Maryland Tree and Forest Carbon Flux

Data and Methodology Documentation

as prepared for the

2020 Maryland Greenhouse Gas Inventory

Maryland Department of the Environment

Maryland Department of Natural Resources

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Maryland Greenhouse Gas Emissions Inventory

This report supports Maryland's 2020 greenhouse gas (GHG) emissions inventory and the revised historical inventories. The state's 2020 inventory was released on September 24, 2022.[1]

Forest Carbon Flux

Annual forest carbon fluxes for Maryland were primarily estimated using a new method for monitoring high-resolution forest above-ground carbon dynamics produced by the NASA Carbon Monitoring System (CMS) and the University of Maryland (UMD). This IPCC Tier-3[2] approach utilizes high-resolution remote sensing data, U.S. Department of Agriculture (USDA) Forest Service Forest Inventory and Analysis (FIA) plot data, and a process-based ecosystem model to detect and quantify annual changes to the State's tree and forest carbon stocks. This work represents a leap forward relative to standard FIA-based estimation, which is currently included within the EPA's State Inventory Tool, by integrating high-resolution wall-to-wall airborne lidar data and optical imagery, medium-resolution satellite imagery, and ecosystem modeling to provide value-added spatially-explicit estimates of annual aboveground forest carbon change over time. The method improves Maryland's GHG inventory by providing wall-to-wall spatial coverage, a mechanistic framework for carbon flux attribution and connection to planning, and a consistent methodology to estimate carbon stock changes for all trees both in and outside of forests, past-to-future.

Method and Data Inputs

Core method

This method began with initialization of the ecosystem model in 2011 using 1m tree canopy and 1m lidar height metrics to map aboveground biomass (AGB) at high spatial resolution. Next, AGB dynamics (e.g. annual carbon stocks and fluxes) were reconstructed over the landscape from 2006-2020 by using the ecosystem model together with meteorology, atmospheric CO_2, and land cover change data over the period. Importantly, all results were constrained by the initialized state. Modeled AGB data at the time of initialization were validated and calibrated by USDA Forest Service FIA data (Hurtt et al 2019, Ma et al 2021). More detail is available from Hurtt et al. 2022.

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[1] The full emissions inventory, including all Land Use, Land-Use Change, and Forestry emissions and sequestration, can be found on Maryland Department of the Environment's website: mde.maryland.gov/programs/air/climatechange/pages/greenhousegasinventory.aspx

[2] A tier represents a level of methodological complexity, where Tier-3 approaches are the most sophisticated and include process-based models (2006 IPCC Guidelines for National Greenhouse Gas Inventories, Chapter 4 Forest Land, ipcc-nggip.iges.or.jp/public/2006gl/pdf/4_Volume4/V4_04_Ch4_Forest_Land.pdf)

Ecosystem model

The Ecosystem Demography (ED) Model was used to quantify vegetation dynamics in Maryland. ED is an individual- and mechanism-based global vegetation model which integrates submodules of growth, mortality, hydrology, carbon cycle, and soil biogeochemistry to track plant dynamics including growth, mortality, and reproduction (Hurtt et al 1998, Moorcroft et al 2001; Ma et al. 2022). Over the last two decades, ED has been continuously developed and combined with lidar and land-use change data to predict ecosystem dynamics and associated water and carbon fluxes across spatial scales (e.g., site, regional, and global) and temporal scales (short-term seasonal to long-term decadal and century) (Hurtt et al 2002, 2004, 2010, 2016, Fisk et al 2013, Flanagan et al 2019; Ma et al. 2022). ED distinguishes itself from most other ecosystem models by explicitly tracking vegetation structure and scaling fine-scale physiological processes to large-scale ecosystem dynamics (Hurtt et al 1998, Moorcroft et al 2001, Fisher et al 2018). Explicitly modeling vegetation height facilitates a potential connection to lidar data.

High-resolution lidar

Tree canopy height and tree canopy cover, derived from airborne lidar point cloud data, was used to initialize ED and establish baseline forest carbon stocks in Maryland. The 1m lidar Canopy Height Model was produced from the lidar point cloud and the 1m tree canopy cover map was derived using an object-based approach that combines lidar canopy height and multi-spectral optical images from the National Agricultural Imagery Program (NAIP) (O'Neil-Dunne et al 2014a, 2014b). Specifically, for each grid cell, the ED model was initialized circa 2011[3] using established methods incorporating high-resolution lidar and optical remote sensing into carbon modeling (Hurtt et al. 2019; Ma et al. 2021).

Land cover change

Two satellite-based remote sensing products were used to determine change in forest area throughout the entire inventory period. First, the North American Forest Dynamics (NAFD) dataset was used to indicate the location and time of forest disturbance and recovery from 2006 to 2016 (Goward et al 2016). This dataset provides annual estimates from 1986-2016 over the conterminous United States derived from a time-series of Landsat imagery using the vegetation change tracker (VCT) algorithm (Huang et al 2010). From 2017-2020, the Global Forest Watch (GFW) dataset, also based on Landsat satellite imagery, was used for forest disturbance after adjustment to harmonize with NAFD (Hansen et al. 2013).

