ENVIRONMENTAL RESEARCH LETTERS

PURPOSE-LED PUBLISHING™

Part of the ENVIRONMENTAL RESEARCH SERIES

LETTER • OPEN ACCESS

Beyond MRV: combining remote sensing and ecosystem modeling for geospatial monitoring and attribution of forest carbon fluxes over Maryland, USA

To cite this article: George C Hurtt *et al* 2024 *Environ. Res. Lett.* **19** 124058

ENVIRONMENTAL RESEARCH
LETTERS

CrossMark

OPEN ACCESS

RECEIVED
27 August 2024

REVISED
21 October 2024

ACCEPTED FOR PUBLICATION
8 November 2024

PUBLISHED
19 November 2024

LETTER

Beyond MRV: combining remote sensing and ecosystem modeling for geospatial monitoring and attribution of forest carbon fluxes over Maryland, USA

George C Hurtt[1,*], Lei Ma[1], Rachel Lamb[1,2], Elliot Campbell[3], Ralph O Dubayah[1], M Hansen[1], Chengquan Huang[1], Haley Leslie-Bole[4], Andrew Lister[5], Jiaming Lu[6], Frances Marie S Panday[1,2], Quan Shen[1], Carlos E Silva[7] and H Tang[8]

1 Department of Geographical Sciences, University of Maryland, College Park, MD, United States of America
2 Maryland Department of Environment, Baltimore, MD, United States of America
3 Maryland Department of Natural Resources, Annapolis, MD, United States of America
4 World Resources Institute, Washington, DC 20002, United States of America
5 Northern Research Station, Forest Inventory and Analysis, National Inventory & Monitoring Applications Center (NIMAC), U. S. Forest Service, York, PA 17402, United States of America
6 School of Biological Sciences, University of Utah, Salt Lake City, UT 84112, United States of America
7 Pachama, Inc., San Francisco, CA, United States of America
8 Department of Geography, National University of Singapore, Singapore 117570, Singapore
* Author to whom any correspondence should be addressed.

E-mail: gchurtt@umd.edu

Keywords: forest, carbon, monitoring, climate mitigation, remote sensing, modeling, lidar

Supplementary material for this article is available online

Abstract

Members of the U.S. Climate Alliance, a coalition of 24 states committed to achieving the emissions reductions outlined in the 2015 Paris Agreement, are considering policy options for inclusion of forest carbon in climate mitigation plans. These initiatives are generally limited by a lack of relevant data on forest carbon stocks and fluxes past-to-future. Previously, we developed a new forest carbon modeling system that combined high-resolution remote sensing, field data, and ecological modeling to estimate contemporary above-ground forest carbon stocks, and projected future forest carbon sequestration potential for the state of Maryland. Here we extended this work to provide a consistent geospatial approach for monitoring changes in forest carbon stocks over time. Utilizing the same data and modeling system developed previously for planning, we integrated historical input data on weather and disturbance to reconstruct the history of vegetation dynamics and forest above-ground carbon stocks annually over the period 1984–2016 at 30 m resolution and provided an extension to 2023. Statewide, forested land had an average annual net above ground carbon sink of 1.37 TgC yr^{-1}, comparable to prior estimates. However, unlike the prior estimates, there was considerable variation around this mean. The statewide net above ground flux ranged interannually from -0.65 to 2.77 Tg C yr^{-1}. At the county scale, the average annual net above ground flux ranged spatially from 0.01 to 0.13 Tg C yr^{-1} and spatiotemporally from -0.43 to 0.24 Tg C yr^{-1}. Attribution analyses indicate the primary importance of persistent and regrowing forests, vegetation structure, local disturbance, and rising CO_2 to the mean flux, and the primary importance of weather to the large-scale interannual variability. These results have important implications for state climate mitigation planning, reporting and assessment. With this approach, it is now possible to monitor changes in forest carbon stocks spatiotemporally over policy relevant domains with a consistent framework that is also enabled for future planning.

1. Introduction

Global climate change has led to an increasing scientific and policy interest in quantifying atmospheric carbon emissions and removals. While most emissions are energy-related, terrestrial ecosystems contribute large fluxes, which are highly uncertain (Friedlingstein *et al* 2023). This uncertainty limits the potential for effective climate mitigation policies.

Within the United States, the subnational scale is key to advancing science and policy on climate change mitigation and terrestrial carbon fluxes. The U.S. Climate Alliance (USCA), consisting of 24 member states, has committed to reducing greenhouse gas (GHG) emissions by at least 26%–28% below 2005 levels by 2025, as outlined in the 2015 Paris Agreement. However, currently only a quarter of the states account for forest carbon in their emission reductions and use a range of scientific methods and approaches with varying quality (Lamb *et al* 2021). Many states have found that the tools and datasets available to them are useful but not sufficient and have expressed the need for more data and/or tools to advance their forest carbon science relative to climate mitigation planning, including in particular: higher resolution data on forest carbon sequestration and carbon sequestration potential, improved annual carbon flux monitoring capabilities, and a specific interest in better utilization of remote sensing technologies to improve forest carbon estimates (including lidar) (Lamb *et al* 2021).

Previously, a new approach was developed to produce mapped data on contemporary forest biomass and future forest carbon sequestration potential for the state Maryland. The approach first utilized high resolution airborne lidar and optical remote sensing together with field data to empirically map forest biomass across the state (Huang *et al* 2015). The same inputs were then used to initialize a mechanistic forest ecosystem model to map forest biomass and then make projections of future carbon sequestration potential for planning (Hurtt *et al* 2019). This approach has since been scaled up to regional and global scales (Huang *et al* 2019, Ma *et al* 2021, 2023, Tang *et al* 2021).

'Monitoring' forest carbon fluxes to meet state needs also requires additional steps beyond traditional approaches. While new scientific methods using remote sensing have the potential to produce improved maps of contemporary carbon stocks and fluxes, most/all climate mitigation plans require monitoring emissions reductions from a much earlier date (e.g. 1990, 2000, or 2005) and include attribution of the associated fluxes to underlying drivers. Moreover, to be most useful, monitoring approaches should be consistent with the methods used for future planning. A key scientific opportunity therefore is to utilize new mapping methods and mechanistic ecosystem models together to map carbon fluxes over time.

Here, we build on the approach developed previously for planning and use the same system with additional inputs to advance 'monitoring'. In this process, the same high-resolution optical and lidar remote sensing data used to initialize the model for future projections were also used to constrain past forest dynamics. Historical weather, CO_2, and disturbance data were integrated as drivers of past variability of carbon stocks and fluxes. The results provide new mapped estimates of annual forest carbon stocks and fluxes from 1984 to 2023. There are over 27 million 30 m land grid cells in Maryland, tracked over 39 years, with more than 3 million forest disturbance events. To our knowledge, this is the first integration of process-based modeling and remote sensing in a consistent geospatial framework to meet state needs for monitoring, assessment and planning of forest carbon stocks and fluxes over time.

2. Methods

2.1. Study area

The study region was the state of Maryland, USA. The state has a temperate climate and three major physiographic regions including the Atlantic coastal plain, Piedmont plateau, and a relatively small mountainous area in the west (Markewich *et al* 1990, Daly *et al* 2008). The dominant potential vegetation type is deciduous forest (Ramankutty and Foley 1999). However, the current landscape is characterized by fragmented forests due to widespread land-use/land-cover changes. According to NLCD, forest plus woody weltand covers 45%, planted/cultivated covers 30% and developed covers 20% of the land area (Dewitz 2023). The state has several important pieces of legislation related to forests and climate mitigation. The Forest Conservation Act of 1991, strengthened in 2013, established the goal of achieving no net loss of forests and maintaining forest cover above 40%. The Greenhouse Gas Reduction Act of 2009, strengthened in 2016, established goals for emissions reductions. Most recently, the Climate Solutions Now Act strengthend these commitments and established the goal of reducing gross emissions 60% from 2006 levels by 2030 and achieving net zero emissions by 2045, and the Tree Solutions Now Act required the planting of 5 million trees by 2031. In 2023, Maryland released its Climate Pollution Reduction Plan (MDE 2023a), outlining the steps necessary to meet these goals.

