Southeast US Climate II

Leveraging Earth Observations to Estimate Carbon Dioxide Emissions from Forest Cover Loss in Alabama and Tennessee

 **Technical Report**

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# 1. Abstract

The balancing of atmospheric carbon dioxide (CO2) sources and sinks is fundamental to curbing climate change. Forests draw CO2 from the atmosphere and accumulate carbon in tree biomass and soil over time, but forest loss releases the carbon stored in aboveground biomass (AGB) back to the atmosphere. This project assessed the feasibility of using different Earth observations to quantify CO2 emissions from forest cover loss across Alabama and Tennessee. The team generated four maps of stable forest and forest cover loss from 2016 through either 2019, 2021, or 2022, using data from Landsat 5 Thematic Mapper, Landsat 7 Enhanced Thematic Mapper Plus, Landsat 8 Operational Land Imager, and open-source land cover datasets, and validated the maps using Sentinel-2 satellite imagery. The Global Ecosystem Dynamics Investigation (GEDI) and Advanced Topographic Laser Altimeter System satellite light detection and ranging instruments measured tree canopy height, yielding estimates of AGB across the study area. The team calculated average annual CO2 emissions from forest cover loss, based on forest loss area and average AGB density of forest land per county. Validation showed that emissions calculated using the National Land Cover Database for forest loss and GEDI for AGB density were most accurate. The team’s partners — the Land Trust of North Alabama, Alabama Forestry Commission, American Forest Foundation, and Tennessee Department of Environment and Conservation’s Division of Air Pollution Control and Division of Water Resources — can compare these remote sensing results against existing ground-based observations to help inform where to focus forest management resources to minimize CO2 emissions from forest loss.

**Key Terms**

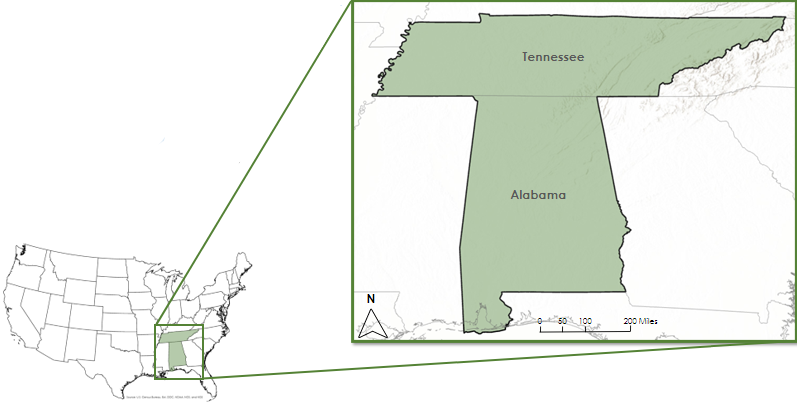
Forest loss, aboveground biomass, carbon emissions, Landsat, GEDI, ATLAS, Alabama, Tennessee

# 2. Introduction

***2.1 Background Information***

The balancing of atmospheric CO2 sources and sinks is fundamental to curbing climate change. Forests are the single largest carbon sink in the United States, offsetting more than 15% of the country’s CO2 emissions in 2021 (U.S. Environmental Protection Agency, 2023). Trees draw carbon from the atmosphere as they grow, accumulating it in their biomass; they then transfer that carbon to dead wood, litter, and soil, or release it to the atmosphere through decomposition or combustion (Domke et al., 2021). The conversion of forest land to non-forest land disrupts this cycle and releases the forest’s carbon stock. Forest loss removes the ability of the land to sequester carbon, and instead releases carbon stored in aboveground biomass (AGB) to the atmosphere. However, if these trees are harvested for wood products, that wood will continue to hold much of its carbon over the course of its use. An increase in forest cover or maturity can serve to sequester large amounts of carbon; conversely, deforestation without subsequent regrowth can be a large source of carbon emissions.

The SERVIR-CArbon Pilot (S-CAP) uses several land cover change datasets together to monitor CO2 emissions from deforestation in SERVIR’s international focus countries (Evans et al., 2022). The first term of this project adapted S-CAP procedures to the Southeastern US. The team estimated the amount of CO2 emitted from deforestation in the Talladega National Forest in Alabama by multiplying its calculated carbon stock by the area of AGB loss (Saatchi et al., 2011). Like the first term, this project deferred to each land cover dataset’s own definition of deforestation. However, this project also derived a validation component of the methodology from Olofsson et al. (2014), expanded the study area to Alabama and Tennessee (Figure 1), and incorporated regional partners. This project studied forest cover loss from 2016 to 2022. The team used data from May through September of each year, to ensure that trees had foliage to make them detectable by satellite and that minimal cloud cover was present.



*Figure 1.* Study area map of Tennessee and Alabama. Source:TIGER (U.S. Census Bureau), ESRI, CGIAR, USGS

Forests are intrinsic to the ecology of Alabama. In 2018, forests covered 71% of the state’s land area, compared to over 90% prior to European colonization in the 1500s (Chappell et al., 2020). After extensive logging in the late 19th and early 20th centuries, the total forest area increased and as of 2015, had stayed relatively stable since 1963 and in fact, was at a record high (Hartsell, 2018). Loblolly pine plantations increased from 8% of the state’s forest land in 1972 to 33% in 2015, replacing natural hardwood and softwood forest (Hartsell, 2018). Roughly 50% of Tennessee was forest land in 2016 (Oswalt et al., 2022). Much of the newly forested land in the study area, especially in west Tennessee, is abandoned agricultural land, but these small steady gains in forested areas could decrease as cities continue to grow (Oswalt et al., 2022).

