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# Environmental Research Letters

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## Beyond MRV: high-resolution forest carbon modeling for climate mitigation planning over Maryland, USA

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**Abstract**

Forests are important ecosystems that are under increasing pressure from human use and environmental change, and have a significant ability to remove carbon dioxide from the atmosphere, and are therefore the focus of policy efforts aimed at reducing deforestation and degradation as well as increasing afforestation and reforestation for climate mitigation. Critical to these efforts is the accurate monitoring, reporting and verification of current forest cover and carbon stocks. For planning, the additional step of modeling is required to quantitatively estimate forest carbon sequestration potential in response to alternative land-use and management decisions. To be most useful and of decision-relevant quality, these model estimates must be at very high spatial resolution and with very high accuracy to capture important heterogeneity on the land surface and connect to monitoring efforts. Here, we present results from a new forest carbon monitoring and modeling system that combines high-resolution remote sensing, field data, and ecological modeling to estimate contemporary above-ground forest carbon stocks, and project future forest carbon sequestration potential for the state of Maryland at 90 m resolution. Statewide, the contemporary above-ground carbon stock was estimated to be 110.8 Tg C (100.3–125.8 Tg C), with a corresponding mean above-ground biomass density of 103.7 Mg ha<sup>-1</sup> which was within 2% of independent empirically-based estimates. The forest above-ground carbon sequestration potential for the state was estimated to be much larger at 314.8 Tg C, and the forest above-ground carbon sequestration potential gap (i.e. potential-current) was estimated to be 204.1 Tg C, nearly double the current stock. These results imply a large statewide potential for future carbon sequestration from afforestation and reforestation activities. The high spatial resolution of the model estimates underpinning these totals demonstrate important heterogeneity across the state and can inform prioritization of actual afforestation/reforestation opportunities. With this approach, it is now possible to quantify both the forest carbon stock and future carbon sequestration potential over large policy relevant areas with sufficient accuracy and spatial resolution to significantly advance planning.

## 1. Introduction

Forests are important ecosystems that provide a broad range of ecosystem services including carbon storage, climate change mitigation, and wildlife habitat (Costanza *et al* 1997, Pan *et al* 2013). Historically, vast areas of the world's forests have been lost or degraded because of land-use activities, and the forests that remain are under increasing pressures from both socioeconomic and climate changes (Hurtt *et al* 2011, Hansen *et al* 2013). Forests are also increasingly the focus of afforestation and reforestation efforts, as well as improved management practices, designed to reverse some of the negative effects of forest loss and contribute positively to climate mitigation efforts (Grassi *et al* 2012). In this context, local, national and international policies and programs have an increasing need for science in monitoring forest extent and carbon stock, and for modeling the potential future forest extent and carbon stock for planning purposes (Grassi *et al* 2017).

The last several decades have witnessed a tremendous advance in forest carbon mapping capabilities. In the 1980s, large scale land carbon was mapped at  $0.5^\circ \times 0.5^\circ$  ( $\sim 50$  km) spatial resolution and organized in 32 broad categories (Olson *et al* 1983). Since then, advances in computing, remote sensing, modeling and field work, have enabled the creation of high-resolution maps of above-ground biomass (Blackard *et al* 2008, Wilson *et al* 2013). In particular, 3D structure information on vegetation acquired from lidar remote sensing has helped provide by far the most accurate forest estimates across broad geographical extents (Dubayah and Drake 2000, Drake *et al* 2002, Dubayah *et al* 2010, Goetz and Dubayah 2011, O'Neil-Dunne *et al* 2014, Johnson *et al* 2015). High-resolution 'wall-to-wall' carbon maps ( $\sim 30$  m) can be generated from airborne lidar data at county or state level with a normalized residual standard error from 10%–50% (Zolkos *et al* 2013, Huang *et al* 2015, Huang *et al* 2017), while several coarser resolution (90 m–1 km) continental-scale maps of vegetation height and biomass have been produced from spaceborne lidar (NASA's ICESat/GLAS) with the aid of many ancillary datasets (Simard *et al* 2011, Saatchi *et al* 2011). This progress has wide ranging applications for climate science and ecology, emphasizing the importance of continued investments in airborne lidar acquisitions and spaceborne lidar missions.

In parallel to mapping forest carbon, the demand for information on forest carbon changes and forest carbon sequestration potential has also increased. National and international projects have identified land/land-use change as having the highest uncertainty among major sources and sinks of carbon gases (Ciais *et al* 2013, Le Quéré *et al* 2015, Erb *et al* 2016). Meanwhile, policy efforts on climate mitigation include major international commitments for afforestation/reforestation and improved forest management. Initiative 20  $\times$  20 (<http://wri.org>), the Bonn

Challenge (<http://bonnchallenge.org>), and other programs represent global commitments for afforestation/reforestation on the order of  $10^6$ – $10^8$  ha. More locally, the Maryland Greenhouse Gas Reduction Act (GGRA) of 2016 requires a 40% reduction in greenhouse gas emissions from 2006 levels by 2030, and the formation of a plan to meet those commitments including the forest sector. To advance planning, it is necessary to quantify both how much carbon could be sequestered in the future and over what time frame.

