Community Managed vs. Protected Forests: A Remote Sensing Workflow for Assessing Forest Conservation in Liberia (2002–2024)

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Keywords: Remote Sensing; Google Earth Engine; ArcGIS Pro; Liberia; Community Forests; Machine Learning

Abstract

This study assesses long-term forest change in Liberia’s Community Forest Management Areas for Conservation (CFMACs) and Protected Areas (PAs) from 2002 to 2024 using an integrated Landsat–Google Earth Engine (GEE) and an ArcGIS Pro workflow. Annual dry-season composites for three time periods were classified using a Random Forest model with 81.7% accuracy (Kappa = 0.781). Results show contrasting governance outcomes: CFMACs experienced modest forest gains from 2002–2014 and localized losses thereafter, while PAs exhibited larger overall gains but also greater cumulative forest loss, particularly along concession boundaries. Stability analysis revealed that PAs retained a higher proportion of Mature Forest, whereas CFMACs showed more dynamic turnover and localized regrowth. The combined GEE/ArcGIS approach provides a scalable, transparent monitoring framework and demonstrates how governance type influences forest persistence, degradation, and recovery across Liberia’s tropical landscapes.

1. Introduction

Liberia contains the largest remaining expanse of the West African Upper Guinean rainforest, a globally recognized biodiversity hotspot and major carbon sink (Myers et al., 2000; Mittermeier et al., 2011). Forests cover an estimated 6.6 million hectares in Liberia, representing approximately 69% of the country’s land area (FAO, 2020). These ecosystems support local livelihoods, provide critical ecosystem services, and play a significant role in international climate mitigation commitments. After much civil conflict, the Liberian government adopted new legal frameworks to regulate forest governance. Protected Areas were designated beginning in the early 2000s, with Sapo National Park as the flagship example, later joined by additional reserves. In parallel, the National Forestry Reform Law of 2006 and the Community Rights Law of 2009 introduced governed regime designations such as Community Forest Management Areas for Conservation (CFMACs), granting local communities legal rights to manage forest resources. Collectively, these designations now cover nearly one-third of Liberia’s territory.

Despite these legal reforms and policy developments, deforestation pressures persist due to agricultural expansion (including recent, rapid growth of cacao farming), timber production (both legal and illegal), and mining activities (Bayol et al., 2012; Bera et al., 2021; Boubekraoui et al., 2024; Ruf and Galo, 2024). The effectiveness of governance regimes is contested: while protected areas are often assumed to ensure stronger conservation outcomes, they may be undermined by weak enforcement or concession overlap and illegal activities (Mukpo and Giahyue, 2020; Kamara, 2022). Conversely, CFMACs remain under-studied, though evidence suggests that local management may produce more sustainable outcomes under certain conditions.

Remote sensing offers an objective and replicable approach to evaluate the performance of these forest governance models. Multi-temporal Landsat data enable tracking of long-term forest cover change, while cloud-based platforms such as Google Earth Engine (GEE) allow scalable classification workflows (Hansen et al., 2013; Achard & Hansen, 2013; Hansen et al., 2000; Townshend et al., 2012). While datasets such as those from Global Forest Watch (GFW) provide valuable global baselines of forest loss and gain, they are limited in distinguishing specific land cover classes or capturing localized recovery patterns relevant to Liberia’s CFMACs and Protected Areas. Therefore, a customized classification approach was developed to map Liberian forest and non-forest transitions at finer thematic detail and assess forest dynamics under each governance regime. Coupled with ArcGIS Pro’s land change analysis tools, cloud-based methods provide robust spatial evidence for comparing land cover dynamics across governance regimes.
The purpose of this research is to:

1. Quantify land cover change in Liberia between 2002, 2004, and 2024 using GEE-based machine learning classification of a time series of Landsat imagery.
2. Determine if forest types and health in CFMACs managed for conservation are comparable to conditions in Protected Areas.
3. Evaluate the utility of integrated GEE and ArcGIS Pro workflows for assessing Liberia’s national forest monitoring policy.