2.2. Model

This study used the Ecosystem Demography (ED) model to simulate vegetation dynamics (i.e., carbon stocks, carbon fluxes and canopy height) with drivers including meteorology, CO_2 and soil properties (Hurtt *et al* 1998, 2002, Moorcroft *et al* 2001, Ma *et al* 2022). ED is an individual- and mechanism-based global ecosystem model with integrated submodels of plant growth, mortality, phenology, biodiversity, disturbance, hydrology, and soil biogeochemistry. ED explicitly tracks vegetation dynamics and characterizes competition for resources at the individual plant scale and efficiently scales up to the ecosystem scale. An advantage of ED is that it tracks vegetation height and carbon together which allows for direct linkage to remote sensing observations of forest structure. The model has been used in multiple studies pioneering the use of airborne lidar remote sensing in ecosystem modeling for carbon studies across a range of domains including statewide application (Hurtt *et al* 2004, 2010, 2016, 2019, Ma *et al* 2021, Thomas *et al* 2008). The most recent version (ED v3.0) used here was developed and calibrated at global scale and model simulations were evaluated against a suite of benchmarking datasets including field measurements and remote sensing observations (Ma *et al* 2022).

2.3. Data

High-resolution (1 m) airborne lidar and optical remote sensing were used to characterize tree canopy height and cover over the state (O'Neil-Dunne *et al* 2014a, 2014b, Dubayah *et al* 2018). To produce this product, a 1 m Canopy Height Model was derived from commercial airborne lidar point cloud data collected under leaf-off conditions over the state from 2004–2014. Tree canopy cover data at 1 m were derived from associated National Agricultural Imagery Program imagery together with lidar canopy height using an object-based tree canopy classification approach.

Landsat data were used to characterize forest disturbance and recovery. Two existing datasets were used: the North American Forest Dynamics (NAFD) (Goward *et al* 2016) and Global Forest Watch (GFW) (Hansen *et al* 2013) products. These datasets contain information on the annual location of forest disturbances at 30 m. NAFD provides estimates for the period 1985–2016 and the locations of water, forest, non-forest, or disturbance. For each location, the classification time series following the disturbance year indicates whether forest recovery occurred. The GFW product maps forest extent and forest loss years over the period of 2001–2023.

Meteorological data included temporally and spatially varying air temperature, humidity, downward shortwave radiation and precipitation. The former three variables were derived by fusing datasets of NASA Daymet and MERRA2 for 1984–2023 to produce monthly data (hourly) at 1 km (Ma *et al* 2021). The monthly precipitation at 1 km was from the Daymet dataset. Atmospheric CO_2 data, which were from the NOAA Carbon Tracker product, were constant over space but varied annually. Soil property data were from the Probabilistic Remapping of SSURGO (Chaney *et al* 2016) and CONUS-SOIL (Miller and White 1998) products.

2.4. Model-data integration

We implemented a new algorithm that began with model initialization using high-resolution remote sensing observations of canopy height and tree canopy cover obtained between 2004 and 2014, and worked to reconstruct the optimal historical time series of forest biomass consistent with the initialization and the history of environmental forcing and disturbances. A model experimental design was implemented for attribution, and results were validated against a range of benchmarks. The components of the system are shown in figure 1.

We initialized ED using high-resolution lidar and optical remote sensing to establish a baseline map of forest biomass at 30 m (Hurtt *et al* 2019, Ma *et al* 2021). Reconstruction was then begun by first consulting the remote sensing disturbance and recovery history to partition grid cells that had not been disturbed during the reconstruction period from those that had (figure 2). For non-disturbed cells, ED was initialized at the beginning of the reconstruction period with a trial set of potential initial values and ran forward to contemporary conditions. The two closest trial cases that contained the baseline aboveground biomass (AGB) value were selected and their associated time series of forest dynamics were linearly weighted as the optimal reconstruction for that grid cell (figure 2(b)). For the disturbed grid cells, the reconstruction period was split into segments defined by the disturbance events. An iterative process based on the above algorithm was then performed for each segment (figure 2(c)). First, working backwards from the segment that includes the baseline, a trial set of potential initial values for each grid cell following the previous disturbance was used to run ED forward to contemporary conditions and the optimal trial pair was identified and used as described above. The next prior segment was reconstructed similarly, and in these cases forest biomass pre-disturbance was assumed to be the statewide average in that year. This process was then repeated for all prior segments for all grid cells until the beginning of the reconstruction period. For disturbances after the baseline period, forest biomass continued growth from the baseline period until disturbance, and forest biomass post-disturbance was assumed to be based on the statewide average disturbance intensity and began to recover following.

2.5. Attribution

To attribute fluxes to underlying land cover changes, net AGB fluxes were broken down into three

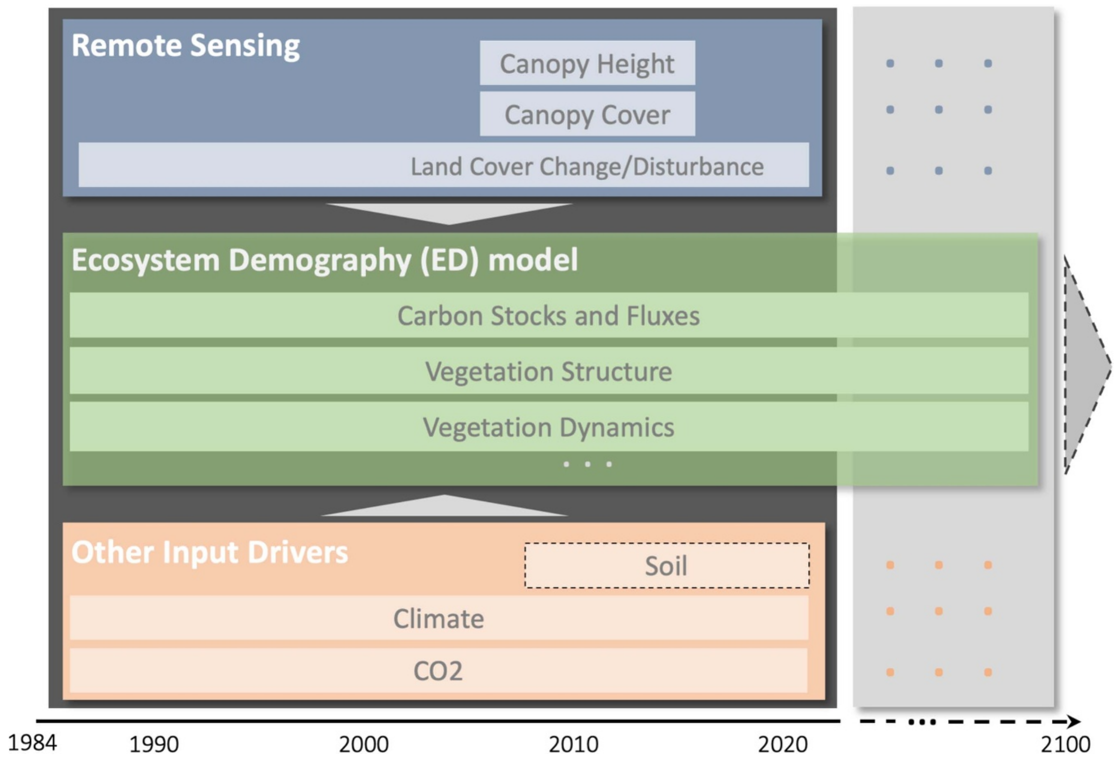

Figure 1. Conceptual diagram of the components of the forest carbon monitoring and modeling system. Remote sensing and other input drivers are integrated into the Ecosystem Demography model to quantify past vegetation structure, dynamics, and carbon stocks and fluxes over the state consistent with contemporary baseline conditions. The same modeling system can then be used to make consistent future projections for planning.