***2.2 Project Partners & Objectives***

This team partnered with five organizations that are stakeholders in Alabama’s and Tennessee’s forests. The Alabama Forestry Commission is a state governmental agency that educates the public about the benefits provided by forested land, assists landowners in forest management strategies, and protects the natural resources of forested lands for economic and recreational purposes. The Land Trust of North Alabama is a non-profit organization that preserves the scenic, historic, and ecological resources in northern Alabama through conservation, advocacy, recreation, and education. The Tennessee Department of Environment and Conservation, a state governmental agency, is comprised of the Division of Air Pollution Control (DAPC) and the Division of Water Resources (DWR). The team partnered with both the DAPC and DWR. The DAPC regulates and remediates air pollution, while the DWR manages and protects water quality. The final partner organization, the American Forest Foundation, is a non-profit that connects small private forest owners to expert advice, resources, and management strategies to increase carbon sequestration on privately-owned land.

The partners have used remotely sensed data products to detect forest cover change and verify carbon accounting. This project assessed the feasibility of determining the carbon emissions from forest cover loss using the S-CAP methodologies refined by the previous DEVELOP team. This team generated forest cover loss maps using Landsat satellite data and open-source land cover datasets; validated the maps using Collect Earth Online (CEO), and estimated CO2 emissions from forest cover loss and to inform the partners’ decision-making practices.

# 3. Methodology

The team created maps of forest cover loss during the study period using four different land cover datasets (Global Forest Watch [GFW], LandTrendr, National Land Cover Database [NLCD], and Landscape Change Monitoring System [LCMS]), and validated them using CEO to determine the most accurate land cover dataset for use in the Southeastern US. They also used LiDAR data to find AGB density estimates from canopy height measurements in deforested areas and stable forests. The previous team validated these data using airborne LiDAR, the results of which this team used. Finally, this team applied a carbon stock equation using deforested area estimates from the land change maps and canopy height estimates from the LiDAR data to find changes in carbon emissions due to deforestation. This process is charted in Figure A1 and detailed further in the sections below.

***3.1 Data Acquisition***

This project estimated land cover change and canopy height with remote sensing data from six sources (Table A1). The team also produced descriptions of each, including information on data sources, spatial resolution, processing level, and how the project used the data (Table A1). The team evaluated and estimated forest cover extent and change using data from Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 Operational Land Imager (OLI), and calculated AGB density estimates using data from the Global Ecosystem Dynamics Investigation (GEDI) and ICESat-2 Ice, Cloud and Land Elevation Satellite Advanced Topographic Laser Altimetry System (ATLAS). The team used ancillary datasets (Table A2) to analyze forest cover change over time, calculate AGB density and CO2 emission estimates, and create a study area shapefile. For the Sentinel-2 reference imagery in CEO, the application has a built-in feature to directly bring in satellite imagery, so the team did not need to download Sentinel-2 data externally.

***3.2 Data Processing***

*3.2.1 Creating Four Land Change Maps*

The team accessed the LandTrendr spectral-temporal segmentation algorithm using the Google Earth Engine (GEE) application programming interface managed by the Oregon State University eMapR Lab (Kennedy et al., 2018). The LandTrendr application programming interface functions use U.S. Geological Survey (USGS) Landsat Surface Reflectance Tier 1 datasets. The team added the “users/eMapR Lab/public repository” to their GEE, then to the team repository folder, adapted a file within the “Scripts” folder called “LandTrendr Greatest Disturbance Mapping,” and set the area of interest to the study area. The LandTrendr Greatest Disturbance Mapping Tool primarily classifies land cover change based on the magnitude of change of the Landsat Normalized Burn Ratio (NBR) spectral index value from the baseline, rate of change, and the year LandTrendr detected the change. The team used NBR (Equation 1; García & Caselles, 1991) since Kennedy, Yang, & Cohen (2010) identified the index as the most effective one to detect forest disturbances using Landsat satellite data.

NBR = (1)

The team reduced noise in the analysis by using a high-magnitude threshold classifier, which increased the accuracy of loss detection. The team filtered the year of interest to analyze events within the study period (2016–2022). After exporting the LandTrendr output based on these parameters, this project used the GFW 2000 forest cover layer to clip LandTrendr-classified disturbance events to established forest cover to ensure LandTrendr did not select disturbance events outside of forested areas. The team isolated sections of the study area highlighted by the LandTrendr algorithm to create maps of forest cover lost throughout the study period, forest that was stable in 2000 and at the start of the study period, and areas of non-forest at the start of the study period.

The team also detected forest cover loss using the GFW data, a preprocessed dataset of 30-m resolution Landsat Tier 1 Top of Atmosphere reflectance data measured from 2000 to 2021 and created by the World Resources Institute (Hansen et al., 2013). These data are available from the Department of Geological Sciences at University of Maryland’s Hansen Laboratory and are easily importable into GEE (Hansen et al., 2013). This dataset classifies forest as vegetation reaching 5 m or more in height and foregoes classifying any other land cover type (Hansen et al., 2013). It also defines forest loss as “a stand-replacement disturbance” (a change from a forest to non-forest state; Hansen et al., 2013). The team found forest cover loss by restricting the “lossyear” attribute to include only the study period, 2016–2021, which the team derived from data collected by the Landsat 8 OLI. This created a binary output assigning “0” to pixels where forest loss occurred outside the study period and “1” to pixels where forest loss occurred within the study period. Stable forest cover was defined as any pixel identified as tree cover but not identified as forest loss within the study period. Non-forest cover was found by taking the inverse of a combination of the stable forest and forest loss layers.

The third forest change detection analysis was conducted using the U.S. Forest Service’s (USFS) LCMS, a processed dataset of 30-m resolution Landsat Tier 1 atmospherically corrected surface reflectance data that is available on GEE. Using LCMS, the team visualized land use and land cover between 2016 and 2021 and the rate of forest cover loss (USFS, 2022b). To determine loss in forest cover during the study period, they reclassified the land cover band to create a binary layer classifying only forest and non-forest areas at the start and end of the study period. This reclassification scheme can be found in Table A3.

For the final land cover change map, the team utilized the land cover band of NLCD which they acquired from GEE (Dewitz and USGS, 2021). Similar to LCMS, they reclassified the landcover type band to show a binary layer separating forest from non-forest areas. They used this information to discern forest change that occurred only during the study period. The NLCD-specific reclassification scheme is referenced in Table A4.

