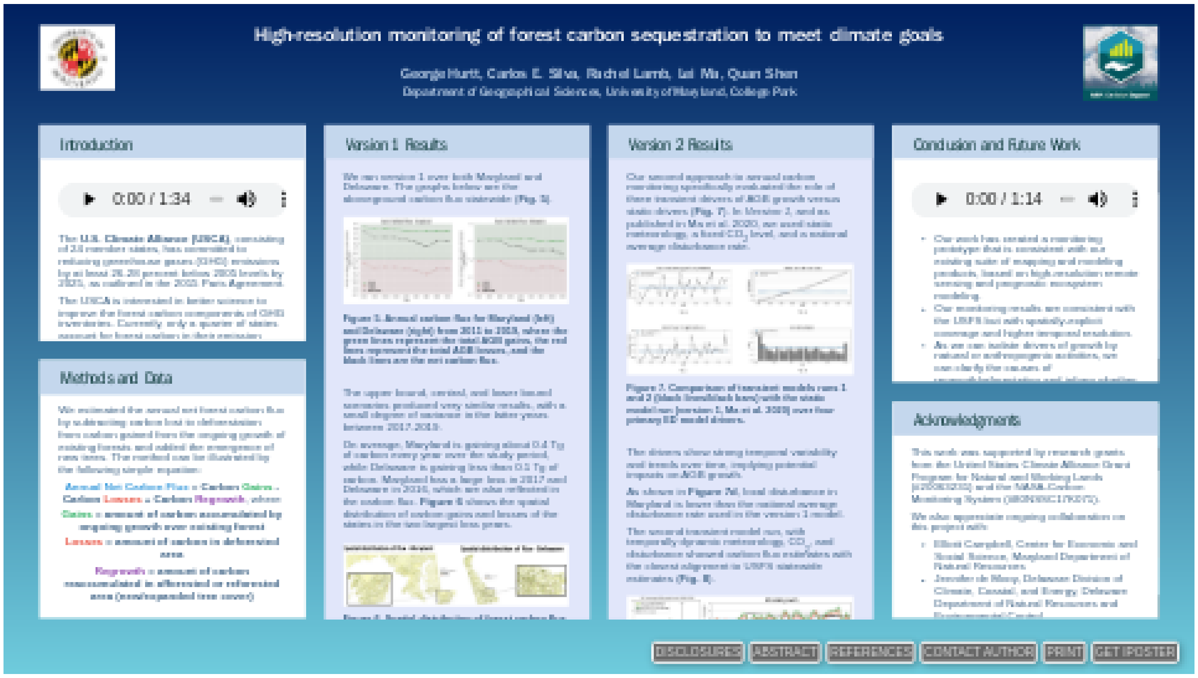
High-resolution monitoring of forest carbon sequestration to meet climate goals



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MRV | Decision Support

PRESENTED AT:

AGU FALL MEETING
Online Everywhere | 1–17 December 2020

INTRODUCTION

The **U.S. Climate Alliance (USCA)**, consisting of 24 member states, has committed to reducing greenhouse gases (GHG) emissions by at least 26-28 percent below 2005 levels by 2025, as outlined in the 2015 Paris Agreement.

The USCA is interested in better science to improve the forest carbon components of GHG inventories. Currently, only a quarter of states account for forest carbon in their emission reductions, but they are using a range of scientific methods and approaches with varying quality (Lamb et al. 2020).

More high-resolution data and/or tools are needed to enhance the states' forest carbon science. The USCA Natural and Working Lands Challenge has supported prototype projects to improve methods of land carbon monitoring.

With the state governments of MD and DE, **the objective of this specific project was to provide an annual geospatial estimate of forest carbon flux that can be used to evaluate progress under the state's climate action goals**.

Our study used **consistent science products across the spectrum of applications**, including 1) baseline mapping of contemporary carbon stocks, (2) projections of future carbon stocks for planning, and (3) annual monitoring for assessment (**Fig. 1**).

This study focuses on our products' ability to monitor annual carbon stocks, which would provide valid assessments for GHG inventories of USCA members.