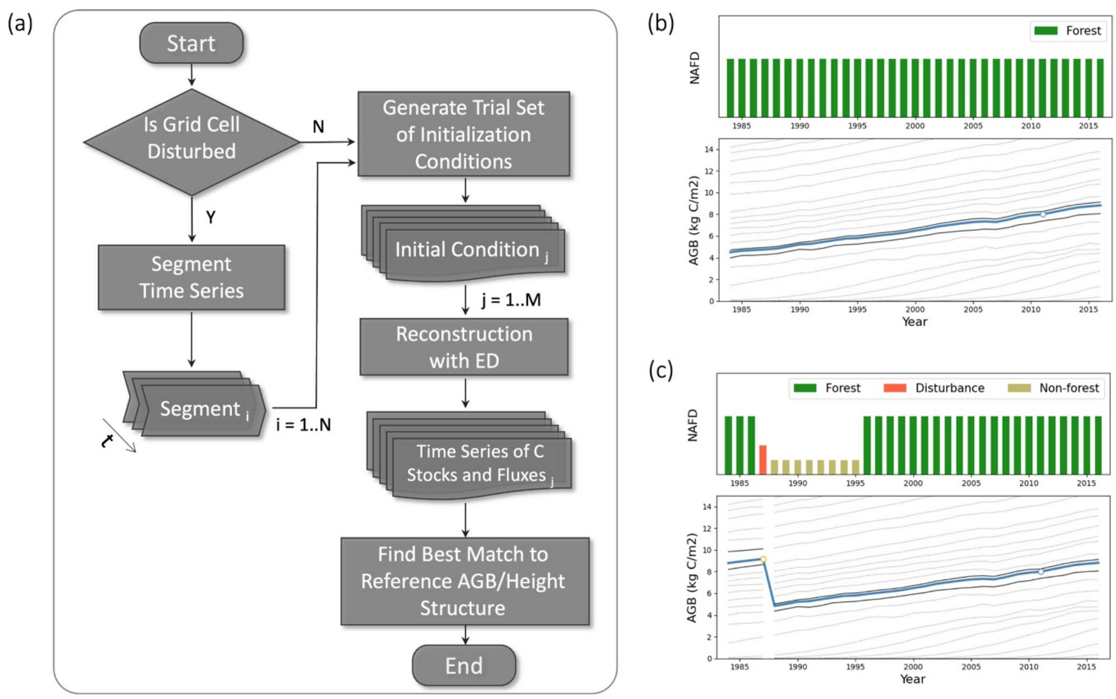

Figure 2. Method illustration depicting (a) workflow and grid cell level reconstruction for two cases: (b) no disturbance and (c) disturbance.

Table 1. Summary of experiments and configurations (incl. Best (ED-B) and attribution (ED-A) exp.). V and C indicate whether a driver was kept variable or constant in an experiment.

	Drivers					
	Meteorology		CO_2		Disturbance	
Experiments	Temporal	Spatial	Temporal	Spatial	Temporal	Spatial
ED-B	V	V	V	C	V	V
ED-A4	V	V	V	C	V	C
ED-A3	V	V	V	C	C (MD avg.)	C
ED-A2	C	V	C	C	C (MD avg.)	C
ED-A1	C	V	C	C	C (CONUS avg.)	C

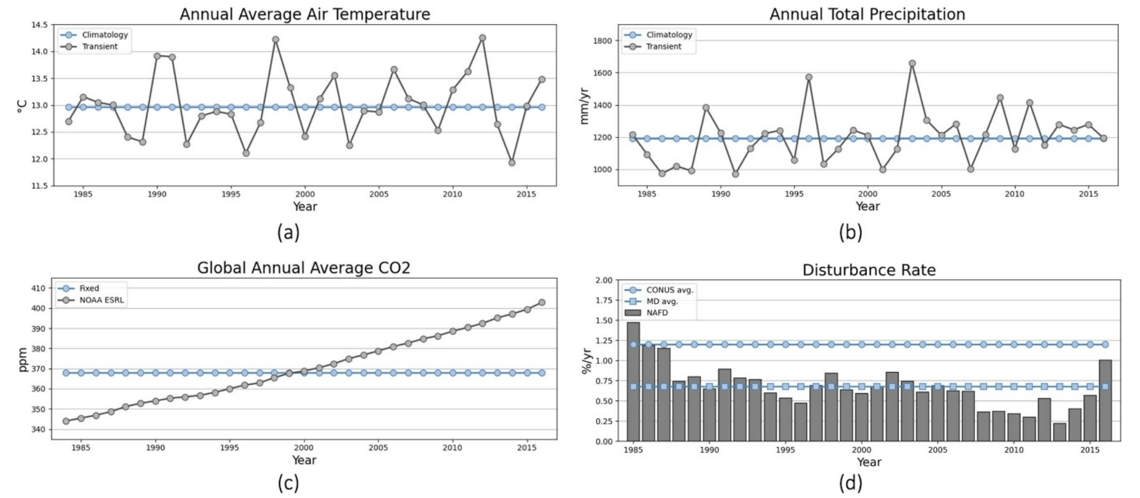

Figure 3. Annual drivers of air temperature, precipitation, disturbance, and CO_2.

component categories ('persistent', 'recovering', and 'disturbed') based on local land cover change history during the study period. Persistent fluxes represented the biomass change over grid cells that had not been disturbed, disturbed fluxes represented the biomass change over grid cells that were disturbed, and recovering fluxes represented the biomass change over disturbed grid cells after those disturbance events.

To attribute fluxes to underlying drivers, a partial model factorial experiment was conducted by driving ED with different combinations of temporal and/or spatial aggregations of input data on meteorology, CO_2, and disturbance (table 1, figure 3). The baseline configuration was labeled ED-B and used spatially and temporarily variable inputs for all factors, except CO_2 which was spatially constant but varied temporally. ED-A4 shared the same configuration, but removed the spatial pattern of disturbance and implemented a spatially averaged disturbance rate. ED-A3 shared the same configuration as ED-A4, but also removed the temporal variation in disturbance and implemented a spatially and temporally averaged disturbance rate. ED-A2 shared the same configuration as ED-A3 but also removed the temporal variation in meteorology and CO_2. Finally, ED-A1 shared the same configuration as ED-A2, but implemented a different (larger) average disturbance rate.

Comparisons between the model configurations were performed by differencing results from appropriate trials from table 1 to assess the impacts of the six factors on carbon flux. Specifically, differencing the results from ED-B and ED-A4 was used to diagnose the importance of spatially explicit modeling disturbance. Differencing the results from ED-A4 and ED-A3 was used to diagnose the impact of transient disturbance rate. Differencing the results from ED-A3 and ED-A2 was used to diagnose the impacts of transient meteorology and CO_2. Differencing the results from ED-A2 and ED-A1 was used to determine the importance of the average disturbance rate. The magnitude of the differences in state-level means and variability were used as an indicator of which input configurations were the most impactful.

2.6. Validation

Validation of the model results was multivariable and multiscale; it included Net Primary Production (NPP) at the state level and AGB at the state, plot, and grid cell levels. Modeled NPP was compared against an independent dataset, Landsat-derived NPP developed by the University of Montana Numerical Terradynamic Simulation Group (NTSG) (Robinson *et al* 2018). Modeled AGB fluxes were compared to data from the USFS nationwide forest inventory provided by the Forest Inventory and Analysis Program (FIA) at both the state and plot scales. At the state scale, the total net AGB flux was compared to USFS estimates (Domke *et al* 2020). At the plot scale, average AGB and its annual changes were compared to results from corresponding FIA plots. Finally, the spatially explicit AGB change ratio (change in AGB relative to pre-disturbance AGB) over disturbed grid cells were compared to the NAFD Disturbance Intensity (NAFD-DI) dataset. NAFD-DI is an independent Landsat product estimating disturbance intensity based on the basal area removed by disturbances (Lu *et al* 2022, 2023).

3. Results

Statewide forest dynamics were modeled at an annual timestep and a spatial resolution of 30 m. The results are presented in detail for 1984–2016, which was the period of NAFD coverage, then for calibration/validation and extension with GFW coverage 2000–2023.

Fine-scale spatial patterns of forest growth and disturbance events were captured using the system. Figure 4 shows a local example of a series of events. Landsat imagery over the region in 2000 and 2001 shows a heterogeneous forested landscape with areas identified as disturbed in red. These same areas were observed in the corresponding NAFD product of forest disturbance. The corresponding AGB estimates derived from the ED model showed high pre-disturbance values in 2000 that, due to forest loss, were reduced in 2001 by disturbance events. The pattern of AGB change associated with disturbance events is most clearly seen in the corresponding AGB change map. This map also shows the background accumulation of carbon in areas with undisturbed forest.