2. Study Area and Data

2.1 Study Area

Liberia is located on the West African coast between Sierra Leone, Guinea, and Côte d’Ivoire, with a land area of approximately 111,370 km². The country’s forests represent part of the Upper Guinean rainforest, which is among the most threatened tropical ecosystems globally (Myers et al., 2000). Elevations range from lowland coastal plains to mid-altitude hills, influencing vegetation patterns and land use. The country has a humid tropical climate with high temperatures averaging 31° C throughout the year, average annual precipitation of 3,128 mm and a rainy season that lasts from May to October (Weatherandclimate, 2025).

This contribution has been peer-reviewed. The double-blind peer-review was conducted on the basis of the full paper.
https://doi.org/10.5194/isprs-annals-XI-3-2026-501-2026

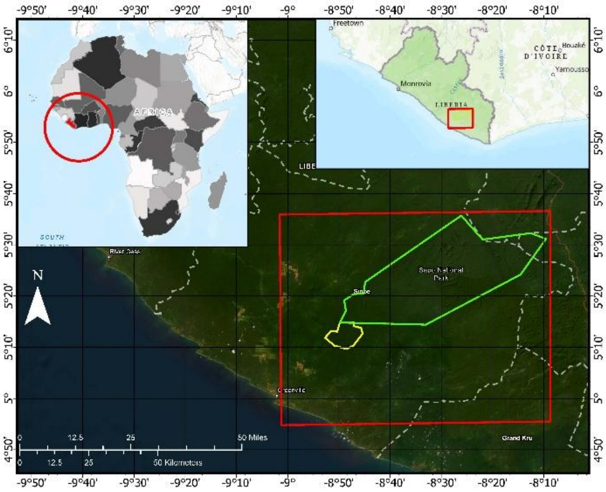

Figure 1. Study area map of Liberia showing the Community Forest Management Area for Conservation (CFMAC) adjacent to Sapo National Park outlined in yellow and the Sapo National Park Protected Area (PA) outlined in green (Forestry Development Authority, 2023).

Two principal governance regimes shape forest management: 1) Protected Areas (PAs) established in the early 2000s, with Sapo National Park being Liberia’s largest and oldest national park; and 2) Community Forest Management Areas for Conservation (CFMACs) legalized through the National Forestry Reform Law (2006) and Community Rights Law (2009) (Tropenbos International, 2019). These frameworks were designed to balance conservation, local livelihoods, and commercial interests. The CFMAC analysed in this study lies adjacent to the western boundary of Sapo National Park in southeastern Liberia. It encompasses approximately 82.04 km², while the Sapo PA covers roughly 1,496.84 km². The study area location and governance boundaries are illustrated in Figure 1.

2.2 Concessions Data and Site Selection

Liberia’s forest landscapes are heavily influenced by external pressures such as logging, mining, and agricultural concessions. To ensure that our analysis captured these dynamics, we used data from the National Concessions Portal, developed on the Landfolio platform as part of Liberia’s Concessions Information Management System (CIMS), (USAID, 2014). This publicly accessible portal provides official concession boundaries across sectors including forestry, mining, and agriculture (Spatial Dimension, 2016).

Concession boundaries were intersected with CFMAC and Protected Area polygons provided by the Forestry Development Authority (FDA), (Forestry Development Authority, 2023). This allowed us to identify sites where community and state-managed forests overlap with concession zones. Selection of study areas prioritized the following characteristics.

- CFMACs adjacent to logging concessions, to test resilience under community management.
- Protected Areas with nearby concessions, to evaluate enforcement under state management.
- Regions that experienced consistent Landsat coverage between 2002 and 2024, minimizing cloud contamination.

This approach ensured a balanced comparison of governance regimes under similar external pressures.