*3.2.2 Estimating AGB using GEDI and ATLAS Data*

The project utilized both GEDI and ATLAS LiDAR datasets to estimate canopy height in the study area. From these canopy height estimates, the team calculated a mean AGB density estimate for each county in the study area using an allometric model. Paired with the land change maps, the team used AGB estimates to calculate AGB lost from forest cover loss. GEDI is a full-waveform LiDAR instrument aboard the International Space Station that takes detailed 3D measurements of the structure of Earth’s surface (NASA GSFC & UMD, 2023). This project used the GEDI L4B Gridded Aboveground Biomass Density, Version 2 dataset, which provides 1-km resolution AGB density estimates for the period April 18, 2019, to August 4, 2021 (Dubayah et al., 2022). The GEDI L4B dataset is available in GEE. The ATLAS instrument on the ICESat-2 observatory utilizes a photon-counting LiDAR and ancillary systems to measure the time it takes a photon to travel from ATLAS to Earth and back which produces elevation estimates for Earth’s surface (Neuenschwander et al., 2021). The team used ATLAS/ICESat-2 L3A Land and Vegetation Height, Version 5 (ATL08) data for this project, which contains along-track terrain and canopy height estimates above the World Geodetic System 1984 ellipsoid in point form (Neuenschwander et al., 2021).

The team downloaded ATL08 files from NASA Earthdata Search in HDF5 file format for each available date during the 2019 dry season (May 1–September 29). They then processed the files using a Python code that converted the HDF5 files into shapefiles, and then compiled them all into one shapefile (Cherrington, 2020). The team uploaded the shapefile into ArcGIS Pro, clipped it to the study area, and calculated AGB density using a linear regression that converts canopy heights into AGB estimates for mixed wood continental US vegetation (Equation 2; Nelson et al., 2017).

Compared to two other allometric equations used by the first term, the equation outputs relatively moderate AGB density estimates for mature forests, but relatively higher estimates for shrub/scrub early succession forests (Rogers et al., 2022). This term decided to use the Nelson et al. (2017) allometric equation because it was developed specifically for US vegetation, unlike the other equations tested by the first term (Rogers et al., 2022). The team converted GEDI from raster to point form, to make it consistent with ATLAS data. After calculating county AGB means for both LiDAR datasets, the team estimated total AGB lost per county in the study area according to the forest cover loss area identified by each land change map. This resulted in eight different AGB means, and subsequent CO2 emissions estimates based on GEDI and ATLAS data.

*3.2.3 Airborne LiDAR Data Processing*

Due to time constraints, the team did not validate the GEDI and ATLAS LiDAR measurements, and instead used the validation results from last term to predict which CO2 emission estimate was most accurate. In order to validate the GEDI and ATLAS LiDAR measurements, the first term obtained airborne LiDAR discrete-return point cloud data from the USGS 3D Elevation Program (3DEP) using the data query tool in OpenTopography (USGS, 2022). After processing the 3DEP data, the first term derived a tree canopy height model from the LiDAR data (Khosravipour et al., 2014; Rogers et al., 2022).

***3.3 Data Analysis***

*3.3.1 Validating Earth Observation LiDAR with Airborne LiDAR*

Following the steps described in section 3.2.3, last term’s team used the processed airborne LiDAR data to validate ICESat-2 ATLAS canopy height estimates. To do this, the team first rasterized and imported the airborne LiDAR height model into GEE for analysis within their study area (Talladega National Forest). Then, the first term overlayed ATLAS points with a version of the height model that had been clipped to stable forest. They sampled areas of overlap and compared height values from both datasets (Rogers et al. 2022).

*3.3.2 Validating Forest Cover and Loss Maps with Collect Earth Online*

The team validated all forest cover and loss maps, to assess the accuracy of each dataset. To sufficiently validate each forest cover change map with CEO, the team determined the minimum sample size needed for an acceptable margin of error for each map. Each of the four land cover datasets indicated a forest cover loss of less than 5% of the originally forested area in the study area during the study period. According to S-CAP methodology, this meant that stratified random sampling would require a sample size smaller than that of simple random sampling to achieve the same margin of error (Christine Evans, personal communication, February 6, 2023).

The team calculated sample size using the proportion of the sample area in each stratum, the proportion of forest cover loss in each stratum, and the desired margin of error (Equations 3–5; Olofsson, 2021). *Wh* is the weight of stratum *h*, SD*h* is the standard deviation of stratum *h*, SE(*p̂*) is the target standard error of forest cover loss area, *qh* is the proportion of stratum *h* that lost forest cover, *MoE* is the target margin of error, and *p̂* is the proportion of the study area that lost forest cover.

The team assumed that the area classified as forest cover loss was 80% accurate, that 0.1% each of the areas classified as stable forest and non-forest were instead forest cover loss, and chose a 30% margin of error (Pontus Olofsson, personal communication, March 6, 2023).

To create stratified random sampling points for the validation process in CEO, the team imported composite maps for each dataset containing three separate layers: forest loss, stable forest, and non-forest. The team created these composite maps in ArcGIS Pro by combining the forest loss and stable forest maps created in GEE and creating an inverse layer to represent the non-forest layer. GEE has a stratifiedSample() function that the team used to generate points within each layer since the team was not using the same sample points across all four datasets. In order to generate sufficient different sets of random samples for each land cover dataset, the team changed the ‘seed’ argument in the stratifiedSample() function to have the algorithm apply a stratified random sample differently every time. The team used a seed of 0 for LandTrendr (the default integer in GEE), 1 for GFW, 2 for NLCD, and 3 for LCMS.

The team used Sentinel-2 imagery as the reference base map to compare the accuracy of the datasets in CEO. Table 1 shows the survey questions used in the validation process. Due to time constraints, the team had only one surveyor for each project. If the surveyor had low confidence in assessing the image (e.g., there was no available Sentinel-2 imagery near the month specified, or the imagery was blurry), the validator flagged that plot. The team brought flagged points into Google Earth Pro as a kml file to evaluate that plot using the timelapse tool. The team exported the survey answers from CEO into Microsoft Excel in order to create confusion matrices, assessing how well each map classified forest cover loss (Tables A5–A8).