Broad-scale spatial patterns of forest AGB and AGB changes varied across the state (figure 5). Forest carbon maps illustrate relatively high concentrations of forest carbon in the south central and northwest, and relatively lower values in the central and eastern shore. At the county scale, Garrett, Charles, and Baltimore had the largest carbon stocks and fluxes compared to other counties (table S2.1, figure S2.1). The histogram of AGB changes illustrates that the majority of locations in the state gained carbon, whereas a relatively small fraction lost carbon during disturbance events.

Net AGB change is a result of gross carbon gain in persistent and recovering forests and loss from forest removal. The net AGB change over the state is broken down into these three component flux types for 1985–2016 (figure 6). These three types vary in their area and rate of gain/loss. Persistent growth dominates the total AGB growth because of the large area of forests with no disturbance relative to the area of recovering forests. The AGB loss exhibits interannual variation primarily following the NAFD-based disturbance rate. On average, the AGB gain from continued growth was 1.68 Tg C yr^{-1}, AGB gain from new growth (grid cells that were disturbed at any prior point during the interval) was 0.20 Tg C yr^{-1}, and AGB loss was 0.51 Tg C yr^{-1}. The carbon gain from new growth did not offset the carbon loss from disturbance for most years.

Statewide net AGB change averaged 1.56 Tg C yr^{-1} 1990–2016, which was comparable to the USFS estimate over the same interval (figure 7). However, the net AGB gain varied considerably from year to year in this analysis. Attribution experiments revealed the respective contributions of drivers to the interannual variation and average rates of change. Removal of the spatial pattern of disturbance had a relatively small effect on the statewide average flux (ED-A4, Green). The removal of the temporally variable disturbance rate (i.e. using a constant value) had a larger effect (ED-A3, Blue). The removal of variable meteorology and CO_2 had a larger effect still and removed most of the interannual variability (ED-A2, Orange). Removal of the local disturbance rate lowered the statewide average flux by overestimating disturbance in the state (ED-A1, Pink). Figure 8 shows the magnitude of the effects of these drivers on the average net flux and interannual variability of the net flux. The disturbance rate had the largest effect on average net flux. Transient meteorology had the largest effect on interannual variability. The other factors had intermediate effects, with a generally inverse effect on these variables.

Statewide average annual estimates of NPP over forests compared favorably to the corresponding remote sensing based estimates from NTSG (figure S1.1). Modeled average annual NPP was 0.82 ± 0.09 kg C m^{-2} yr^{-1} compared to 0.80 ± 0.06 kg C m^{-2} yr^{-1}, and both had comparable increasing trends over the interval 1990–2016. Both also estimated a decline beginning in 2008–2009 followed by recovery, although the NTSG estimate showed a deeper period of decline. At the plot scale, modeled estimates of AGB explained moderate variations ($R^2 = 0.34$, RMSE = 3.21 kg C m^{-2}, bias = 0.54 kg C m^{-2}) in corresponding FIA measurements (figure S2.2).

Gridded estimates of biomass change were compared with the corresponding estimates from the NAFD-DI dataset (figures 9 and S1). From 1985 to 2015, the average AGB change ratio was 91.19% and the average DI was 82.08%. The ED AGB maps were able to capture partial disturbances, however the area of partial disturbance was lower than that reported by NAFD and the area of stand clearing was larger.

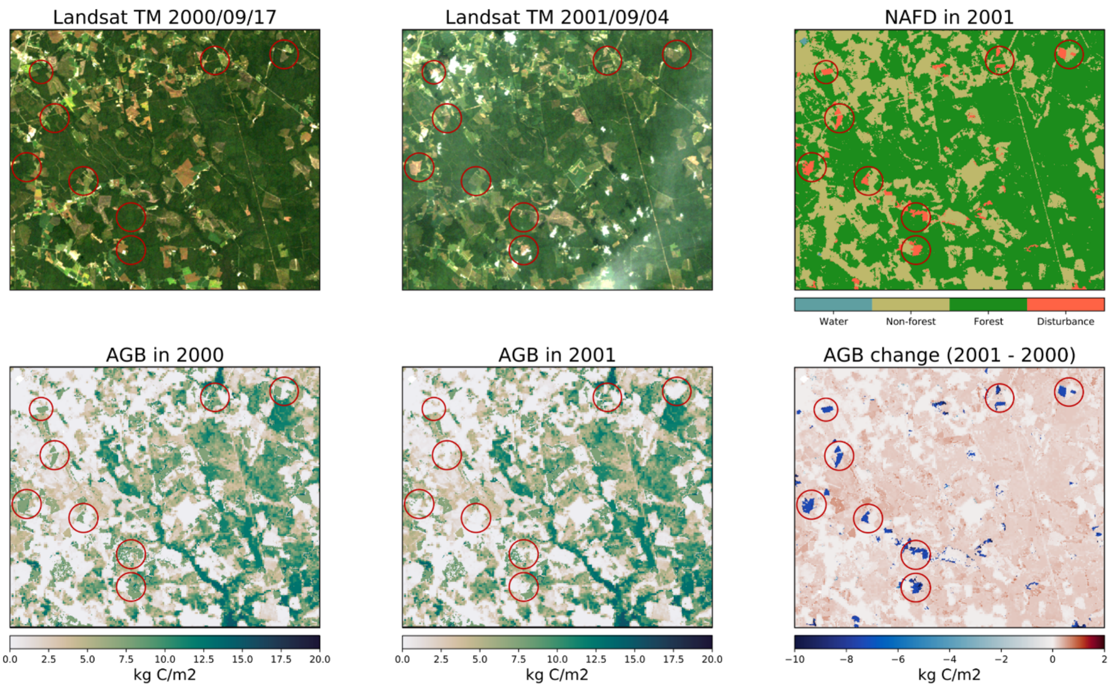

Figure 4. Disturbance events and associated AGB changes. Top row, Landsat TM natural color composite images for September 2000 (left), September 2001 (center) and the corresponding NAFD product with forest (green) non-forest (brown). Red circles are drawn around change areas for reference. Bottom row, the corresponding AGB and AGB change estimates from the ED model.

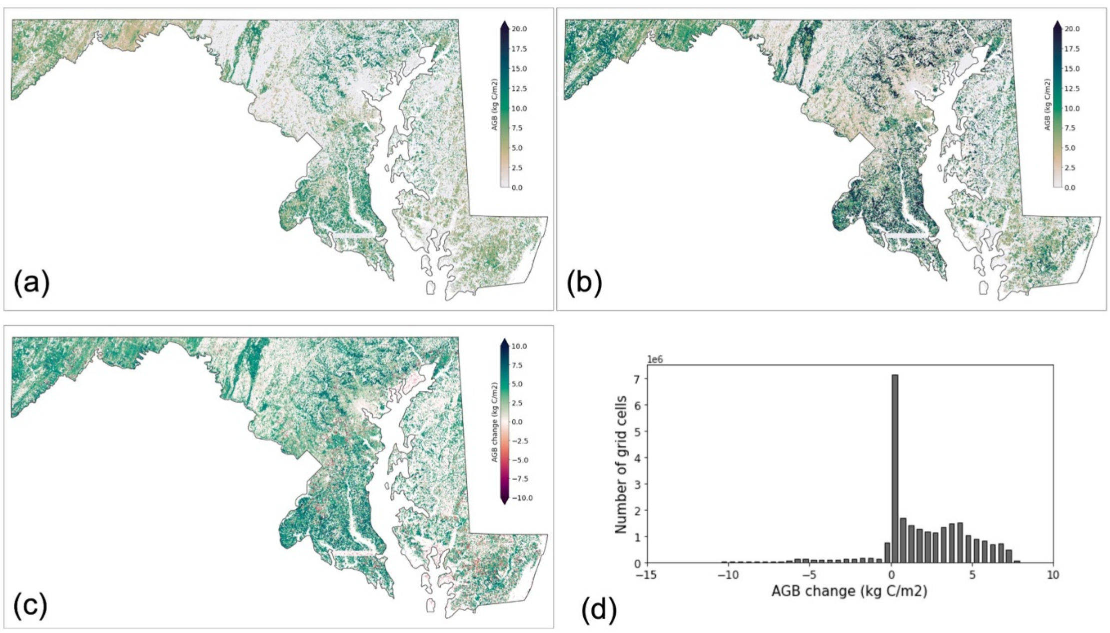

Figure 5. AGB in (a) 1984 and (b) 2016. (c) AGB change from 1984 to 2016 and (d) histogram of AGB change in forested grid cells.