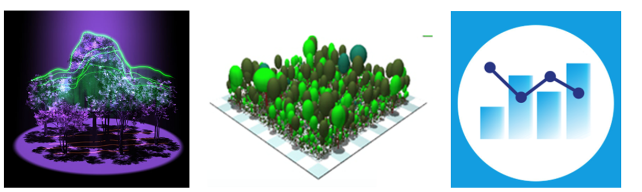

Figure 1. Three common applications using consistent scientific tools: mapping current carbon stocks, projecting future carbon stocks, and monitoring annual carbon flux.

METHODS AND DATA

We estimated the annual net forest carbon flux by subtracting carbon lost to deforestation from carbon gained from the ongoing growth of existing forests and added the emergence of new trees. The method can be illustrated by the following simple equation:

Annual Net Carbon Flux = Carbon Gains - Carbon Losses + Carbon Regrowth, where

Gains = amount of carbon accumulated by ongoing growth over existing forest

Losses = amount of carbon in deforested area

Regrowth = amount of carbon reaccumulated in afforested or reforested area (new/expanded tree cover)

We used two approaches/versions to test the method (**Fig. 2**). The first version used both modeled above ground biomass (AGB) projection from 2011 to 2019, and remotely sensed forest change products to estimate changes in forest area. The second version assessed various factors of AGB growth rates and their impact on overall flux. The growth rates are computed from different transient drivers include meteorology, carbon dioxide, and natural disturbance. Both versions can successfully monitor the carbon flux.

Version	Goal	Period	Forest Area Changes (RS)		AGB Growth Drivers in ED		
			Gain	Loss	Meteorology	CO_2	Disturbance
V1	Efficacy of capturing remotely sensed changes in forest area	2011-2019	NLCD	GFW	climatology	constant	constant
V2	Efficacy of using transient drivers (meteorology, CO_2 and disturbance) in model	1980-2018	--	--	transient	transient	constant
		1980-2018	--	--	transient	transient	transient

Figure 2. Data used in the two versions.

In the first approach, we used the Ecosystem Demography (ED) model results for the carbon gains term (**Fig. 3a**) (Ma et al. 2020). The ED model is an individual-based model of vegetation dynamics with integrated submodels of plant growth, mortality, phenology, biodiversity, disturbance, hydrology, and soil biogeochemistry (Hurtt et al. 2002; Hurtt et al. 2019). By simulating physiological processes of individual vegetation, ED has been used to map and model forest carbon stocks and fluxes (Moorcroft et al. 2001; Huang et al. 2015; Huang et al. 2019; Hurtt et al. 2002; Hurtt et al. 2011; Hurtt et al. 2019; Tang et al. 2020; Ma et al. 2020).

The Global Forest Watch (GWF) forest loss dataset (Hansen et al. 2013) was used to extract the deforested areas each year from 2011 to 2019 (**Fig. 3b**). We used the National Land Cover Database (NLCD) land cover type datasets to detected aforestated or reforested areas (**Fig. 3c**). Although GWF has a forest gain dataset, the dataset is from 2000 to 2012, and thus does not match our study period. Since both NLCD and GFW datasets were generated using Landsat 30m resolution remotely sensed images, we used NLCD dataset instead. The NLCD landcover datasets area available for 2011, 2013, and 2016. We will incorporate the 2019 data when it is released.