Table 1

*Survey questions for validating each forest cover loss map in Collect Earth Online*

|  |  |  |
| --- | --- | --- |
| Was the area forested in May 2016? | If so, was the area forested in Sept. [of the forest cover loss map’s end year]? | Actual land classification |
| no | — | Non-forest |
| YES | YES | Stable forest |
| no | Forest cover loss |

*3.3.3 Estimating CO2 Emissions*

The team used a two-step equation to estimate the CO2 emitted by forest cover loss for each change map. Carbon stock (Mg C/ha2) is equal to the estimated mean AGB density (Mg/ha2) for each county within the study area, with no forest cover loss multiplied by the dry matter carbon fraction (Equation 6; Goslee et al., 2018). The team used the Intergovernmental Panel on Climate Change’s global estimate of the average live wood carbon fraction, 0.47 Mg C/Mg dry tree matter (Aalde et al., 2006). The team then calculated CO2 emissions from forest cover loss by multiplying the area of forest cover loss in each county for each change map by the carbon stock and by the molecular mass ratio of carbon dioxide to carbon (Equation 7). Because the team created four change maps and used two AGB estimate datasets, they generated eight estimates of carbon emissions for the entire study area as well as for each county in the study area. The team completed this in ArcGIS Pro.

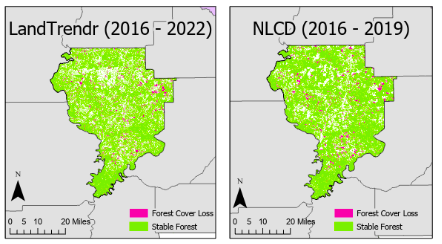
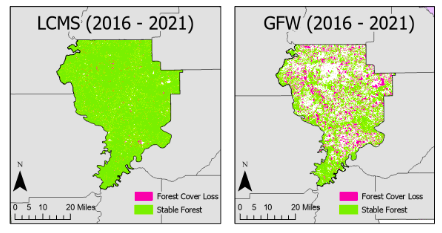
# 4. Results & Discussion

***4.1 Analysis of Results***

The generated forest cover loss maps estimated an annual loss of 65,264 to 208,506 hectares of forest cover across Tennessee and Alabama. Validation showed that NLCD provided the most accurate and precise forest loss classification method, estimating 99,022 hectares of forest cover lost each year in the study area. After pairing these forest cover loss maps with AGB density data, the team estimated CO2 emissions ranging from 12,768,917 tonnes/year to 71,893,882 tonnes/year. The first term of this project concluded that GEDI’s AGB density estimates were more accurate than ATLAS’s in the Talladega National Forest. This term did not assess the accuracy of either LiDAR dataset for the larger study area, and instead chose to assume that GEDI data would also be more accurate there. The most accurate CO2 emissions estimate would then result from NLCD’s forest cover loss map combined with GEDI AGB density estimates, which estimated that 22,719,204 tonnes of CO2 were emitted each year in the study area.

*4.1.1 Change Map Classifications*

Each change map classified forest and forest cover loss differently. Figure 2 shows how each dataset classified forest cover loss in a subset of the study area: Clarke County, Alabama. LCMS classified the least amount of forest cover loss among the four change maps, whereas GFW classified the most.

*Figure 2.* Maps of stable forest and forest cover loss in Clarke County, in Southwestern Alabama. Green areas represent stable forest, and pink areas represent forest cover loss.

*4.1.2 Forest Cover Loss Validation*

Figure 3 shows how well each map did at assessing forest cover loss. NLCD was the most accurate map, correctly classifying forest cover loss. GFW was the most sensitive, meaning that if forest loss occurred, it was likely reflected in the classification. However, it did so at the cost of being the least precise, meaning it incorrectly classified areas forest loss. The NLCD forest loss map was also the most accurate overall.

*Figure 3.* Bar chart showing confusion matrix results regarding accuracy, sensitivity, and precision of each change map’s classification of forest cover loss

*4.1.3 Carbon Dioxide Emission Estimates*

The team produced eight different CO2 emission estimates for the study area from the different AGB density and forest cover change datasets (Table 2). All CO2 emission estimates found the highest annual CO2 emissions to be in southern Alabama (Figure 4), specifically southwestern Alabama. This is the most densely forested area of Alabama, as well as the area with the highest annual tree removals in Alabama by volume (Hartsell, 2018). The team determined the NLCD-GEDI estimate to be the most accurate per the validation results, which it was used to create the map in Figure 4, showing how CO2 emissions vary by county in the study area.

Table 2

*Change map classification and study period, paired with the respective AGB density and CO2 emission estimates*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Change Map** | **Average annual forest cover loss (ha/year)** | **AGB data source** | **AGB mean density (Mg/ha)** | **CO2 emissions (Mg)** | **Average annual CO2 Emissions (Mg/year)** |
| GFW (2016–2021) | 208,506 | GEDI | 146 | 243,626,380 | 40,604,397 |
| ATLAS | 255 | 431,363,292 | 71,893,882 |
| LandTrendr (2016–2022) | 65,264 | GEDI | 148 | 89,382,421 | 12,768,917 |
| ATLAS | 249 | 155,079,040 | 22,154,149 |
| NLCD  (2016–2019) | 99,022 | GEDI | 145 | 90,876,819 | 22,719,204 |
| ATLAS | 251 | 162,612,240 | 40,653,060 |
| LCMS (2016–2021) | 135,852 | GEDI | 137 | 149,691,082 | 24,948,513 |
| ATLAS | 240 | 269,280,811 | 44,880,135 |

A picture containing diagram

Description automatically generated

*Figure 4.* Map of CO2 emissions by county within the study area, with counties emitting more emissions shaded in darker red and counties emitting less shaded in a light orange, as defined by NLCD forest cover loss data (2016–2019) and GEDI AGB density data (2019–2021).