2.3 Remote Sensing

Given Liberia’s tropical climate and high degree of cloud cover, annual dry-season surface reflectance composite images were created for the years 2002, 2014 and 2024 using Google Earth Engine and satellite imagery from Landsat 5 Thematic Mapper (TM), Landsat Enhanced Thematic Mapper Plus (ETM+) and Landsat 8 Operational Land Imager (OLI) multispectral sensors, respectively (Global Forest Watch, 2024). The Landsat imagery at 30-m spatial resolution were used for forest and general land use/land cover (LULC) classification with 3-m PlanetScope (2022-2024) and the high resolution Esri ArcGIS basemap imagery for independent validation, manual interpretation and accuracy assessment. Additional ancillary data included OpenStreetMap road, waterways, and settlement data for context and a map of Liberia’s Protected Areas and CFMACs from the Liberian Forest Development Authority (FDA). Concession boundaries from the Landfolio Concessions Portal (Spatial Dimension, 2016) were obtained to understand the potential impacts of surrounding mining operations on deforestation.

3. Methodology

To achieve the study objectives, we designed a two-stage geospatial workflow. First, annual dry season Landsat composites for the years 2002, 2004, and 2024 were created and Random Forest LULC classification was performed in Google Earth Engine. Second, classified LULC raster files were exported to ArcGIS Pro where land change detection analyses were conducted to quantify landscape transitions and compare governance regimes, consistent with Landsat-based global forest monitoring efforts (Townshend et al., 2012; Hansen et al., 2013). The workflow was designed to be replicable, scalable, and aligned with Liberia’s existing forest monitoring frameworks.

3.1 Image Processing in Google Earth Engine

The online image processing platform, Google Earth Engine, was used to perform decadal satellite image selection, LULC classification using Machine Learning and the derivation of vegetation indices indicating forest type and health. The tropical monsoon climate of the Liberian study area required multi-temporal composite satellite images be created using 30-m Landsat Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+) and Operational Land Imager (OLI) data. Image composites selecting best cloud-free pixels from multiple months in 2002, 2014 and 2024 documented LULC and the decadal status of forest cover over the past 20 years. The spectral index, Normalized Difference Vegetation Index (NDVI), was derived for each date as a predictor variable to improve land cover discrimination.

A Random Forest supervised classification approach was applied in Google Earth Engine, building on established classification tree approaches in global forest mapping (Hansen et al., 2000). Training and validation data of approximately 2,000 sample areas were manually interpreted and digitized to represent major land cover and forest types of mature forest, secondary forest, agriculture, developed settlements, bare land and water. The Random Forest model was trained with 70 percent of the sample pixels and 30 percent were reserved to test the model’s classification accuracy. After approximately 20 iterations, the classification results were deemed to be over 82 percent accurate. The LULC raster layers for the three dates, along with shapefiles for CFMACs, federal Protected Areas and mining concession boundaries were imported to ArcGIS Pro for change analysis.

3.2 Change Detection in ArcGIS Pro

The ArcGIS Pro Change Detection Wizard was used to analyse pixel-based transitions between LULC classes to quantify forest loss and gain over time. This tool compares the LULC classes assigned to each grid cell of LULC rasters of two different dates. The user decides which classes they are most interested in examining for change. We focused on forest pixels that changed to other LULC classes, pixels of other classes that changed to forest and forest pixels that remained forest. In this way, the wizard identified mature and secondary forest gains and losses, land use transitions and stable forest coverage for 2002 to 2014, 2014 to 2024 and over all 2002 to 2024 time periods.

A separate accuracy assessment was conducted to independently evaluate the most recent LULC classification of 2024. A total of 500 random points stratified equally by LULC classification were generated and superimposed on a false-color display of a 3.7-m PlanetScope image acquired in December, 2024. Two interpreters independently examined each point to determine the LULC and create a confusion matrix indicating the observed (interpreted) vs. predicted (Random Forest classified) agreements and errors.

4. Total Area of LULC in 2002, 2014 and 2024 and Accuracy Assessment Results

4.1 Image Processing in Google Earth Engine

An example of Landsat OLI satellite imagery and the resulting LULC classification for a CFMAC and PA in southern Liberia is shown in Figure 2. The results of the accuracy assessment of the Random Forest classification of LULC in the 3,700 km² study area encompassing the Sapo Protected Area and the adjacent CFMAC are presented in Table 1. The Random Forest model achieved an overall accuracy of 81.7 % and a Kappa statistic of 0.78.