ED and NAFD exhibited consistent temporal trends in both stand-clearing and partial disturbance areas.

Finally, the model results were extended to 2023 to meet state reporting needs (figure 10). The end of the updates to the NAFD product in 2016 necessitated a change in the input data for the ED model to the GFW product, which overlapped and extended beyond the time period for which the NAFD was maintained (2001 onward). The period of overlap between the NAFD and the GFW data products (2001–2016) provided another opportunity for validation and assessment of the sensitivity of model outputs to input data sources. During this overlapping period, the magnitude and variability of the AGB flux were nearly identical between the two methods. The extension period of 2017–2023 had an average annual AGB flux of 1.42 Tg C yr^{-1}. The corresponding county-level results were

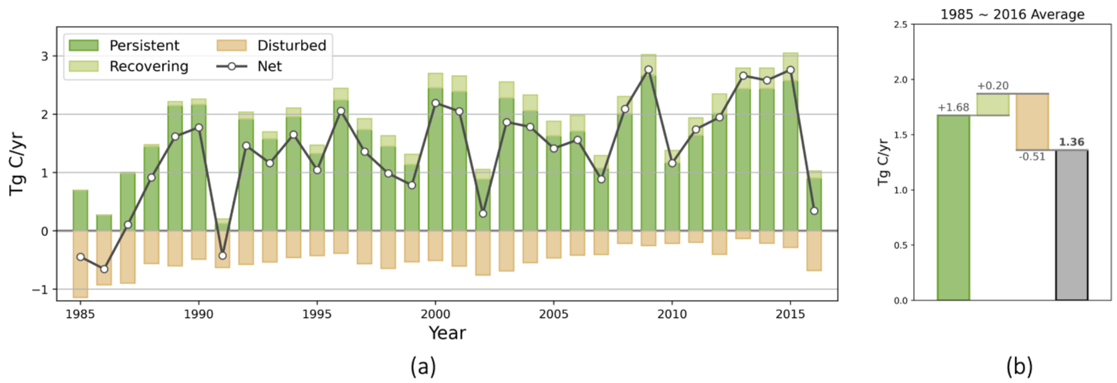

Figure 6. Partition net AGB change by flux category: persistent, recovering, disturbed, and net: (a) time series, (b) annual average 1985–2016.

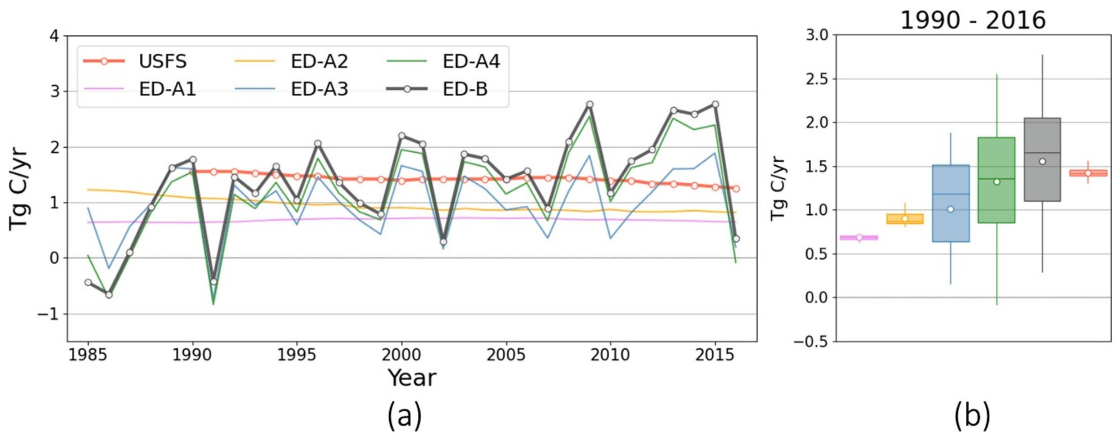

Figure 7. Statewide net AGB change. (a) Time series of net AGB change 1985–2016 with USFS reference 1990–2016 (Domke *et al* 2020), ED (cases from table 1). (b) Average annual net AGB change for each case over 1990–2016 for comparison. In a box plot, the box represents the interannual variability (interquartile range from the first quartile, Q1, to the third quartile, Q3), the whiskers extend to the range of the data within 1.5 times the interquartile range (Q1–1.5*(Q3–Q1) to Q3 + 1.5*(Q3–Q1)), the horizontal line within the box indicates the median, and the marker denotes the mean.

also calculated and presented (table S2.1 and figure S2.1).

4. Discussion

Globally, forests store a large amount of carbon, contribute large carbon fluxes to the atmosphere, and serve as a significant annual carbon sink (Friedlingstein *et al* 2023, Pan *et al* 2024). Policy efforts to account for changes in forest carbon require the ability to accurately quantify forest carbon fluxes on the required spatial and temporal scales. Within the US, 24 states have state-level policies requiring carbon emission reductions and 33 have state climate action plans. However, even in some of the most ambitious regions, including the Regional Greenhouse Gas Initiative region, forest carbon data are insufficient to meet state needs (Lamb *et al* 2021). Therefore, many states do not include forest carbon in their reduction goals or plans.

Recent global remote sensing-based approaches have been used to map annual changes in AGB (Liu *et al* 2015, Tang *et al* 2020, Harris *et al* 2021, Xu *et al* 2021, Yang *et al* 2023). These approaches generally establish empirical relationships between ground measurements and lidar samples with optical and radar observations and then extrapolate to areas lacking lidar observations. Although proven capable of detecting carbon loss from deforestation, they are challenged to quantify forest growth with closed canopies due to the weak sensitivity of optical images to structural changes and a lack of capability to attribute changes to underlying drivers. Other studies have linked remote sensing to process based ecosystem models for carbon (Running *et al* 1989, Lucas and Curran 1999, Ranson *et al* 2001, Turner *et al* 2004, Masek and Collatz 2006, Antonarkis *et al* 2011, Williams *et al* 2014, Masek *et al* 2015, Rodig *et al* 2019). This study builds on these and employed a new method that combined 1 m high-resolution