The team found that ATLAS estimated higher canopy heights, and therefore higher CO2 emissions, than GEDI. This is consistent with last term’s LiDAR validation findings: that when compared to airborne LiDAR, ATLAS consistently overestimated canopy height while GEDI did not. GFW estimated the highest CO2 emissions of all four land cover maps (Figure 5), but validation showed it was the least precise. The estimate based on NLCD and GEDI data, which the team found most accurate, is one of the more moderate estimates, at 22,719,204 tonnes of CO2 emitted per year. Table 2 lists the full range of estimates and their sources.

*Figure 5.* Bar chart showing CO2 emission estimates produced by different AGB and forest loss map inputs

***4.2 Future Work***

Due to time constraints, the team was unable to account for either forest regrowth that may have occurred after tree removal or reforestation due to tree planting. Reforestation and regrowth impact the amount of carbon sequestered in an area and should be accounted for to report net CO2 emissions estimates (Han et.al., 2007). One foreseeable way to accomplish this would be to include an additional land cover layer that specifically analyzes forest gain during the study period. This analysis would require that each land classification dataset include a forest gain layer and acquire an equation that accounts for forest gain to compute net emissions. The LandTrendr ‘Greatest Disturbance Mapping’ script in GEE has a vegetation ‘gain’ feature to look at forest regrowth events. LandTrendr also has an online interface application that the team recommends the partners use in determining the best parameters for their area of interest.

Additional validation of the results of this study could include a statistical comparison of these findings against the USFS Forest Inventory and Analysis (FIA) program, which provides the basis for current national greenhouse gas estimates (USFS, 2022a). This would provide further verification of the methodology presented in this paper for estimating CO2 emissions from forest cover change, especially the perspective of comparison to industry standards. While the last term was able to validate LiDAR datasets by comparing them to airborne LiDAR data, this term did not validate LiDAR datasets in the expanded study area. Future validation should take this into account and validate LiDAR data for any expanded study area.

Many other land cover classification datasets and LiDAR databases exist but their analysis was outside the scope of this project. Future work should include additional comparison and validation of other datasets and algorithms, such as the Continuous Change Detection and Classification - Spectral Mixture Analysis algorithm (Chen et al., 2021), as they could prove more accurate for representing the southeastern U.S. than any of the four-land classification and two LiDAR datasets analyzed here. The team also restricted the study area to Alabama and Tennessee, so it would be prescient to expand the study area and validate any new results to verify that the methodology presented here remains valid when applied across the entire southeast.

# 5. Conclusions

The four forest cover loss maps created by the team highlight areas where more forest loss is occurring. These maps help local decision makers choose the best land management strategies for the natural resources in their region. The four forest cover loss maps had varied forest cover loss area estimates and subsequent variable CO2 emissions estimates, but the team found that the NLCD forest loss map was the most accurate. They also found that GEDI provided the more accurate AGB density estimate, since ATLAS estimated higher tree canopy height and CO2 emissions. These findings will allow partners to perform their own validation to determine which data are the most accurate for answering their particular investigative questions. This study will also allow partners to compute emissions estimates in new study areas, including larger or smaller land tracts than the team analyzed here.

From the NLCD and GEDI estimates, the team calculated that 22,719,204 tonnes of CO2 were emitted each year from 2016 to 2019 in Alabama and Tennessee. By clipping the data to the county level, the team found that southwest Alabama had the highest CO2 emission estimates across the study area. This finding is consistent with the region containing the most densely forested area and pine plantations that are routinely harvested and replanted. Regional partners can use the team’s county-level emissions maps to identify emission trends and thus practice targeted forest management within their areas of interest. Analyses at this scale make it easier for researchers to pinpoint further areas of interest where emission estimates do not align with expected emissions in an area.

At the conclusion of this two-term project, the team found that applying SERVIR’s S-CAP model to the southeastern US is feasible with a few caveats. First, the study’s CO2 emissions estimates need to be validated by FIA measurements. SERVIR developed the open-source S-CAP model since there tends to not be an FIA equivalent in their focus countries that conducts country-wide forest inventory assessments (Scott, 2010). The remote sensing methods used by this project can help meet the FIA’s goal of improving the spatial and temporal resolution of carbon stock and emissions estimates (USFS, 2022a). This can empower local partners to perform their own carbon estimates, especially in small areas of interest, instead of relying solely on FIA reports. This project’s results show CO2 emission trends across Alabama and Tennessee at the county level, but the resulting estimates cannot be considered authoritative without validating the findings using FIA data. Second, the partners need to determine the best land cover change dataset, AGB density estimates, and carbon fraction for their areas of interest. The project’s methodology is useful as a framework, but it cannot provide a recipe to expedite the carbon emissions estimation process. Finally, if expanding the study area to more of the southeastern US, future researchers will need to consider the temporal and spatial availability of LiDAR across their study area.

# 6. Acknowledgments

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# 7. Glossary

**AGB** – Aboveground biomass

**ATLAS** –Advanced Topographic Laser Altimeter System

**Carbon stock** – The amount of carbon stored in soil or living or dead biomass

**CEO** – Collect Earth Online

**CO2** –Carbon dioxide

**Deforestation** – Sustained loss of forest cover, where the area of canopy cover is no longer >10%.

**Earth observations** – Satellites and sensors that collect information about the Earth’s physical, chemical, and biological systems over space and time

**ESA** – European Space Agency

**ETM+** – Enhanced Thematic Mapper Plus

**FIA** – U.S. Forest Service’s Forest Inventory and Analysis program

**Forest** – Area of land that is at least 10 percent absolute cover of tree canopy, including lands that formerly had such cover and will be naturally or artificially reforested