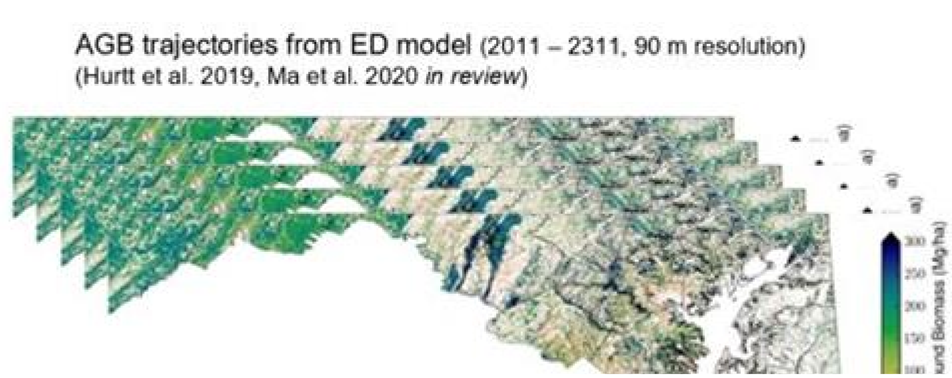

Fig. a

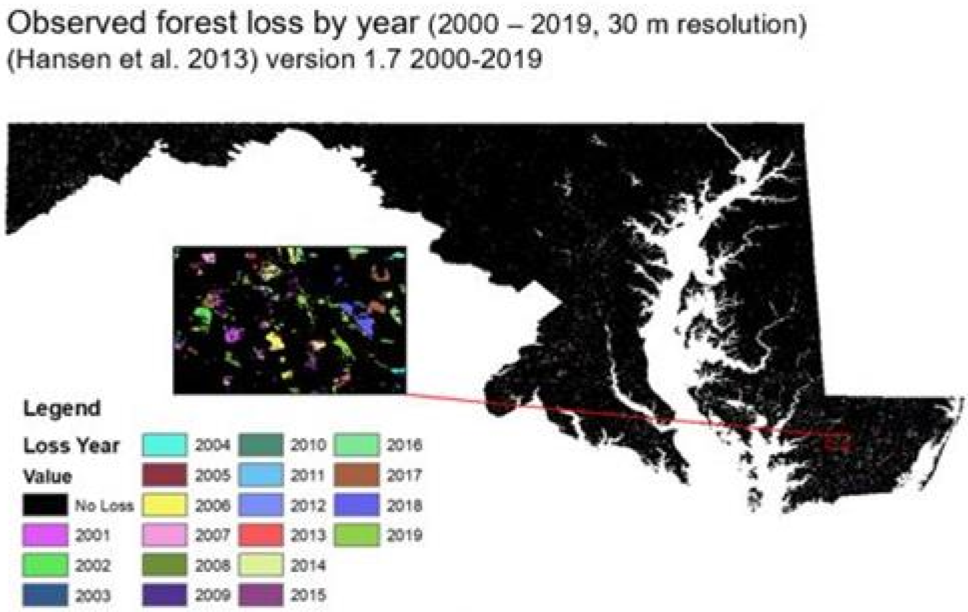

Fig. b

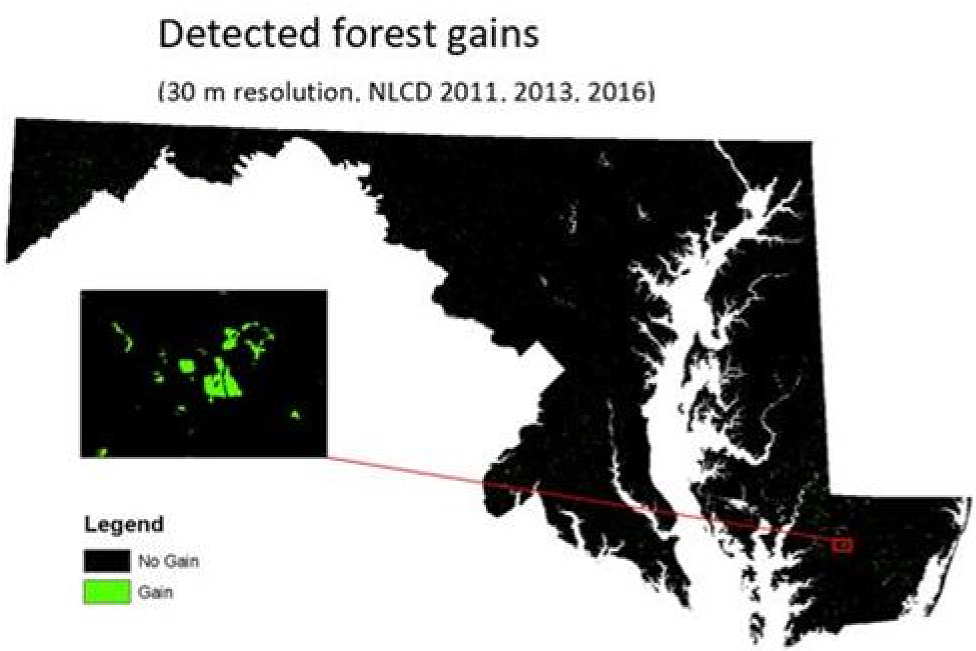

Fig. c

Figure 3. ED model results as the gains (a), GFW as the losses (b), and NLCD as the regrowth (c).