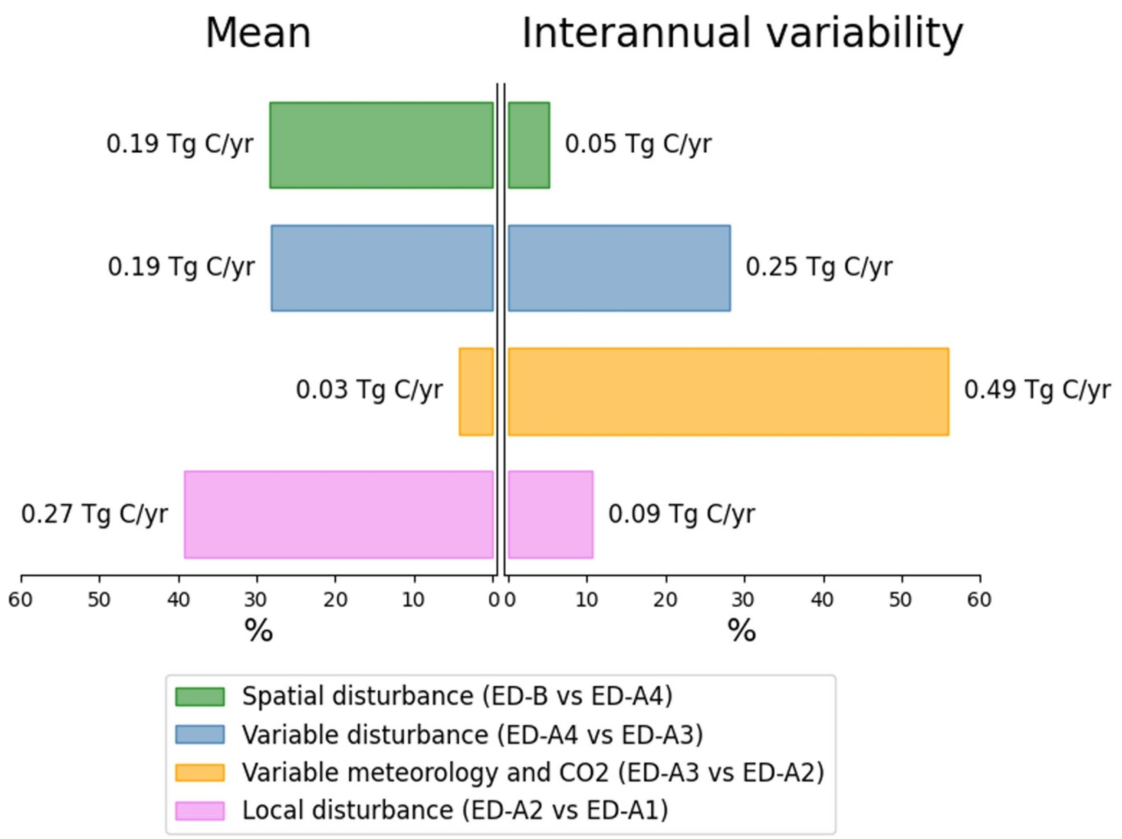

Figure 8. Partition of the mean and interannual variability of net AGB fluxes by driver 1985–2016. Left, differences between average annual net AGB fluxes. Right, differences between standard deviation of annual net AGB fluxes.

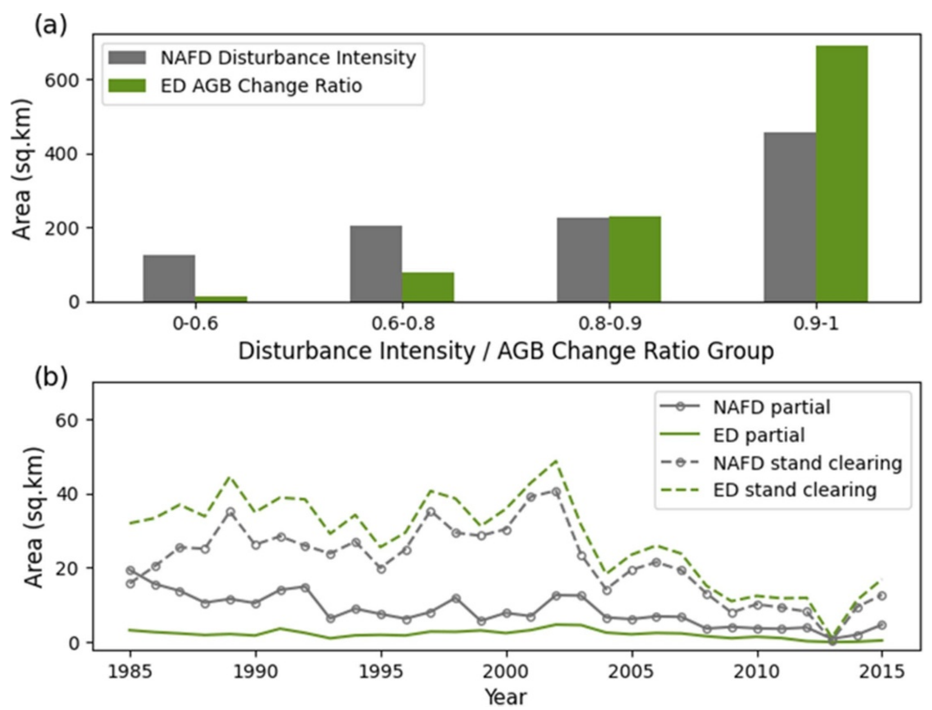

Figure 9. Disturbance intensity by severity and over time. (a) Disturbance severity by intensity category. (b) Temporal trends of partial and stand-clearing disturbed area (calculated by NAFD-DI and ED AGB Ratio).

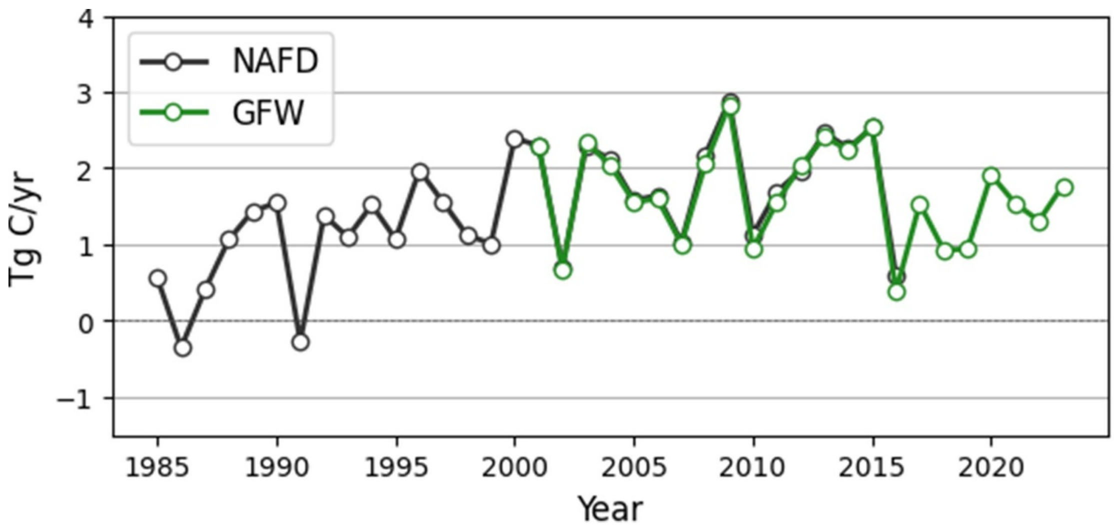

Figure 10. Comparison of reconstructed net AGB flux from NAFD and GFW as input sources.

remote sensing data (lidar and optical) data and a height-structured mechanistic ecosystem model to meet state needs for forest carbon fluxes. Critical to the calibration and validation of our approach was the use of FIA data.

Our findings have several important implications. First, the significant interannual variability in net fluxes found highlights the effects of weather/climate on terrestrial carbon fluxes, presents complications for policies that set target years for achieving specific emission reductions goals and potentially obscures the effects of management actions or trends. Second, the strong influence of disturbance to the state mean net flux emphasizes the importance of natural and human disturbances for carbon sequestration. Third, the large contribution from persistent growth, relative to new growth, reinforces the importance of conserving existing tree cover, while the contribution from new growth is also important but more limited. Finally, the geospatial coverage afforded by this approach enabled the consistent monitoring and reporting of results across multiple relevant spatial (state, county, event) and temporal scales (annual, decadal), all in a framework also enabled for planning.

The trend in the forest carbon sink is an important topic for planning and policy. Previous studies have warned of the potential effects of forest aging and increased disturbance rates on forest carbon sinks (Hurtt *et al* 2002, McDowell *et al* 2020), and of potential enhancements from meteorology and/or rising CO_2 (Ruehr *et al* 2023). The mix of these drivers, and their associated impact on carbon fluxes, is likely to be spatially and temporally dependent, with different states experiencing different combinations of factors (Dolan *et al* 2017). The small declining trend in the sink in USFS data for Maryland was not evident in our results. However, the trend is heavily dependent on the time period of interest and subject to interannual variability which is very different between the two datasets.

This study was based on a one-time ‘wall-to-wall’ high-resolution dataset of 1 m airborne lidar and optical imagery. This dataset has proven to be immensely powerful for mapping, modeling, and monitoring carbon fluxes. Repeated coverage of these data would likewise be potentially very powerful. However, the logistics for generating an updated dataset are costly and challenging; thus, this dataset does not currently exist for other time periods in this domain. This limitation results in important uncertainties.

One related source of uncertainty is disturbance intensity. While disturbance events were detected by optical remote sensing, we had no direct data on the fraction of biomass removed during each event. Instead, the disturbance intensity was estimated for each event using a combination of location specific estimates of pre- and post-disturbance biomass, forest growth rates, and time between disturbance events. A comparison of our underlying maps of disturbance intensity to an independent Landsat product revealed strong similarities, but suggested that our method may have somewhat overestimated stand clearing events and somewhat underestimated partial disturbance events. If true, this implies that we may have overestimated the gross emissions from disturbance events and subsequent negative emissions from regrowth. However, it is also important to consider that there are substantial differences between the two datasets, as NAFD-DI was created based on the basal area removed by disturbances, which is not equal to the change ratio calculated using AGB. Additionally, internal uncertainties inherent in the methods used to produce these maps including assumptions of pre-disturbance AGB, and the spatial-temporal mismatches between FIA measurements and Landsat observations, may also contribute to the differences observed between the two datasets.