**GEDI** – Global Ecosystem Dynamics Investigation  
**GEE** – Google Earth Engine

**GFW** – Global Forest Watch  
**ICESat-2** – Ice, Cloud, and land Elevation Satellite 2

**ISS** – International Space Station

**LiDAR** – Light detection and ranging remote sensing method

**LCMS** – Landscape Change Monitoring System

**LT** –LandTrendr

**Mg** – Megagrams (tonnes)

**NASA** – National Atmospheric and Space Administration  
**NLCD** – National Land Cover Database

**OLI** –Operational Land Imager

**S-CAP** – SERVIR CArbon Pilot program  
**TM** – Thematic Mapper

**USFS** – United States Forest Service

**USGS** – United States Geological Survey

# 8. References

Aalde, H., Gonzales, P., Gytarsky, M., Krug, T., Kurz, W. A., Ogle, S., Raison, J., Schoene, D., Ravindranath, N. H., Elhassan, N. G., Heath, L., Higuchi, N., Kainja, S., Matsumoto, M., Sanchez, M. J. S., Somogyi, Z., Carle, J. B., & Murthy, I. K. (2006). *2006 IPCC Guidelines for National Greenhouse Gas Inventories.* Volume 4: Agriculture, Forestry and other Land Use. <https://www.ipcc-nggip.iges.or.jp/public/2006gl/pdf/4_Volume4/V4_04_Ch4_Forest_Land.pdf>

Alabama Forestry Commission. (2022). *2022 Champion Trees of Alabama.* Alabama Forestry Commission. <https://forestry.alabama.gov/Pages/Management/Forms/Champion_Trees.pdf>

Chappell, D., DeBrunner, D., Stone, D., Ballentine, E., Sikes, C., Faulkner, G., Dhakal, A., Dickens, D., Wiswall, K., & Moncrief, H. (2020). *Alabama’s forest road map 2020*. Alabama Forestry Commission. <https://forestry.alabama.gov/Pages/Management/Forms/Forest_Action_Plan.pdf>

Chen, S., Woodcock, C. E., Bullock, E. L., Arévalo, P., Torchinava, P., Peng, S., & Olofsson, P. (2021). Monitoring temperate forest degradation on Google Earth Engine using Landsat time series analysis. *Remote Sensing of Environment, 265*, 112648. <https://doi.org/10.1016/j.rse.2021.112648>

Cherrington, E. (2020). *Icesat2\_shp.py.* <https://gist.github.com/bzgeo/950f3db986b3513311ed42efe2395171>

Dewitz, J. (2021). *National Land Cover Database (NLCD) 2019 Products* (ver. 2.0, June 2021). [Data set] U.S. Geological Survey. <https://doi.org/10.5066/P9KZCM54>

Domke, G. M., Walters, B. F., Nowak, D. J., Smith, J. E., Nichols, M. C., Ogle, S. M., Coulston, J.W., & Wirth, T. C. (2021). *Greenhouse gas emissions and removals from forest land, woodlands, and urban trees in the United States, 1990–2019.* Resource Update FS–307. United States Department of Agriculture, Forest Service, Northern Research Station. <https://doi.org/10.2737/FS-RU-307>

Dubayah, R.O., Armston, J., Healey, S.P., Yang, Z., Patterson, P.L., Saarela, S., Stahl, G., Duncanson, L., & Kellner, J.R. (2022). *GEDI L4B Gridded Aboveground Biomass Density* (Version 2) [Data set]. ORNL DAAC. [https://doi.org/10.3334/ORNLDAAC/2017](https://linkprotect.cudasvc.com/url?a=https%3a%2f%2fdoi.org%2f10.3334%2fORNLDAAC%2f2017&c=E,1,OKiAIsh7dZnj5jBwva7Q5nXqhHHsR0uhgFBblyDn0MTPuzlcROCm-iEfSxhWzMtZvkRy4nYZPfUUc49fVLB_-FJSn5Xb5FygqtvPHmPFO0Za&typo=1)

Earth Resources Observation and Science Center. *Landsat 4-5 Thematic Mapper* (Collection 2 Level-2) [Data set]. United States Geological Survey. <https://doi.org/10.5066/P9IAXOVV>

Earth Resources Observation and Science Center. *Landsat 7 Enhanced Thematic Mapper (ETM+)* (Collection 2 Level-2) [Data set]. United States Geological Survey. <https://doi.org/10.5066/P9C7I13B>

Earth Resources Observation and Science Center. *Landsat 8 Operational Land Imager (OLI)* (Collection 2 Level-2) [Data set]. United States Geological Survey. <https://doi.org/10.5066/P9OGBGM6>

European Space Agency. (2015). *Sentinel-2 MSI: Multispectral Instrument* [Data set]. Earth Engine Data Catalog/USGS. <https://doi.org/10.5270/S2_-6eb6imz>

Evans, C., Cherrington, E., Cordova, A. I. F., Muench, R., & Griffin, R. (2022). *SERVIR: Cross-Comparison of Carbon Emission Estimates Based on Variable Land Use Land Cover Changes within SERVIR Focus Regions*. In American Geophysical Union Fall 2022 Meeting.

García, M. L., & Caselles, V. (1991). Mapping burns and natural reforestation using Thematic Mapper data. *Geocarto International*, 6(1), 31-37. <https://doi.org/10.1080/10106049109354290>

Goslee, K., Walker, S. M., Grais, A., Murray, L., Casarim, F., & Brown, S. (2018). *LEAF technical guidance series for the development of a forest carbon monitoring system for REDD+:* *Module C-CS: Calculations for estimating carbon stocks.* USAID Lowering Emissions in Asia’s Forests. <https://winrock.org/wp-content/uploads/2018/08/Winrock-Guidance-on-calculating-carbon-stocks.pdf>

Han, F. X., Plodinec, M. J., Su, Y., Monts, D. L., & Li, Z. (2007). Terrestrial carbon pools in southeast and south-central United States. *Climatic Change,* 84.