Planning to meet forest sector goals requires modeling ecosystem dynamics, a step beyond traditional monitoring, reporting and verification (MRV) (Birdsey *et al* 2013, DeVries *et al* 2013, Hurtt *et al* 2014). Just decades ago, the pioneering global terrestrial models were typically run at relatively coarse spatial resolutions ( $>50$  km), parameterized with highly aggregated representations of the land-surface variables, and typically lacked important process detail such as photosynthesis, disturbance and succession (Melillo *et al* 1993, Potter *et al* 1993, Hurtt *et al* 1998). The most detailed models, individual-based forest gap models, tracked individual plants but were geographically limited to relatively small domains due to their computational requirements (Shugart and Smith 1996, Pacala *et al* 1996). Now, a community of dynamic global vegetation models simulate the combined effects of climate and land use history on the carbon balance to inform global budgets (Sitch *et al* 2008, Le Quéré *et al* 2015), and some models include detailed representations of individual-based 3D vegetation structure and dynamics, operate on times scales from minutes to centuries, over local to global spatial scales, and can be initialized using lidar remote sensing (Moorcroft *et al* 2001, Hurtt *et al* 2004, 2010, Fisher *et al* 2017).

This work builds on these advances and uses high-resolution forest carbon modeling initialized by remote sensing to produce maps of current forest carbon stocks, and forest carbon sequestration potential, over the state of Maryland. In this process, the same high-resolution optical and lidar data used in producing high resolution empirical maps of forest biomass for the state are used to initialize the forest ecosystem model to make projections of future carbon sequestration potential and time in years to reach it, all at 90 m resolution statewide. There are over  $\sim 3.1$  million 90 m land cells in Maryland. To our knowledge, no similar assessment of forest carbon stocks and forest carbon sequestration potential has been made at such high spatial resolution over such large spatial domain and validated as extensively.

## 2. Data and methods

### 2.1. Study area

The domain of study was the state of Maryland, USA, located at approximately  $39.97^\circ$ N longitude  $76.49^\circ$

W. The state is comprised of three major geographic landforms: the Atlantic coastal plain, Piedmont plateau, and a relatively small area of Appalachian Mountains in the west (Markewich *et al* 1990). There are 24 counties and county equivalents (see supplemental material is available online at [stacks.iop.org/ERL/14/045013/mmedia](https://stacks.iop.org/ERL/14/045013/mmedia)). The annual average temperature is 12.80 °C, and total precipitation 1106 mm (Daly *et al* 2008). The state has a clear seasonality in temperature but no clear seasonality for precipitation. The dominant potential vegetation type for the state is deciduous forest (Ramankutty and Foley 1999). Due to widespread human-induced land cover/use change, the landscape is characterized by fragmented forests. Depending on forest definition and method, forest covers 33%–41% and croplands account for 32% of the land area (Jin *et al* 2013, Lister and Widmann 2016). The Baltimore City—Washington DC corridor is largely urban or suburban, with relatively little remaining forest. Most of the forests on the eastern shore of Maryland have been converted to croplands or suburban townships. A portion of western Maryland is part of the Appalachian Mountains, which experienced less land-use change although much of the area has been harvested and regenerated. As with the majority of the US Eastern seaboard, 90% of Maryland was cleared of forest and converted to agriculture by the mid-19th century, converted partially back to forest in the early 20th century as the economic importance of agriculture declined in the state, and then began to lose significant quantities of forest to development in the mid to late 20th century.

Currently, the state has important legislation related to forestry and climate mitigation. The Forest Conservation Act was enacted in 1992 by the Maryland legislature, and strengthened in 2013 with the intent for no-net loss of forests and to maintain forest cover above 40% in the state. The GGRA was passed in 2009 directing the state to reduce climate pollution 25% from 2006 levels by 2020 and create the state's Greenhouse Gas Reduction Plan. In 2016, the GGRA was reauthorized and strengthened to 40% reduction by 2030 (SB0323), requiring an updated plan to meet that target.

## 2.2. Model

The authors have spent the last two decades developing the ecosystem demography model (ED), integrating it with data on vegetation 3D structure from lidar, and are using the most advanced version of the model in this study (Hurtt *et al* 1998, Moorcroft *et al* 2001, Hurtt *et al* 2002, 2004, 2010, Thomas *et al* 2008, Flanagan *et al* 2016, Hurtt *et al* 2016). ED is an individual-based model of vegetation dynamics with integrated sub-models of plant growth, mortality, phenology, biodiversity, disturbance, hydrology, and soil biogeochemistry. Individual plants of different

functional types compete mechanistically in ED under local environmental conditions for light, water, and nutrients. In contrast with many other terrestrial models, ED estimates the physiological processes of individual trees, and uses this information to simulate competition, vegetation dynamics, and ecosystem fluxes at larger scales. Additionally, ED simultaneously models the effects of natural disturbances, land use, and the dynamics of recovering lands. A defining feature of ED is its explicit and scalable treatment of 3D vegetation dynamics together with associated carbon stocks and fluxes. The current version of the ED model has been entirely updated such that it can now operate at spatial resolutions from <1 ha to >1°, over local to global domains, simulate hourly to century-scale vegetation and carbon dynamics, be forced with land-use history changes, and initialized from remote sensing products. A pre-/post-processing workflow was used in conjunction with the model to make the mapped model projections for this study (see supplemental material).