Additional uncertainties and opportunities for future research remain. Maryland is a coastal state with significant wetlands, which are included here for completeness using a common representation of plant functional types and ecological dynamics. However, these systems have distinct species, biogeochemistry, and dynamics. Further delineation and diagnosis of the associated fluxes relative to the results presented here is needed. In addition, forest management is conducted on approximately 40 000 acres of public and private forests per year. This estimate is based on data collected by the Maryland Forest Service and likely underestimates management actions on private land. Some management actions, such as harvests, would likely be detected as disturbance events and the carbon loss captured in the model. Other actions, such as thinning or degradation, may not be captured as disturbances but would impact carbon storage and future forest growth. Finally, this study focused specifically on AGB because it is the most observable and directly related to recent advances in lidar remote sensing. Progress on this term now greatly exceeds other important terms including soil carbon and product pools, raising the importance of equivalent science advances on those terms in future studies.

The results from this framework have been used to officially quantify and report forest carbon fluxes for Maryland, including annual net above ground forest carbon flux for state inventory and carbon sequestration potential for afforestation/reforestation planning (MDE 2022a, 2022b, 2023a, 2023b, Kennedy *et al* 2023). Advanced forest carbon monitoring capabilities, such as those demonstrated here, are also needed for other jurisdictions and time periods. Existing and new commercial airborne lidar and optical data could be used in this modeling system to satisfy some of these requirements. At larger scales, NASA has developed and deployed two orbital lidar missions GEDI and ICESat-2 which provide global sample lidar coverage from consistent platforms (Markus *et al* 2017, Dubayah *et al* 2020, 2022). Other planned and proposed missions, including NISAR and EDGE, could further increase capability through increased spatial resolution, temporal coverage, or both. NASA is also enabling the continued development and application of the required ecosystem modeling as part of the Carbon Monitoring System (Hurtt *et al* 2022) and the US National Greenhouse Gas Center and other programs. Together, these scientific investments will help expand, refresh and improve science products needed to meet state needs for forest carbon monitoring and planning.

Data availability statement

Data for this study are publicly available at: (https://doi.org/10.3334/ORNLDAAC/2384) (Hurtt and Ma 2024).

Acknowledgments

This work was funded by the NASA Carbon Monitoring System (NASA-CMS) under award 80NSSC21K1059, the USCA Technical Assistance Fund, and the Maryland Department of the Environment. We also acknowledge the in-kind support from the US Forest Service, Forest Inventory and Analysis Program. The DATA used in or part of this publication/presentation was made possible, in part, by an Agreement from the United States Department of Agriculture's Forest Service (FS). This publication/presentation may not necessarily express the views or opinions of the FS.

ORCID iDs

George C Hurtt https://orcid.org/0000-0001-7278-202X
Lei Ma https://orcid.org/0000-0002-3959-4155
Rachel Lamb https://orcid.org/0000-0001-6237-4778
Elliot Campbell https://orcid.org/0000-0003-3248-7637
Ralph O Dubayah https://orcid.org/0000-0003-1440-6346
M Hansen https://orcid.org/0000-0003-0042-2767
Chengquan Huang https://orcid.org/0000-0003-0055-9798
Andrew Lister https://orcid.org/0000-0002-0412-7039
Jiaming Lu https://orcid.org/0000-0001-6326-6330
Frances Marie S Panday https://orcid.org/0000-0002-7544-1586
Quan Shen https://orcid.org/0000-0002-0654-0978
Carlos E Silva https://orcid.org/0000-0002-0451-9737
H Tang https://orcid.org/0000-0001-7935-5848

References

Antonarkis A, Saatchi S, Chazdon R L and Moorcroft P 2011 Using lidar and radar measurements to constrain predictions of forest ecosystem structure and function *Ecol. Appl.* **21** 1120–37

Chaney N W, Wood E F, McBratney A B, Hempel J W, Nauman T W, Brungard C W and Odgers N P 2016