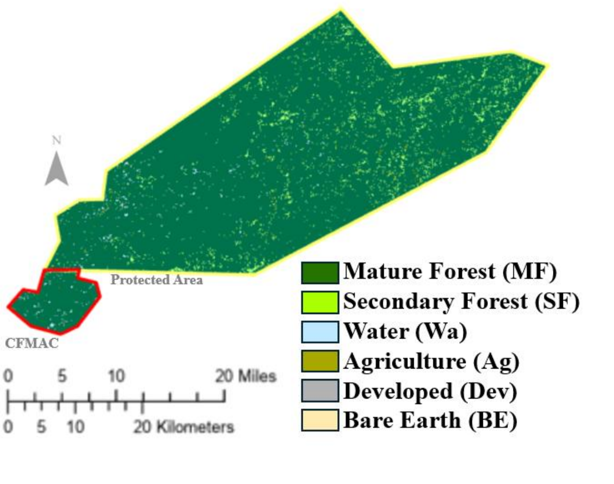

Figure 2. Example of LULC classification for a CFMAC and PA in southern Liberia from 2024.

LULC Class	MF	SF	Ag	Dev	BE	Wa	Total Samples	User's Accuracy
MF	78	1	0	0	0	0	79	0.99
SF	7	73	1	0	2	0	83	0.88
Ag	12	16	52	0	2	1	83	0.63
Dev	2	0	0	80	1	0	83	0.96
BE	9	11	0	0	63	0	83	0.76
Wa	17	6	2	0	0	57	82	0.70
Total Samples	125	107	55	80	68	58	493	
Producer's Accuracy	0.62	0.68	0.95	1.00	0.93	0.98		
Overall Accuracy: 0.817 (81.7%), Kappa Coefficient: 0.781								

Table 1. Accuracy Assessment Confusion matrix showing agreement between classified (columns) and reference (rows) samples for the 2024 land cover classification. Classes are Mature Forest (MF), Secondary Forest (SF), Agriculture (Ag), Developed (Dev), Bare Earth (BE) and Water (Wa).

4.2 Trends in Forest Cover Gains and Losses

Between 2002 and 2024, both CFMACs and Protected Areas experienced measurable changes in mature and secondary forest cover. Within the study area, the analysis revealed a pattern of forest gain in the early 2000s (2002–2014) followed by increasing forest loss during the second decade from 2014 to 2024. As shown in Table 2, forest gains in CFMACs peaked during 2002–2014 but slowed dramatically in the subsequent decade, while losses increased slightly.

Time Period	CFMAC Gain (km²)	CFMAC Loss (km²)	PA Gain (km²)	PA Loss (km²)	CFMAC Net (km²)	PA Net (km²)
2002-2014	2.69	0.00	15.67	3.38	2.69	12.29
2014-2024	0.08	0.86	0.87	8.32	-0.79	-7.45
2002-2024	2.66	1.11	14.59	8.31	1.55	6.28

Table 2. Forest area gain, loss and net change in Community Forest Management Conservation Areas (CFMACs) and Protected Areas (PAs) in Liberia, 2002–2024.

Forest gain was highest in the CFMACs between 2002 and 2014, with 2.69 km² gained (~3.3% of CFMAC area) (Figure 3). Gains slowed considerably from 2014 to 2024 to ~0.1% or 0.08 km². The gain in forest cover within PAs was larger in absolute terms, reaching 15.7 km² (1.05%) from 2002–2014, but declined to 0.9 km² (0.06%) from 2014–2024 (Figure 4). Over the full study period (2002–2024), cumulative gain in PAs was 14.59 km² (~1.0%), compared to 2.66 km² (~3.2%) in CFMACs.

Forest losses in CFMACs were greatest in the 2014–2024 period, when 0.86 km² (~1.1%) of forest cover was lost, compared to negligible loss in the previous decade. Cumulatively, CFMACs lost 1.11 km² (~1.35%) of forest by 2024. Forest loss in PAs, however, was 3.38 km² (0.23%) from 2002–2014 and 8.32 km² (0.56%) from 2014–2024, totalling 8.31 km² (~0.55%) over the full 20-year period. Protected Areas, thus, exhibited higher total forest loss than CFMACs, particularly in later years.