This version contains three scenarios to calculate the upper bound, the central, and the lower bound of gains and losses. The upper bound scenario assumes that every deforested area has 25% tree canopy cover remaining, and every reforestation area regains 100% tree canopy area. The lower bound, however, assumes 100% tree canopy loss for deforestation areas, and only 25% tree canopy gained from reforestation. The central scenario randomly samples post-deforestation and reforestation areas from truncated exponential distribution. The three scenarios are presented in Fig. 5 in section *Version 1 Results*.

The second approach focused on assessing how the key drivers affect the aboveground biomass (AGB) growth rate in the ED model, and thus affected the gains term (**Fig. 4**). This approach had three runs: a static model run and two transient model runs. Figure 4 shows the comparison among the three runs. The static model run used static meteorological data from Daymet-MERRA2, and kept CO2 concentration and disturbance rate constant. The first transient run incorporated annual weather data from Daymet-MERRA2 and global annual mean CO2 concentration from NOAA ESRL, but the disturbance rate remained constant. The second transient run built on the first transient run and added annual disturbance data from NAFD. The comparisons of the data used can be found in section *Version 2 Results*.

Drivers	Climatological run (Ma et al 2020 ERL)	Transient run (CC, CO2)	Transient run (CC, CO2, DIS)
Meteorology	Daymet-MERRA2 climatology (1980-2018)	Annual Daymet-MERRA2 (1980-2018)	Annual Daymet-MERRA2 (1980-2018)
CO_2	360 ppm	NOAA ESRL Global Annual Mean (338.8 ppm in 1980, +1.83 ppm/yr)	NOAA ESRL Global Annual Mean (338.8 ppm in 1980, +1.83 ppm/yr)
Disturbance rate	1.2%	1.2%	Annual NAFD 1986-2010

Figure 4. Comparisons among data used in the three runs.

VERSION 1 RESULTS

We ran version 1 over both Maryland and Delaware. The graphs below are the aboveground carbon flux statewide (**Fig. 5**).

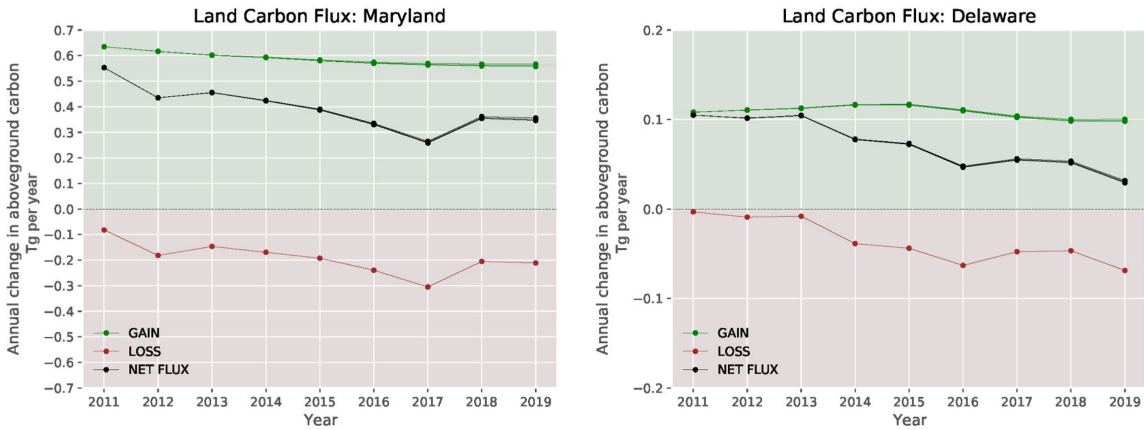

Figure 5. Annual carbon flux for Maryland (left) and Delaware (right) from 2011 to 2019, where the green lines represent the total AGB gains, the red lines represent the total AGB losses, and the black lines are the net carbon flux.

The upper bound, central, and lower bound scenarios produced very similar results, with a small degree of variance in the latter years between 2017-2019.

