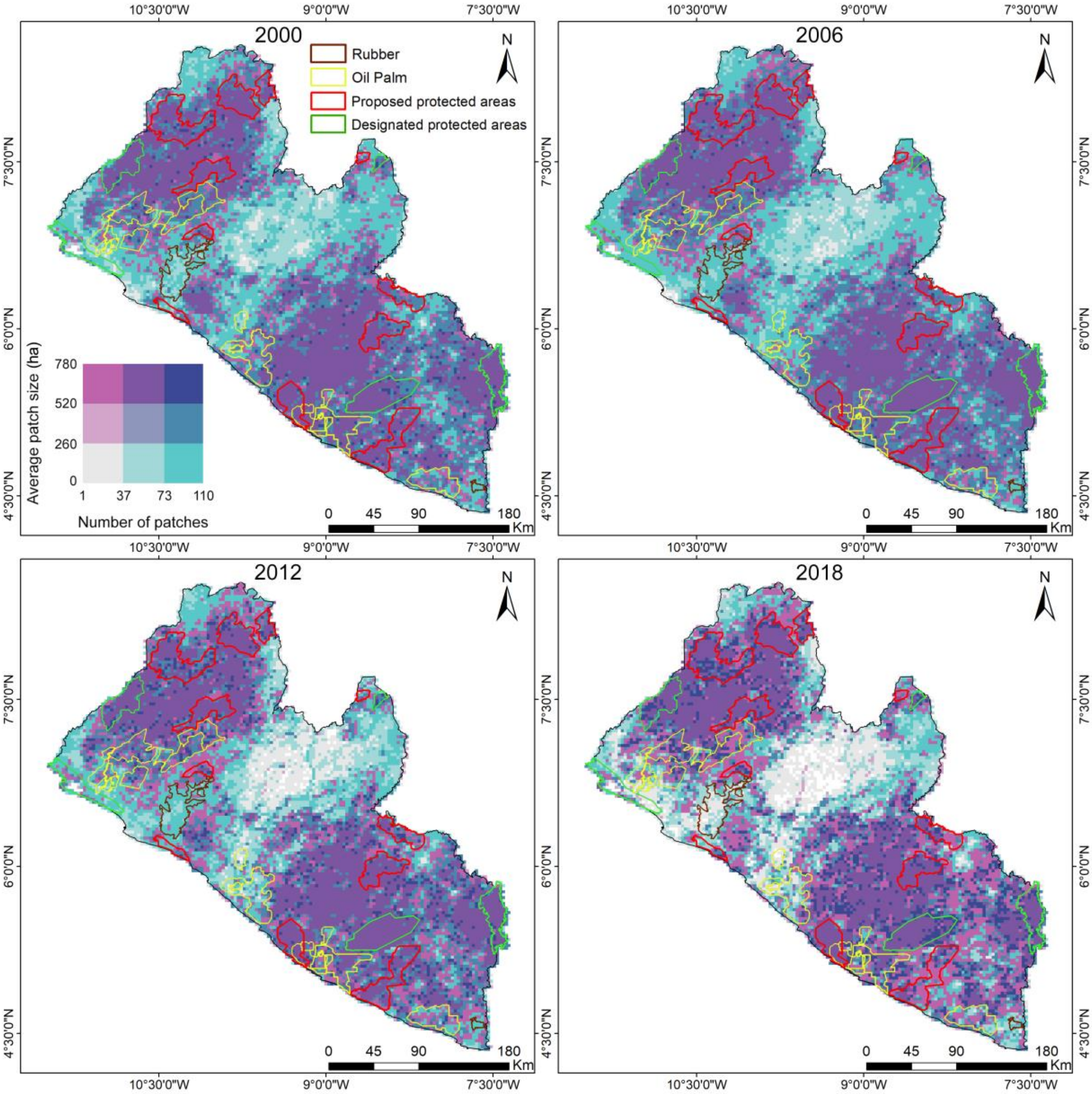
Supplemental Materials Figure 5 | Small scale subsets extracted from the LULC extent maps showing examples of change in other land cover classes. Different years are represented in the columns and different locations are represented in the rows: (A) Expansion of the capital city of Liberia, (B) construction of the Saint Paul River's hydroelectric dam in 2017/2018, (C) oil palm plantation next to mangroves, and (D) fragmentation of a patch of dense treed area and conversion to open canopy. In each location, the decrease in the extent of mature forests is also evident.