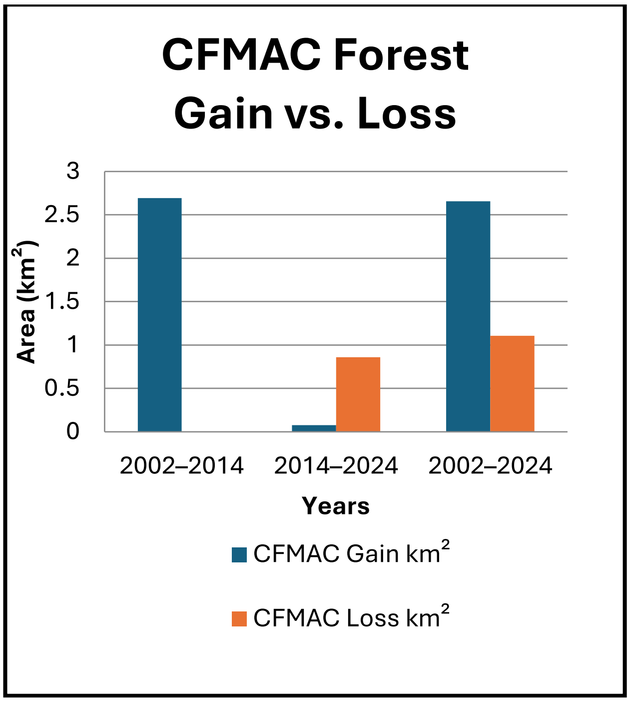

Figure 3. Forest gain and loss in Community Forest Management Area for Conservation (CFMACs) for three intervals: 2002–2014, 2014–2024, and 2002–2024.

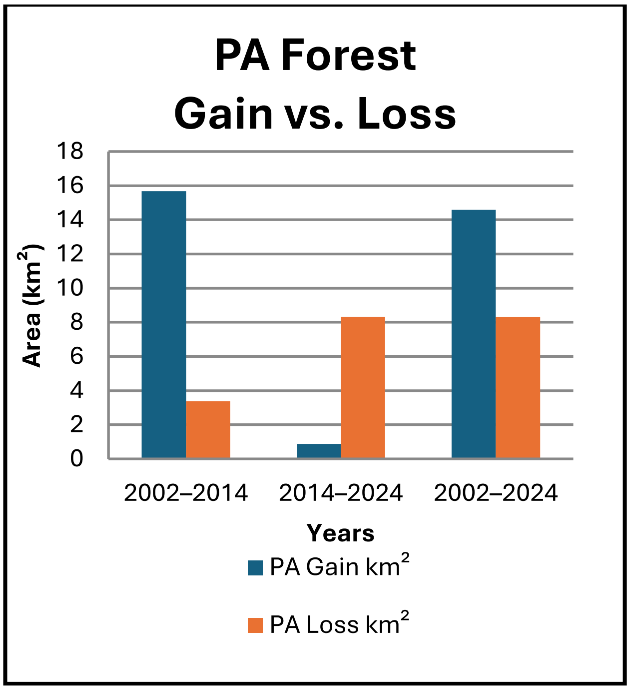

Figure 4. Forest gain and loss in Protected Areas (PAs) for three intervals: 2002–2014, 2014–2024, and 2002–2024.

4.3 Trends in Forest Stability

Stability analysis highlighted Mature and Secondary Forest areas that remained intact during the time periods of forest change assessment. Some important contrasts were observed in CFMACs. Mature Forest (MF) stability declined from 79.76% (2002–2014) to 59.97% (2014–2024), with 68.19% stability across the full period (Table 3). In PAs, MF stability was consistently higher, at 86.16% (2002–2014) and 84.12% (2014–2024), with a cumulative stability of 87.31% from 2002–2024.