On average, Maryland is gaining about 0.4 Tg of carbon every year over the study period, while Delaware is gaining less than 0.1 Tg of carbon. Maryland has a large loss in 2017 and Delaware in 2016, which are also reflected in the carbon flux. **Figure 6** shows the spatial distribution of carbon gains and losses of the states in the two largest loss years.

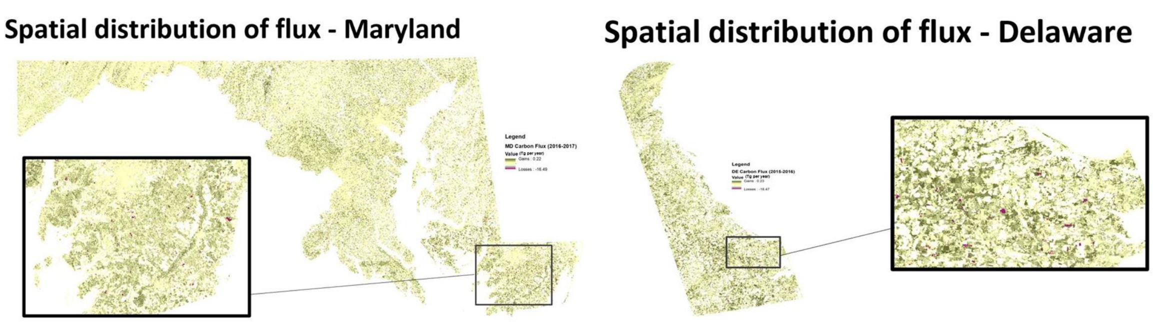

Figure 6. Spatial distribution of forest carbon flux across Maryland in 2017 (left) and across Delaware in 2016 (right).

VERSION 2 RESULTS

Our second approach to annual carbon monitoring specifically evaluated the role of three transient drivers of AGB growth versus static drivers (**Fig. 7**). In *Version 1*, and as published in Ma et al. 2020, we used static meteorology, a fixed CO_2 level, and a national average disturbance rate.

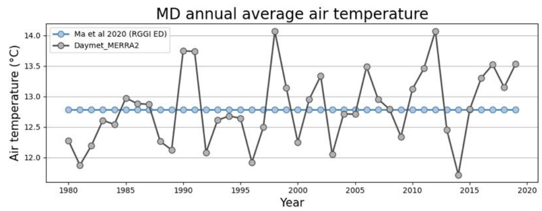

Fig. a

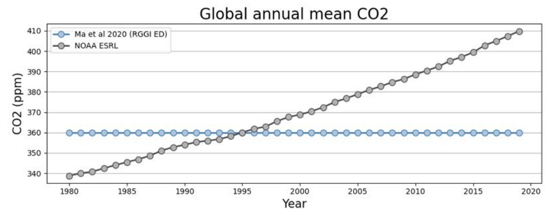

Fig. b

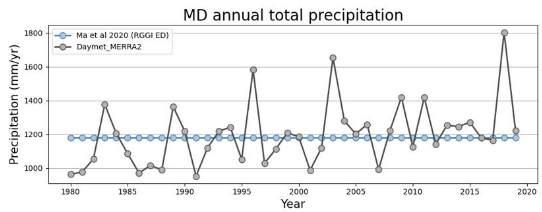

Fig. c

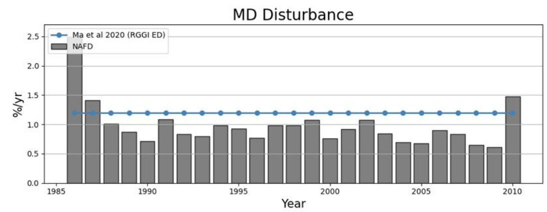

Fig. d

Figure 7. Comparison of transient models runs 1 and 2 (black lines/black bars) with the static model run (version 1, Ma et al. 2020) over four primary ED model drivers.

The drivers show strong temporal variability and trends over time, implying potential impacts on AGB growth.

As shown in **Figure 7d**, local disturbance in Maryland is lower than the national average disturbance rate used in the version 1 model.