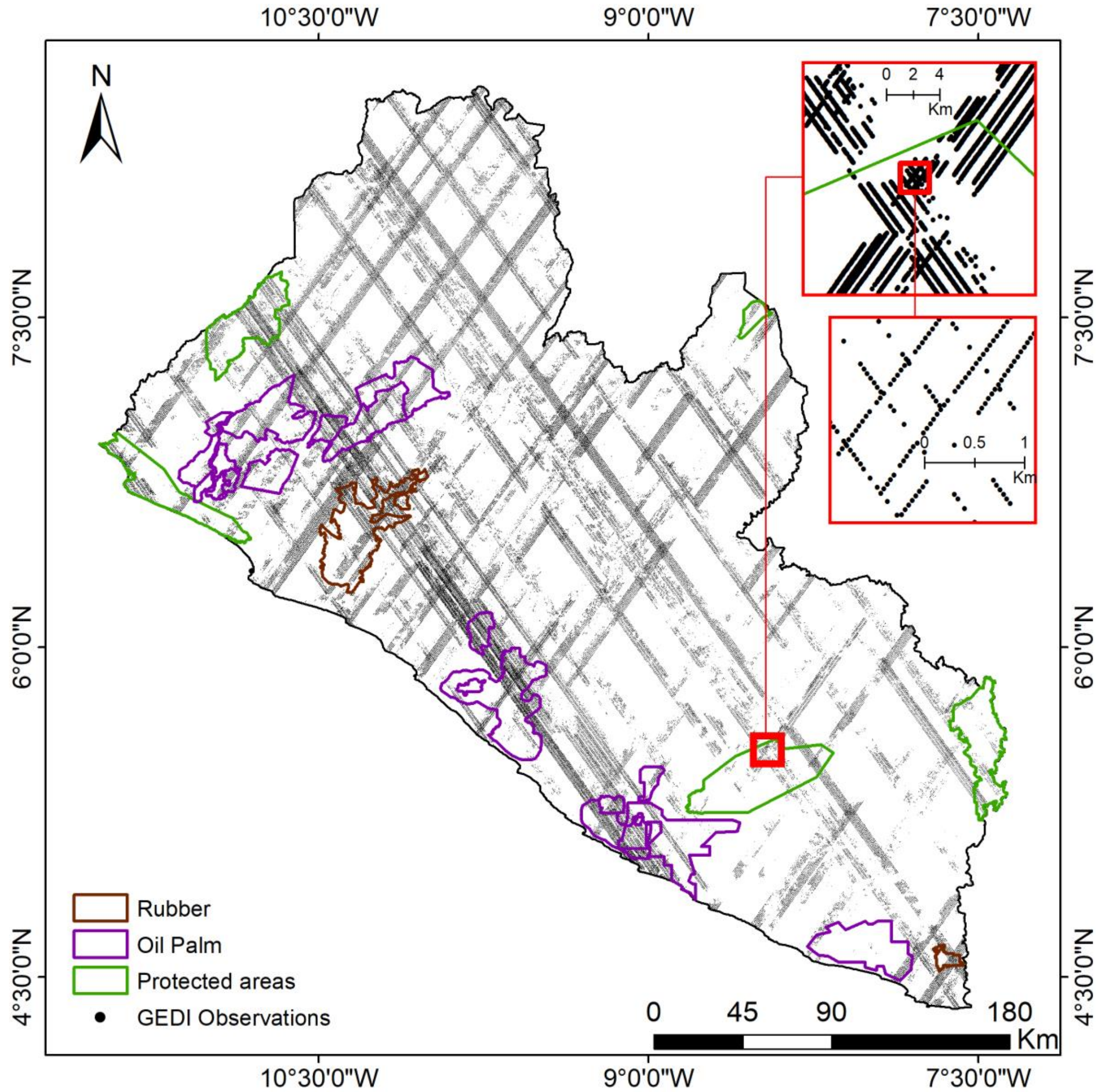
Supplemental Materials Figure 6 | Land cover change in Liberia from 2000-2018. Yearly percentage of change for the ten classes of the land cover maps in the time series.