For Secondary Forests (SF), both CFMACs and PAs showed very low SF stability, typically below 1%, except in CFMACs during 2014–2024 (6.06%). This suggests high turnover of Secondary Forest within areas under both types of protection, with frequent transitions to other land uses such as Ag, Dev, and BE. The stability analysis demonstrates that PAs retained a higher proportion of Mature Forest compared to CFMACs, although both declined in later years (Figure 5).

Protection and Forest Type	Time Period	Stable Area (km²)	% Stable Area
CFMAC MF	2002-2014	65.43	79.76
	2014-2024	49.20	59.97
	2002-2024	55.94	68.19
CFMAC SF	2002-2014	0.01	0.01
	2014-2024	4.97	6.06
	2002-2024	0.04	0.05
PA MF	2002-2014	1289.70	86.16
	2014-2024	1259.21	84.12
	2002-2024	1306.90	87.31
PA SF	2002-2014	3.63	0.24
	2014-2024	12.14	0.81
	2002-2024	3.35	0.22

Table 3. Stability of Mature Forest (MF) and Secondary Forest (SF) in CFMACs and PAs across three time periods (2002–2024).

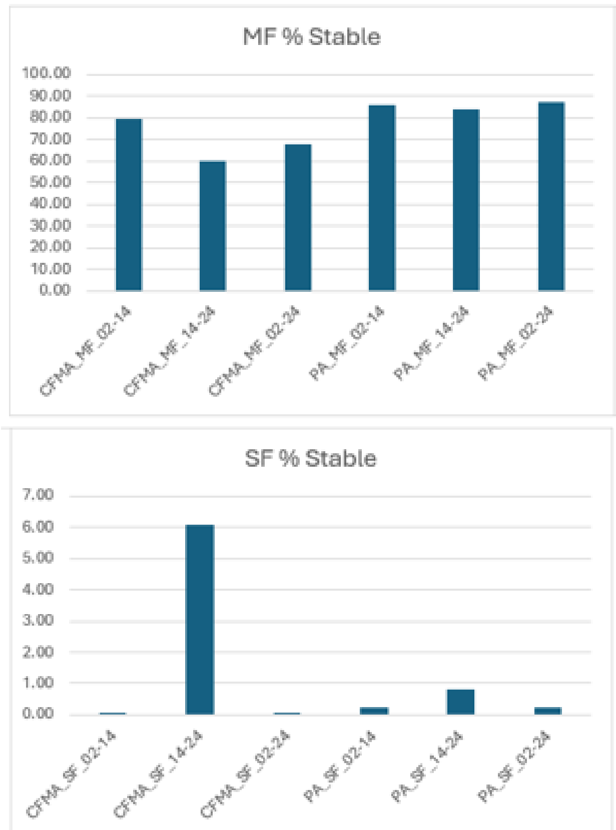

Figure 5. Stability of Mature Forest (MF) and Secondary Forest (SF) in CFMACs and PAs across three time periods.

5. Discussion of Forest Trends Related to Governance Effectiveness

The results of this study highlight important differences between forest changes in two protection governances in Liberia, namely, Community Forest Management Areas for Conservation (CFMACs) and Protected Areas (PAs). An independent accuracy assessment of the 2024 Random Forest classification using over 400 randomly selected sample locations overlaid on a Planet satellite image of high spatial resolution resulted in an overall classification accuracy of 81.7% with Kappa Coefficient of 0.781. This demonstrated high confidence in the classification. It should be noted that while User Accuracy was high for mapping Mature Forest (MF) (98.7%) and Secondary Forest (SF) (88.0%) there was confusion between MF and Agriculture due to oil palm plantations being classified as forest and forest shadow being classified as Water. Agriculture had the lowest User Accuracy (62.7%) due to confusion with both MF and SF.