Meteorology and atmospheric CO_2

Meteorological variables within the model included air temperature, air humidity, downward shortwave radiation and precipitation. These data were derived by fusing NASA Daymet and NASA MERRA2 data between 1984 and 2020 (Ma et al 2021). Precipitation was derived directly

[3] The date of initialization for each pixel is based on the respective date of lidar collection.

from the Daymet dataset. Atmospheric CO_2 was derived from the NOAA CarbonTracker; this data varies annually but remains constant over space.

Reporting

The net forest carbon flux estimate for Maryland includes annual changes in aboveground biomass (AGB), belowground biomass (BGB), deadwood, litter, mineral soils, and organic soils.[4]

Net aboveground carbon flux

The NASA-CMS/UMD product is used to report annual net AGB fluxes from 2006-2020. From 2006 to 2016, net AGB carbon flux is tracked and reported at 30m resolution using three subcategories (Table 1), including:

1. *gross carbon flux from trees within "forest remaining forest" or "non-forest remaining non-forest"*: area change and carbon per area related changes on the tree canopy fraction of grid cells that are already considered "forest" or carbon per area-related changes on the tree canopy fraction of any other "non-forest" grid cells;

2. *gross carbon flux from forest to non-forest:* area change and carbon per area related changes on forest grid cells newly detected as "disturbed"; changes grid cell status from "forest" to "non-forest"; and

3. *gross carbon flux from non-forest to forest:* area change and carbon per area related changes on non-forest grid cells newly detected as "recovered"; changes grid cell status from "non-forest" to "forest"

Net AGB Flux = Flux from existing trees
+ Flux from Forest to Non-forest conversion
+ Flux from Non-forest to Forest conversion

Table 1: Annual estimates of above ground biomass (AGB) stocks (Tg C) and fluxes (Tg C/year) in Maryland.

Year	AGB stocks (Tg C)	Net AGB flux (Tg C/yr)	AGB Flux from existing trees (Tg C/yr)[1]	AGB Flux from Forest to Non-forest conversion (Tg C/yr)	AGB Flux from Non-forest to Forest conversion (Tg C/yr)
2006	99.016	1.562	1.950	-0.416	0.028
2007	99.903	0.887	1.273	-0.405	0.019

[4] These results are also available in summary format via Maryland's Open Data Portal (opendata.maryland.gov) and as spatial layers via Maryland's GIS Data Catalog (data.imap.maryland.gov).

2008	101.996	2.093	2.285	-0.214	0.023
2009	104.769	2.773	2.990	-0.250	0.033
2010	105.933	1.164	1.351	-0.215	0.028
2011	107.676	1.743	1.893	-0.197	0.047
2012	109.625	1.95	2.315	-0.401	0.036
2013	112.289	2.664	2.767	-0.130	0.027
2014	114.872	2.583	2.753	-0.210	0.041
2015	117.636	2.764	3.014	-0.284	0.035
2016	117.982	0.346	0.996	-0.680	0.030
2017	119.252	1.27	--	--	--
2018	120.062	0.81	--	--	--
2019	120.838	0.776	--	--	--
2020	122.452	1.614	--	--	--

[1] F = forest, NF = nonforest, as defined by NAFD

Prior to 2017, annual changes to the tree canopy fractions of each grid cell are also tracked and reported for the same three subcategories (Table 2). Beginning in 2017, the total tree area remained fixed, and the area of recovery was assumed to equal the area disturbed in each year.[5]

Table 2: Annual estimates of tree area change in Maryland.

Year	Total tree area (km^2)	Area changes for existing trees (km^2/yr)	Area changes Forest to Non-forest Conversion (km^2/yr)	Area changes from Non-forest to Forest Conversion (km^2/yr)
2006	12263.73	29.331	-29.594	7.825
2007	12270.56	28.552	-28.52	7.048
2008	12293.88	26.983	-13.802	10.688
2009	12319.43	25.246	-17.192	18.199
2010	12344.42	23.189	-13.758	15.854
2011	12376.66	21.477	-12.993	24.19
2012	12385.07	20.538	-28.358	16.772
2013	12407.64	18.936	-9.681	13.942
2014	12433.63	15.866	-13.186	23.945
2015	12450.26	13.809	-15.764	19.205
2016	12434.00	10.667	-47.685	21.025
2017	12434.00	--	--	--
2018	12434.00	--	--	--

[5] As forest recovery data was unavailable from either NAFD or GFW after 2017, a forest recovery rate equal to the disturbance rate was conservatively assumed between 2017 and 2020.

2019	12434.00	--	--	--
2020	12434.00	--	--	--

Below ground carbon flux

Due to the close relationship between aboveground and belowground biomass (e.g., root-to-shoot ratio (RSR)), below-ground biomass flux was annually reported as 19.6% of the NASA CMS/UMD aboveground biomass flux based on established ratios within USFS forest inventory reporting (Domke et al. 2021). Over the 1990-2019 time period of the USFS inventory, the ratio between reported AGB and BGB estimates ranges between 0.193 and 0.204. For application in the State inventory, the RSR was averaged over the USFS inventory time period of 2006-2019 and annually applied to dynamic estimates of AGB at a single consistent ratio.