Supplemental Materials Figure 7 | Kendall rank (tau) correlation coefficient for the trends of forest fragmentation in Liberia, 2000 - 2018. a, Strong association between the number of patches and the 19-years period is observed across Liberia in both directions (negative and positive). **b**, Average size of patches showed a more wide-spread negative Kendall's coefficient values. Areas of rubber and oil palm concessions as well as designated and proposed protected areas were included for reference.



Supplemental Materials Figure 8 | Bivariate maps depicting forest fragmentation in Liberia at selected years of the 2000-2018 time series. Number of forest patches at the landscape unit only tells half of the story. The combination of the two metrics reveal that the decreasing number of patches are due to the conversion of existing patches to other land cover areas and not by patches growing and merging into larger ones. This trend was particularly evident in central Liberia. In contrast, landscape units within protected areas showed relatively larger and more numerous mature forest fragments compared to the surroundings. Areas of rubber and oil palm concessions as well as designated and proposed protected areas were included for reference.



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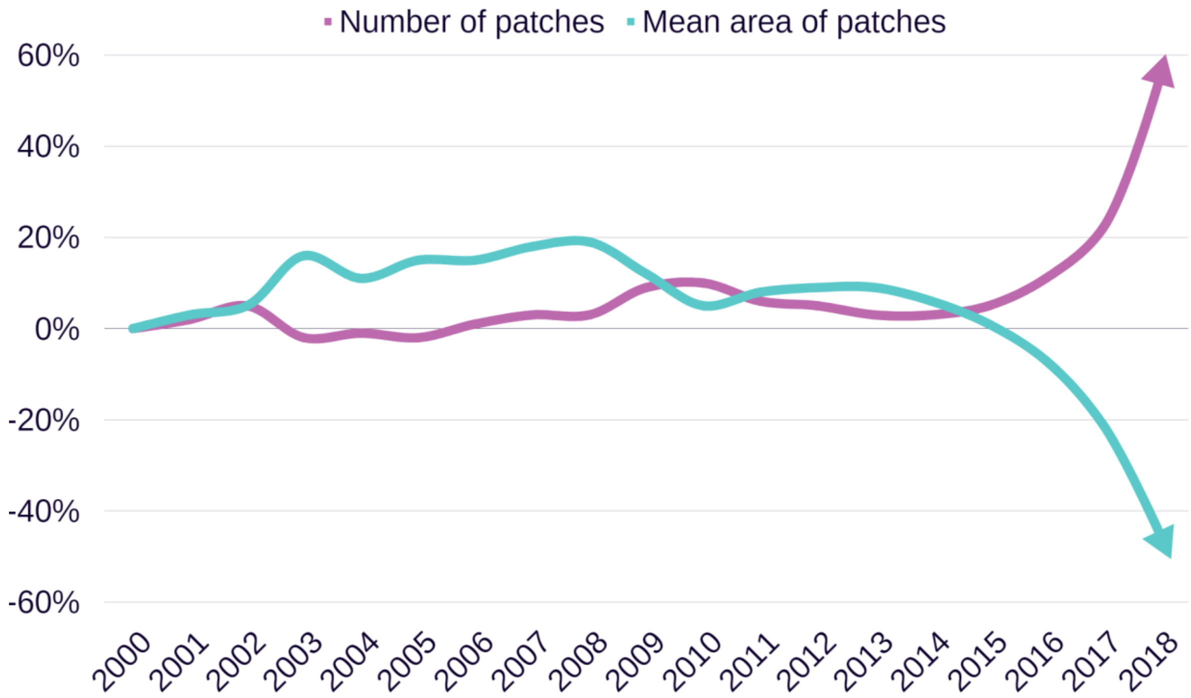
641 **Supplemental Materials Figure 9 | 25-m L2B GEDI footprints over Liberia.** GEDI canopy cover and
642 canopy height data at each footprint was used to infer about forest integrity in Liberia. Areas of interest were

added fore reference.



Supplemental Materials Figure 10 | Annual change in fragmentation metrics observed between 2000-2018. The fragmentation metrics used for the Theil-sen non-parametric regression analysis, i.e., number of forest patches (purple line) and average size of patches (light blue line) plotted side by side as percent of annual change since 2000. In 2000 we observed 93,000 forest patches with average size of 220 ha. Both metrics stayed relatively flat until 2015. From 2015 onwards we observed an exponential change both in the number of patches as well average patch size resulting in a 55% increase in the number of forest patches and 45% decrease in the average patch size.

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