The second transient model run, with temporally dynamic meteorology, CO_2, and disturbance showed carbon flux estimates with the closest alignment to USFS statewide estimates (**Fig. 8**).

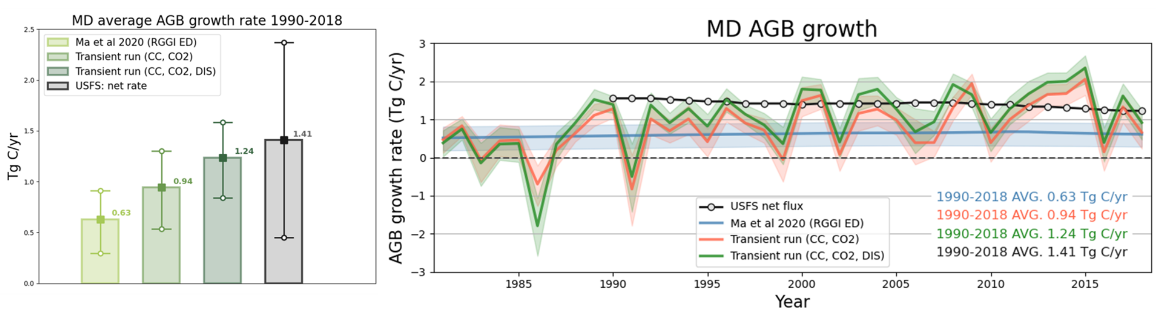

Figure 8. The resulting plant growth rates were compared with the growth rate of the U.S. Forest Service (USFS), as published in their 2020 report (Domke et al. 2020).

Our results also show that our transient models capture more temporal variation in AGB growth than the USFS.

CONCLUSION AND FUTURE WORK

- Our work has created a monitoring prototype that is consistent with our existing suite of mapping and modeling products, based on high-resolution remote sensing and prognostic ecosystem modeling.
- Our monitoring results are consistent with the USFS but with spatially-explicit coverage and higher temporal resolution.
- As we can isolate drivers of growth by natural or anthropogenic activities, we can clarify the causes of regrowth/reforestation and inform whether or not these changes should be documented within GHG inventories and count towards climate mitigation goals.
- Monitoring efforts moving forward should consider the impact of transient meteorology, CO_2, and disturbance on AGB growth.
- We seek to operationalize within Maryland and Delaware, expand to other states in the USCA, and expand this monitoring approach nationally by harnessing GEDI LiDAR, ICESat-2, and/or Landsat.

ACKNOWLEDGMENTS

This work was supported by research grants from the United States Climate Alliance Grant Program for Natural and Working Lands (#20063231) and the NASA-Carbon Monitoring System (#80NSSC17K071).

We also appreciate ongoing collaboration on this project with:

- Elliott Campbell, Center for Economic and Social Science, Maryland Department of Natural Resources
- Jennifer de Mooy, Delaware Division of Climate, Coastal, and Energy, Delaware Department of Natural Resources and Environmental Control
- Alex Rudee, Associate, U.S. Climate Initiatives, World Resources Institute

A full list of supporting references can also be found by clicking the references box at the bottom of the poster.

DISCLOSURES

This work was supported by research grants from the United States Climate Alliance Grant Program for Natural and Working Lands (#20063231) and the NASA-Carbon Monitoring System (#80NSSC17K071).

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. Required forest carbon data consist of integrated: (1) baseline mapping of contemporary carbon stocks, (2) projections of future carbon stocks for planning, and (3) annual monitoring for assessment. Previously, we developed high-resolution mapping of contemporary carbon stocks and 300-yr projections of annual carbon sequestration potential (CSP) for Maryland at 90m resolution by integrating airborne LiDAR with mechanistic ecosystem modeling (Ecosystem Demography (ED) model). Here we extend this work to Delaware and present the first consistent, annual monitoring results for both states (Maryland and Delaware). For monitoring, we intersect annual carbon stock estimates with 30m Landsat-derived changes in forest area to compute realized carbon gains and losses over the period 2011—2019. Moving forward, we expect to extend this pilot system developed for Maryland and Delaware to an additional 9 U.S. states. As the framework is flexible, developing a nationwide or global system is increasingly feasible, particularly with the recent availability of GEDI LiDAR observations from space.

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