Analysis of stable forest cover revealed that PAs consistently retained a higher share of Mature Forest (MF), with stability rates above 84% throughout the study period (See Figure 5). By comparison, stable forests in CFMACs declined from nearly 80% MF in 2002–2014 to 60% in 2014–2024. This suggests that while community governance allowed for some regrowth (notably Secondary Forest expansion), forests also experienced higher turnover and more frequent transitions between land uses. The contrast underscores a key trade-off. PAs appear to be more effective at maintaining mature core forests, while CFMACs provide opportunities for regeneration, but are more dynamic.
Spatial overlays with data from the Liberian National Concessions Portal showed that forest loss clustered near mining and agricultural concession zones, regardless of governance regime. However, the spatial patterns of change diverged. CFMACs showed mosaic patterns of localized clearing surrounded by intact cores, reflecting smallholder agricultural expansion and shifting cultivation. PAs, on the other hand, exhibited edge-driven degradation, with continuous loss along concession boundaries.

These findings suggest that while concessions impact both governance regimes, community-managed areas may buffer against complete degradation by maintaining forest patches, whereas PAs may be subject to variable enforcement and external pressures (Spatial Dimension, 2016). This information may be used to assess policy and encourage enforcement in PAs.

The observed patterns of forest change and stable forest cover over time may be interpreted to have implications for forest governance and policy in Liberia. First, Protected Areas are not immune to degradation. Despite higher stability, PAs experienced significant loss in later years, suggesting the adequacy of enforcement and concession oversight should be examined. While the area of stable Mature Forests in CFMAC landscapes decreased slightly in the second decade, these areas exhibited higher regrowth and relative forest gain, suggesting a role for participatory management in supporting forest restoration. An integrated monitoring system such as the workflow shown here is essential for assessing the effectiveness of forest protection governances. The GEE–ArcGIS Pro workflow provides a replicable framework for national monitoring, complementing Liberia’s existing Concessions Information Management System.

These findings reinforce the importance of governance approaches that combine strict protection with community rights, supported by transparent concession oversight and remote sensing-based monitoring. Our results also align with calls from SDI (2020) for stronger community capacity-building and independent monitoring of CFMAC outcomes.

6. Summary and Conclusions

This study applied a time series of remotely sensed Earth observation satellite data and an integrated Google Earth Engine (GEE) and ArcGIS Pro workflow to evaluate long-term forest cover change in Liberia over a 20-year period between 2002, 2014, and 2024. By comparing Community Forest Management Areas for Conservation (CFMACs) with Protected Areas (PAs), and incorporating concession boundaries from Liberia’s National Concessions Portal, we identified governance-specific patterns of forest gain, loss, and stability.

An independent accuracy assessment of the 2024 Random Forest classification using a Planet satellite image of high spatial resolution resulted in an overall classification accuracy of 81.7% with Kappa Coefficient of 0.781, demonstrating high confidence in the classification. In particular, the User Accuracy for mapping Mature Forest (MF) was 98.7% correct and Secondary Forest (SF) accuracy, 88.0%. Some confusion between MF and Agriculture was due to oil palm plantations being classified as forest and classified Water being shadow from the large crowns of MF.

Gains in forest area in both the CFMAC and PA were greatest during the early period between 2002 and 2014, but slowed considerably in subsequent years. In contrast, forest losses intensified between 2014 and 2024, particularly within the PA. Although the PA retained higher levels of mature forest stability overall, this area still experienced notable degradation potentially due to the location of adjacent concessions for mining and agriculture. The CFMAC exhibited greater forest turnover, reflecting a balance of modest gains and losses, but with declining stability over time.

Methodologically, this study highlights the value of scalable remote sensing workflows that combine cloud-based satellite retrieval and machine learning analysis with ArcGIS Pro change detection for long-term national forest monitoring. Such approaches can strengthen Liberia’s capacity to meet international reporting obligations and inform its stakeholders, while providing replicable models for other tropical forest nations. Future work will expand the study area within Liberia to determine if results from the largest CFMAC and PA are representative of national trends. We will also explore texture and pattern analysis to distinguish oil palm plantations from natural forest and refine training data to decrease confusion between water and shadow in mature forests. Finally, socio-economic factors and enforcement policies will be assessed to explore drivers of change related to protection and use of Liberian tropical forests.

Acknowledgements

The authors gratefully acknowledge support from the School of Public and International Affairs and the Center for Geospatial Research at the University of Georgia for funding this research, along with colleagues who contributed to the geospatial analysis, remote sensing workflows, and review of early project materials.

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