POLARIS: a 30-meter probabilistic soil series map of the contiguous United States *Geoderma* **274** 54–67
Daly C, Halbleib M, Smith J I, Gibson W P, Doggett M K, Taylor G H and Pasteris P P 2008 Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States *Int. J. Climatol.* **28** 2031–64
Dewitz J 2023 National land cover database 2021- landcover and imperviousness (NLCD2021) *Products: U.S. Geological Survey data release* (https://doi.org/10.5066/P9JZ7AO3)
Dolan K A, Hurtt G C, Flanagan S A, Fisk J P, Sahajpal R, Huang C, Page Y L, Dubayah R and Masek J G 2017 Disturbance distance: quantifying forests' vulnerability to disturbance under current and future conditions *Environ. Res. Lett.* **12** 114015–7
Domke G M, Walters B F, Nowak D J, Smith J, Ogle S M, Coulston J W and Wirth T C 2020 Greenhouse gas emissions and removals from forest land, woodlands, and urban trees in the United States, 1990–2018 *Resource Update* FS-227 (U.S. Department of Agriculture, Forest Service, Northern Research Station) (https://doi.org/10.1073/pnas.2010840117)
Dubayah R O, Swatantran A, Huang W, Duncanson L, Johnson K, Tang H, O'Neil-Dunne J and Hurtt G C 2018 LiDAR derived biomass, canopy height and cover for tri-state (MD, PA, DE) region, V2 (ORNL DAAC) (https://doi.org/10.3334/ORNLDAAC/1538)
Dubayah R *et al* 2020 The global ecosystem dynamics investigation: high-resolution laser ranging of the Earth's forests and topography *Sci. Remote Sens.* **1** 100002
Dubayah R *et al* 2022 GEDI launches a new era of biomass inference from space *Environ. Res. Lett.* **17** 095001
Friedlingstein P *et al* 2023 Global carbon budget 2023 *Earth Syst. Sci. Data* **15** 5301–69
Goward S N, Huang C, Zhao F, Schleeweis K, Rishmawi K, Lindsey M, Dungan J L and Michaelis A. 2016 NACP NAFD project: forest disturbance history from landsat, 1986–2010 (ORNL DAAC) (https://doi.org/10.3334/ORNLDAAC/1290)
Hansen M C *et al* 2013 High-resolution global maps of 21st-Century forest cover change *Science* **342** 846–50
Harris N L *et al* 2021 Global maps of twenty-first century forest carbon fluxes *Nat. Clim. Change* **11** 234–40
Huang W, Dolan K, Swatantran A, Johnson K, Tang H, ONeil-Dunne J, Dubayah R and Hurtt G 2019 High-resolution mapping of aboveground biomass for forest carbon monitoring system in the Tri-State region of Maryland, Pennsylvania and Delaware, USA *Environ. Res. Lett.* **14** 095002–17
Huang W, Swatantran A, Johnson K, Duncanson L, Tang H, Dunne J O, Hurtt G and Dubayah R 2015 Local discrepancies in continental scale biomass maps: a case study over forested and non-forested landscapes in Maryland, USA *Carbon Balance Manage.* **10** 1–16
Hurtt G C *et al* 2022 The NASA carbon monitoring system phase 2 synthesis: scope, findings, gaps and recommended next steps *Environ. Res. Lett.* **17** 063010
Hurtt G C, Dubayah R, Drake J, Moorcroft P, Pacala S W, Blair J B and Fearon M G 2004 Beyond potential vegetation: combining lidar data and a height-structured model for carbon studies *Ecol. Appl.* **14** 873–83
Hurtt G C, Fisk J, Thomas R, Dubayah R, Moorcroft P and Shugart H H 2010 Linking models and data on vegetation structure *J. Geophys. Res.* **115** 1–11
Hurtt G C and Ma L 2024 *Forest Aboveground Biomass for Maryland, USA* (ORNL DAAC) (https://doi.org/10.3334/ORNLDAAC/2384)
Hurtt G C, Moorcroft P R, Pacala S W and Levin S A 1998 Terrestrial models and global change: challenges for the future *Glob. Change Biol.* **4** 581–90
Hurtt G C, Pacala S, Moorcroft P and Caspersen J 2002 Projecting the future of the US carbon sink *Proc. Natl Acad. Sci.* **99** 1389–94
Hurtt G C, Thomas R Q, Fisk J P, Dubayah R O and Sheldon S L 2016 The impact of fine-scale disturbances on the predictability of vegetation dynamics and carbon flux ed B Poulter *PLoS One* **11** e0152883–1
Hurtt G *et al* 2019 Beyond MRV: high-resolution forest carbon modeling for climate mitigation planning over Maryland, USA *Environ. Res. Lett.* **14** 045013–5
Kennedy K M *et al* 2023 Maryland's Climate Pathway: An analysis of actions the State can take to achieve Maryland's nation-leading greenhouse gas emissions reduction goals (Center for Global Sustainability, University of Maryland)
Lamb R L *et al* 2021 Context and future directions for integrating forest carbon into sub-national climate mitigation planning in the RGGI region of the U.S *Environ. Res. Lett.* **16** 063001
Liu Y Y, Van Dijk A I, De Jeu R A, Canadell J G, McCabe M F, Evans J P and Wang G 2015 Recent reversal in loss of global terrestrial biomass *Nat. Clim. Change* **5** 470–4
Lu J, Huang C, Tao X, Gong W and Schleeweis K 2022 Annual forest disturbance intensity mapped using Landsat time series and field inventory data for the conterminous United States (1986–2015) *Remote Sens. Environ.* **275** 113003
Lu J, Huang C, Tao X and Schleeweis K 2023 NACP NAFD project: forest disturbance intensity for CONUS from landsat, 1986–2015 (ORNL DAAC) (https://doi.org/10.3334/ORNLDAAC/2059)
Lucas N S and Curran P J 1999 Forest ecosystem simulation modelling: the role of remote sensing *Prog. Phys. Geogr.* **23** 391–423
Ma L *et al* 2021 High-resolution forest carbon modelling for climate mitigation planning over the RGGI region, USA *Environ. Res. Lett.* **16** 045014
Ma L *et al* 2022 Global evaluation of the ecosystem demography model (ED v3.0) *GMD* **15** 1971–94
Ma L *et al* 2023 Spatial heterogeneity of global forest aboveground carbon stocks and fluxes constrained by spaceborne lidar data and mechanistic modeling *Glob. Change Biol.* **29** 3378–94
Markewich H W, Pavich M J and Buell G R 1990 Contrasting soils and landscapes of the Piedmont and Coastal Plain, eastern United States *Geomorphology* **3** 417–47
Markus T *et al* 2017 The ice, cloud, and land elevation Satellite-2 (ICESat-2): science requirements, concept, and implementation *Remote Sens. Environ.* **190** 260–73
Masek J G and Collatz G J 2006 Estimating forest carbon fluxes in a disturbed southeastern landscape: integration of remote sensing, forest inventory, and biogeochemical modeling *J. Geophys. Res.* **111** 15
Masek J G, Hayes D J, Hughes M J, Healey S P and Turner D P 2015 The role of remote sensing in process-scaling studies of managed forest ecosystems *For. Ecol. Manage.* **355** 109–23
McDowell N G *et al* 2020 Pervasive shifts in forest dynamics in a changing world *Science* **368** 1–10
MDE 2022a Reducing greenhouse gas emissions in Maryland: a progress report *The Maryland Department of the Environment* (available at: https://mde.maryland.gov/programs/air/ClimateChange/Documents/GGRA%20PROGRESSS%20REPORT%202022.pdf)
MDE 2022b Final plan for growing 5 million trees in Maryland (The Maryland Department of the Environment) (available at: https://mde.maryland.gov/programs/air/ClimateChange/Documents/FINAL_Plan-for-Growing-5-Million-Trees-in-Maryland_10.28.22%20%281%29.pdf)
MDE 2023a Maryland's climate pollution reduction plan (The Maryland Department of the Environment) (available at: https://mde.maryland.gov/programs/air/ClimateChange/Maryland%20Climate%20Reduction%20Plan/Maryland%27s%20Climate%20Pollution%20Reduction%20Plan%20-%20Final%20-%20Dec%2028%202023.pdf)
MDE 2023b Maryland tree and forest carbon flux data and methodology documentation as prepared for the 2020

Maryland Greenhouse Gas inventory (available at: https://mde.maryland.gov/programs/air/ClimateChange/Documents/VIMAL/MD_ForestCarbon_Flux_Methodology_01.06.23.pdf)
Miller D A and White R A 1998 A conterminous United States multilayer soil characteristics dataset for regional climate and hydrology modeling *Earth Interact.* **2** 1–26
Moorcroft P R, Hurtt G C and Pacala S W 2001 A method for scaling vegetation dynamics: the ecosystem demography model (ED) *Ecol. Monogr.* **71** 557–86
O'Neil-Dunne J, MacFaden S and Royar A 2014a A versatile, production-oriented approach to high-resolution tree-canopy mapping in urban and suburban landscapes using GEOBIA and data fusion *Remote Sens.* **6** 12837–65
O'Neil-Dunne J, MacFaden S, Royar A, Reis M, Dubayah R and Swatantran A 2014b An object-based approach to statewide land cover mapping *Proc. ASPRS 2014 Annual Conf.* pp 23–28
Pan Y *et al* 2024 The enduring world forest carbon sink *Nature* **631** 563–9
Ramankutty N and Foley J A 1999 Estimating historical changes in global land cover: croplands from 1700 to 1992 *Glob. Biogeochem. Cycles* **13** 997–1027
Ranson K J, Sun G, Knox R G, Levine E R, Weishampel J F and Fifer S T 2001 Northern forest ecosystem dynamics using coupled models and remote sensing *Remote Sens. Environ.* **75** 291–302
Robinson N P, Allred B W, Smith W K, Jones M O, Moreno A, Erickson T A, Naugle D E, Running S W, Pettorelli N and Paruelo J 2018 Terrestrial primary production for the conterminous United States derived from Landsat 30 m and MODIS 250 m *Remote Sens. Ecol. Conserv.* **4** 264–80
Rödig E, Knapp N, Fischer R, Bohn F J, Dubayah R, Tang H and Huth A 2019 From small-scale forest structure to Amazon-wide carbon estimates *Nat. Commun.* **10** 5088
Ruehr S *et al* 2023 Evidence and attribution of the enhanced land carbon sink *Nat. Rev. Earth Environ.* **4** 518–34
Running S W, Nemani R R, Peterson D L, Band L E, Potts D F, Pierce L L and Spanner M A 1989 Mapping regional forest evapotranspiration and photosynthesis by coupling satellite data with ecosystem simulation *Ecology* **70** 1090–101
Tang H, Ma L, Lister A, O'Neil-Dunne J, Lu J, Lamb R L, Dubayah R and Hurtt G 2021 High-resolution forest carbon mapping for climate mitigation baselines over the RGGI region, USA *Environ. Res. Lett.* **16** 035011
Tang X, Hutyra L R, Arévalo P, Baccini A, Woodcock C E and Olofsson P 2020 Spatiotemporal tracking of carbon emissions and uptake using time series analysis of Landsat data: a spatially explicit carbon bookkeeping model *Sci. Total Environ.* **720** 137409
Thomas R Q, Hurtt G C and Schilz M H 2008 Using lidar data and a height-structured ecosystem model to estimate forest carbon stocks and fluxes over mountainous terrain *Can. J Remote Sens.* **34** S351–63
Turner D P, Ollinger S V and Kimball J S 2004 Integrating remote sensing and ecosystem process models for landscape- to regional-scale analysis of the carbon cycle *BioScience* **54** 573–84
Williams C A, Collatz G J, Masek J, Huang C and Goward S N 2014 Impacts of disturbance history on forest carbon stocks and fluxes: merging satellite disturbance mapping with forest inventory data in a carbon cycle model framework *Remote Sens. Environ.* **151** 57–71
Xu L *et al* 2021 Changes in global terrestrial live biomass over the 21st century *Sci. Adv.* **7** eabe9829
Yang H *et al* 2023 Global increase in biomass carbon stock dominated by growth of northern young forests over past decade *Nat. Geosci.* **16** 886–92