Other carbon pools

The carbon dynamics between aboveground biomass and other carbon pools cannot be as easily determined using a simple ratio. For this reason, the state inventory reports USFS state-level estimates for the forest carbon pools of deadwood, litter, and soil, as included in the EPA's State Inventory Tool (SIT). Due to the unavailability of 2020 estimates from the EPA, the Maryland inventory reports 2019 estimates for these pools in the 2020 inventory. More information on these methods is available from Domke et al. 2021 and EPA 2022.

USFS separately reports carbon flux from settlement trees[6]. As the lidar and satellite coverage of the NASA-CMS/UMD method captures trees in non-forest areas at the time of model initialization, the USFS category of settlement trees is conservatively excluded from the state inventory to avoid potential double-counting of carbon fluxes in these non-forest areas.

Methodological Advances

The margins of error in assessing forest carbon stock change are traditionally very large. For example, the World Resources Institute estimates that the US national inventory for forests had a 95% confidence interval of +/- 75% of the estimate.[7] Plot-based statistical extrapolation can entail high levels of uncertainty, which increase over small areas like states as the sample size gets smaller. The USFS uses annual field monitoring to update the forest carbon inventory, but only ~20% of the field plots are revisited each year. The resulting statewide estimates of carbon stock change are consequently "rolling averages" over the last 5 years of change. Furthermore, the USFS inventory relies on more approximate methods to estimate the sink from "settlement trees" or urban forest, and does not include non-urban trees outside of what USFS defines as forest. To estimate land cover change, the USFS utilizes the National Land Cover Dataset, which is updated every five years rather than annually.

[6] Carbon stocks and fluxes of settlement trees, trees occurring on developed land uses where human populations and activities are concentrated, are analyzed separately by the US EPA based on per unit area of tree cover.
[7] WRI. 2020. Natural and Working Lands Inventory Improvements: A Guide for States. wri.org/insights/greenhouse-gas-emissions-natural-working-lands

The NASA CMS/UMD method collaborated with USFS to utilize calibrated and validated remote sensing and modeling data to provide mapped coverage over the state (Hurtt et al. 2019). Using remote sensing data removes a key driver of uncertainty because it provides comprehensive (wall-to-wall) data on trees across the landscape, including annual land cover change data from Landsat satellite imagery. There is still uncertainty in calibrating the remote sensing data to plot measurements and then modeling forest changes over time; however, these uncertainties are generally lower than an exclusively plot-based approach. This new method allows Maryland to more frequently and accurately track progress towards the state's forest carbon goals and reflect the annual variability in forest carbon sequestration within the state GHG inventory.

Future Improvements

Reducing data latency

The forest carbon monitoring system is dependent on numerous datasets. Reducing the latency and/or updating these datasets over time can increase the speed and improve the quality of future assessments. For remote sensing, additional lidar data could be used to update the height of trees. Additional optical remote sensing data, classifying annual forest disturbance and recovery, could be used to update and extend over time the mapped estimates of forest carbon fluxes.

Detecting small scale tree loss and recovery

The current landsat-based remote sensing approach means that carbon losses and gains on non-forest areas may not be included. Furthermore, some remote sensing satellites, such as Landsat, find it difficult to detect regrowth during the first 15 years of forest succession and assumptions about forest structure at the time of detection can be challenging. To address these potential limitations, a currently funded project under the Tree Solutions Now Act is utilizing data gathered from MDE's new 5 million trees tracking platform to couple field data on recent afforestation activities with verification from optical imagery to confirm and more quickly initiate forest carbon regrowth within the Ecosystem Demography model. In addition, MDE is exploring the inclusion of refreshed 1m tree canopy data produced over the Chesapeake Bay Watershed by the University of Vermont and Chesapeake Conservancy.[8] While this data does not directly provide updated forest height metrics for ED initialization, the tree canopy map is produced using the same method as the NASA CMS/UMD tree canopy map (circa 2011) and could serve as a data source for sub-30 m changes to tree area within ED.

Including forest management

The current landsat based remote sensing approach detects forest disturbances from all causes and without classification. Ongoing research, including a U.S. Climate Alliance funded

[8] High-resolution land use and land cover data can be accessed through the Chesapeake Conservancy website: chesapeakeconservancy.org/conservation-innovation-center/high-resolution-data/

collaborative project with Michigan State University and the Pennsylvania Department of Natural Resources is refining assumptions about the carbon impacts of particular forest management practices. Including forest management activity that may not be detected by medium-resolution remote sensing data within the state inventory is an avenue for future work.

Accounting for harvested wood products

For this approach, forest carbon losses from disturbances are treated as committed carbon fluxes to the atmosphere. Future research on the fate of forest carbon losses including combustion factors, wood products and residence times could be added to better account for potential delayed release to the atmosphere. Harvest wood products are currently included in the state's GHG Inventory using default estimates for Maryland provided by the EPA SIT.

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