Hansen, M., Potapov, P., Moore, R., Hancher, M., Turubanova, S., Tyukavina, A., Thau, D., Stehman, S., Goetz, S., Loveland, T., Kommareddy, A., Egorov, A., Chini, L., Justice, C., & Townshend, J. (2013). High-resolution global maps of 21st-century forest cover change. *Science*, *342*(6160), 850-853. <https://doi.org/10.1126/science.1244693>

Hartsell, A. J. 2018. *Alabama’s forests, 2015.* Resource Bulletin SRS 220. United States Department of Agriculture, Forest Service, Southern Research Station. <https://doi.org/10.2737/SRS-RB-220>

Khosravipour, A., Skidmore, A., Isenburg, M., Wang, T., & Hussin, Y. (2014). Generating Pit-free Canopy Height Models from Airborne Lidar. *Photogrammetric Engineering & Remote Sensing,* 80. 863-872. <https://doi.org/10.14358/PERS.80.9.863>

Kennedy, R. E., Yang, Z., & Cohen, W. B. (2010). Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr—temporal segmentation algorithms. *Remote Sensing of Environment*, *114*(12), 2897-2910. <https://doi.org/10.1016/j.rse.2010.07.008>

Kennedy, R. E., Yang, Z., Gorelick, N., Braaten, J., Cavalcante, L., Cohen, W. B., & Healey, S. (2018). Implementation of the LandTrendr algorithm on Google Earth Engine. *Remote Sensing*. *10*(5), 691. https://doi.org/10.3390/rs10050691

Nelson, R., Margolis, H., Montesano, P., Sun, G., Cook, B., Corp, L., Andersen, H.-E., deJong, B., Pellat, F. P., Fickel, T., Kauffman, J., & Prisley, S. (2017). Lidar-based estimates of aboveground biomass in the continental US and Mexico using ground, airborne, and satellite observations. *Remote Sensing of Environment*, 188, 127–140. <https://doi.org/10.1016/j.rse.2016.10.038>

Neuenschwander, A. L., Pitts, K. L., Jelley, B. P., Robbins, J., Klotz, B., Popescu, S. C., Nelson, R. F., Harding, D., Pederson, D., & Sheridan, R. (2021). *ATLAS/ICESat-2 L3A Land and Vegetation Height* (Version 5) [Data set]. NASA National Snow and Ice Data Center DAAC. [https://doi.org/10.5067/ATLAS/ATL08.005](https://linkprotect.cudasvc.com/url?a=https%3a%2f%2fdoi.org%2f10.5067%2fATLAS%2fATL08.005&c=E,1,7ZZ9g5PJc_6MlQ6BGD9AI9VS_RUFbXFABauG2fvR7QCFDv_yQOosRHaoDNVzWolpiB_8N1M93bC7MNHn-Y16joCkP-YxLkj-OCbHZeIdKSq2W3mkH5gmkq8,&typo=1)

Olofsson, P., Foody, G.M., Herold, M., Stehman, S.V., Woodcock, C.E., & Wulder, M.A. (2014). Good practices for estimating area and assessing accuracy of land change, *Remote Sensing of Environment, 148*, 42-57. <https://doi.org/10.1016/j.rse.2014.02.015>

Olofsson, P. (2021). *Sampling design for estimation of area and map accuracy*. Open MRV. <https://openmrv.org/web/guest/w/modules/mrv/modules_3/sampling-design-for-estimation-of-area-and-map-accuracy>

Oswalt, C. M., Brandeis, T. J., & Oswalt, S. N. (2022) Tennessee’s forests, 2014 (with updates for 2016). U.S. Department of Agriculture, Forest Service. *Southern Research Station* SRS-232. <https://doi.org/10.2737/SRS-RB-232>

Rogers, H., Smith, M., Mason, M., Holla, A., Evans, C., Cherrington, E., Spruce, J., & Williams, C. (2022). *Southeast US Climate: Leveraging land cover and aboveground biomass products to evaluate carbon emission trends in the Talladega National Forest* [Unpublished manuscript]. NASA DEVELOP National Program, Pop-Up Project – University of Wyoming.

Saatchi, S. S., Harris, N. L., Brown, S., Lefsky, M., Mitchard, E. T. A., Salas, W., Zutta, B. R., Buermann, W., Lewis, S. L., Hagen, S., Petrova, S., White, L., Silman, M., & Morel, A. (2011). Benchmark map of forest carbon stocks in tropical regions across three continents. *Proceedings of the national academy of sciences*, 108(24), 9899-9904. <https://doi.org/10.1073/pnas.1019576108>.

Scott, C. T. (2010). *How is FIA helping other countries monitor their forests?* 2010 Joint Meeting of the Forest Inventory and Analysis (FIA) Symposium and the Southern Mensurationists (SRS-157) <https://www.srs.fs.usda.gov/pubs/gtr/gtr_srs157/gtr_srs157_003.pdf>

United States Department of Agriculture, Forest Service. (2022a). *Carbon.* Forest Service U.S. Department of Agriculture. Washington, D.C. <https://www.fs.usda.gov/managing-land/sc/carbon>

United States Department of Agriculture, Forest Service (2022b). USFS Landscape Change Monitoring System Conterminous United States (version 2021-7). [Data set]. U.S. Forest Service. <https://data.fs.usda.gov/geodata/rastergateway/LCMS/index.php>

U.S. Environmental Protection Agency. (2023). Inventory of U.S. greenhouse gas emissions and sinks: 1990-2021. <https://www.epa.gov/ghgemissions/draft-inventory-us-greenhouse-gas-emissions-and-sinks-1990-2021>

U.S. Geological Survey (2022). *3D Elevation Program* (Version 1.4). [Data set]. U.S. Geological Survey. <https://apps.nationalmap.gov/downloader/>

# 9. Appendix

***Appendix A: Supplementary Information***

Table A1

*Data types, sources, and project application areas*

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Earth Observation | Data Product | Processing Level | Resolution | Data Use | Dates Used | Source of Imagery | Interface Application |
| Landsat 5 TM |  | L2 | 30 m | Forest cover loss maps | 1984–2012 | <https://doi.org/10.5066/P9IAXOVV> | GEE |
| Landsat 7 ETM+ |  | L2 | 30 m | Forest cover loss maps | 1999–2022 | <http://doi.org/10.5066/P9C7I13B> | GEE |
| Landsat 8 OLI |  | L2 | 30 m | Forest cover loss maps | 2013–2022 | <https://doi.org/10.5066/P9OGBGM6> | GEE |
| ISS GEDI |  | L4B | 1 km | AGB density | April 17, 2019– August 4, 2021 | <https://doi.org/10.3334/ORNLDAAC/2017> | GEE |
| ICESat-2 ATLAS | Land and Vegetation Height V005 | L3A | 100 m | AGB density | October 14, 2018–September 2022 | <https://doi.org/10.5067/ATLAS/ATL08.005> | NASA Earthdata |
| Sentinel-2 MSI | True Color Composite | N/A | 10 m | Validation | May 2016–September 2022 | <https://doi.org/10.5270/S2_-6eb6imz> | Collect Earth Online |

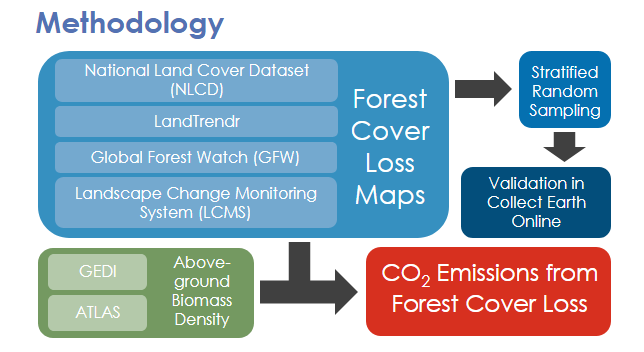


Figure A1

*Workflow of the methodology used to complete research for this project*

Table A2

*Ancillary datasets, \* indicates new source not used last term*

|  |  |  |
| --- | --- | --- |
| **Dataset** | **Source** | **Use** |
| GFW | WRI | Utilize changes in forest cover and calculate against aboveground biomass to estimate carbon emissions |
| Hansen Global Forest Change v1.9 (2000–2021) | USGS | Utilize changes in forest cover and calculate against aboveground biomass to estimate carbon emissions |
| NLCD | USGS | Extract forest cover information and calculate against aboveground biomass to estimate carbon emissions |
| LCMS v2021.7 | USFS | Extract forest cover information and calculate against aboveground biomass to estimate CO2 emissions |
| World Cover 10m 2020 V100 | European Space Agency | Extract forest cover information and calculate against aboveground biomass to estimate carbon emissions |
| Emission Factor Database | IPCC | Reference for AGB |
| Global Aboveground and Belowground Biomass | Oak Ridge National Laboratory | Calculate carbon stock using AGB |
| TIGER: US Census States 2018\* | Census Bureau | Create study area shapefile of Tennessee and Alabama |

Table A3

*LCMS land cover reclassifications*

|  |  |  |
| --- | --- | --- |
| **Landcover Value** | **Forest Reclass Value** | **Description** |
| 1 | 1 | Trees |
| 2 | 1 | Tall Shrubs & Trees Mix |
| 3 | 1 | Shrubs & Trees Mix |
| 4 | 1 | Grass/Forb & Trees Mix |
| 5 | 1 | Barren & Trees Mix |
| 6 | 0 | Tall Shrubs |
| 7 | 0 | Shrubs |
| 8 | 0 | Grass/Forb & Shrubs |
| 9 | 0 | Barren & Shrubs Mix |
| 10 | 0 | Grass/Forb/Herb |
| 11 | 0 | Barren & Grass/Forb |
| 12 | 0 | Barren or Impervious |
| 13 | 0 | Snow or Ice |
| 14 | 0 | Water |
| 15 | 0 | Non-processing Area Mask |

Table A4

*NLCD land cover reclassifications*

|  |  |  |
| --- | --- | --- |
| **Landcover Value** | **Forest Reclass Value** | **Description** |
| 11 | 0 | Open water |
| 12 | 0 | Ice/Snow |
| 21 | 0 | Developed, open space |
| 22 | 0 | Developed, low intensity |
| 23 | 0 | Developed, medium intensity |
| 24 | 0 | Developed, high intensity |
| 31 | 0 | Barren land |
| 41 | 1 | Deciduous forest |
| 42 | 1 | Evergreen forest |
| 43 | 1 | Mixed forest |
| 51 | 0 | Dwarf scrub |
| 52 | 0 | Scrub |
| 71 | 0 | Grassland |
| 72 | 0 | Sedge |
| 73 | 0 | Lichens |
| 74 | 0 | Moss |
| 81 | 0 | Pasture |
| 82 | 0 | Cultivated crops |
| 90 | 0 | Wetland |
| 95 | 0 | Emergent Wetland |

Table A5

*Results of LandTrendr confusion matrices*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| *LandTrendr* | | Actual Class | | |
| Expected Class |  | Forest Loss | Non-Forest | Stable Forest |
| Forest Loss | 18 | 5 | 7 |
| Non-Forest | 11 | 58 | 1 |
| Stable Forest | 4 | 15 | 91 |

Table A6

*Results of Global Forest Watch confusion matrices*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| *GFW* | | Actual Class | | |
| Expected Class |  | Forest Loss | Non-Forest | Stable Forest |
| Forest Loss | 14 | 5 | 11 |
| Non-Forest | 1 | 21 | 8 |
| Stable Forest | 0 | 3 | 27 |

Table A7

*Results of National Land Cover Database confusion matrices*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| *NLCD* | | Actual Class | | |
| Expected Class |  | Forest Loss | Non-Forest | Stable Forest |
| Forest Loss | 22 | 6 | 2 |
| Non-Forest | 0 | 62 | 8 |
| Stable Forest | 6 | 15 | 139 |

Table A8

*Results of Land Change Monitoring System confusion matrices*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| *LCMS* | | Actual Class | | |
| Expected Class |  | Forest Loss | Non-Forest | Stable Forest |
| Forest Loss | 20 | 9 | 1 |
| Non-Forest | 0 | 30 | 0 |
| Stable Forest | 5 | 15 | 60 |