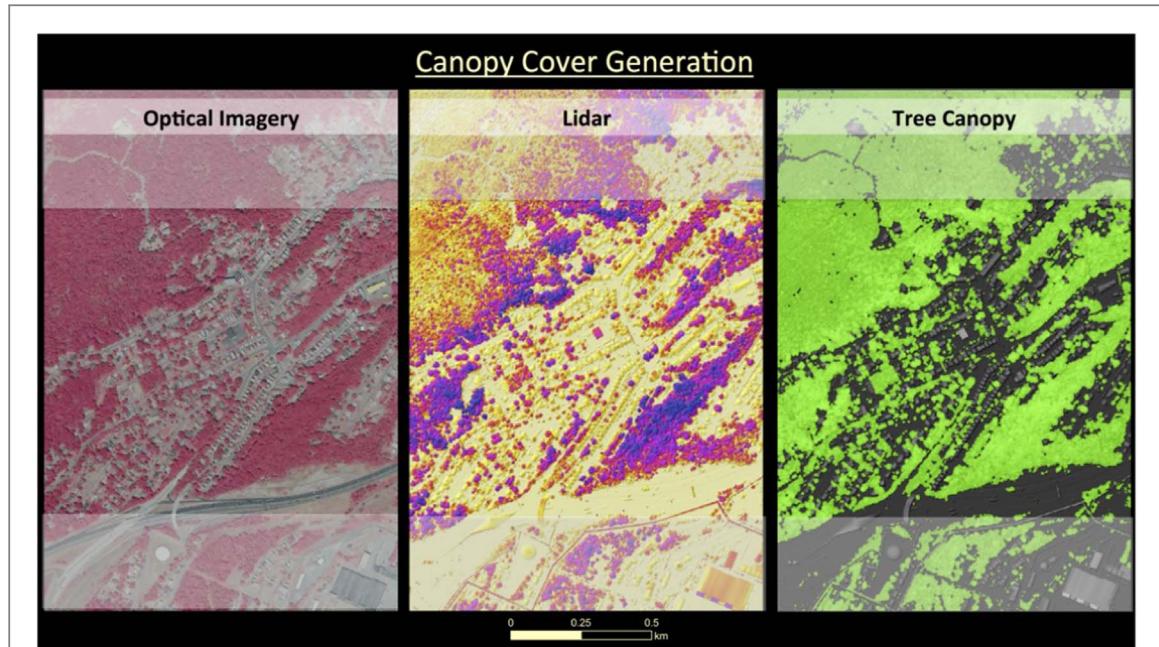
## 2.3. Data

For climate, data were used from the North American Regional Reanalysis (NARR) (Mesinger *et al* 2006), the National Center for Environmental Prediction's high-resolution combined model and assimilated dataset available eight-times daily 1979–2000 at ~32 km resolution. These data were corrected by parameter-elevation relationships on independent slopes model, or PRISM (Daly *et al* 2008). ED requires hourly land surface weather data to calculate carbon assimilation rate and transpiration, and the variables used were 2 m air temperature, dew point, downward solar radiation, precipitation, and soil temperature. These data were linearly interpolated from 3 hourly values to hourly temporal resolution and spatially smoothed to 1 km spatial resolution using nearest neighbor method (Zhao *et al* 2005). Next, the data were corrected following the method proposed by Qian *et al* (2006), which used the average 1 km monthly maximum temperature, minimum temperature and precipitation from PRISM (Daly *et al* 2008) as the true climate magnitude at the monthly level. A long-term climatology 1981–2010 of hourly data for each month was used for consistency with the climatology of 30 year PRISM for the same data period. Minimum temperature was taken as a proxy of dew point (Campbell and Norman 1998) and the difference in the minimum temperature was used to correct the NARR dew point.

For precipitation, the ratio of NARR to PRISM was calculated for each month, where:

$$\text{ratio} = \text{PRISM}/\text{NARR}$$

and the corrected hourly NARR precipitation was computed as:



**Figure 1.** Example inputs and outputs from the high-resolution tree cover classification process combining (a) optical imagery from National Agriculture Imagery Program (NAIP), (b) high spatial resolution (1 m) lidar height, to determine (c) tree cover classification.

$$\text{NARR}_{\text{correct}} = \text{NARR} * \text{ratio}$$

At 1 km scale, the corrected NARR implicitly accounted for the effect of elevation because elevation was accounted for in the PRISM dataset through interpolation of weather data between stations up to a 1 km scale (Daly *et al* 2008). The corrected monthly hourly weather data at 1 km were further downscaled to 90 m by non-linearly interpolating the four surrounding 1 km corrected NARR data to 90 m following a method proposed by Zhao *et al* (2005). The atmospheric CO<sub>2</sub> concentration was set to 360 ppm, near the middle of the range over the climate interval (Keeling 2008).

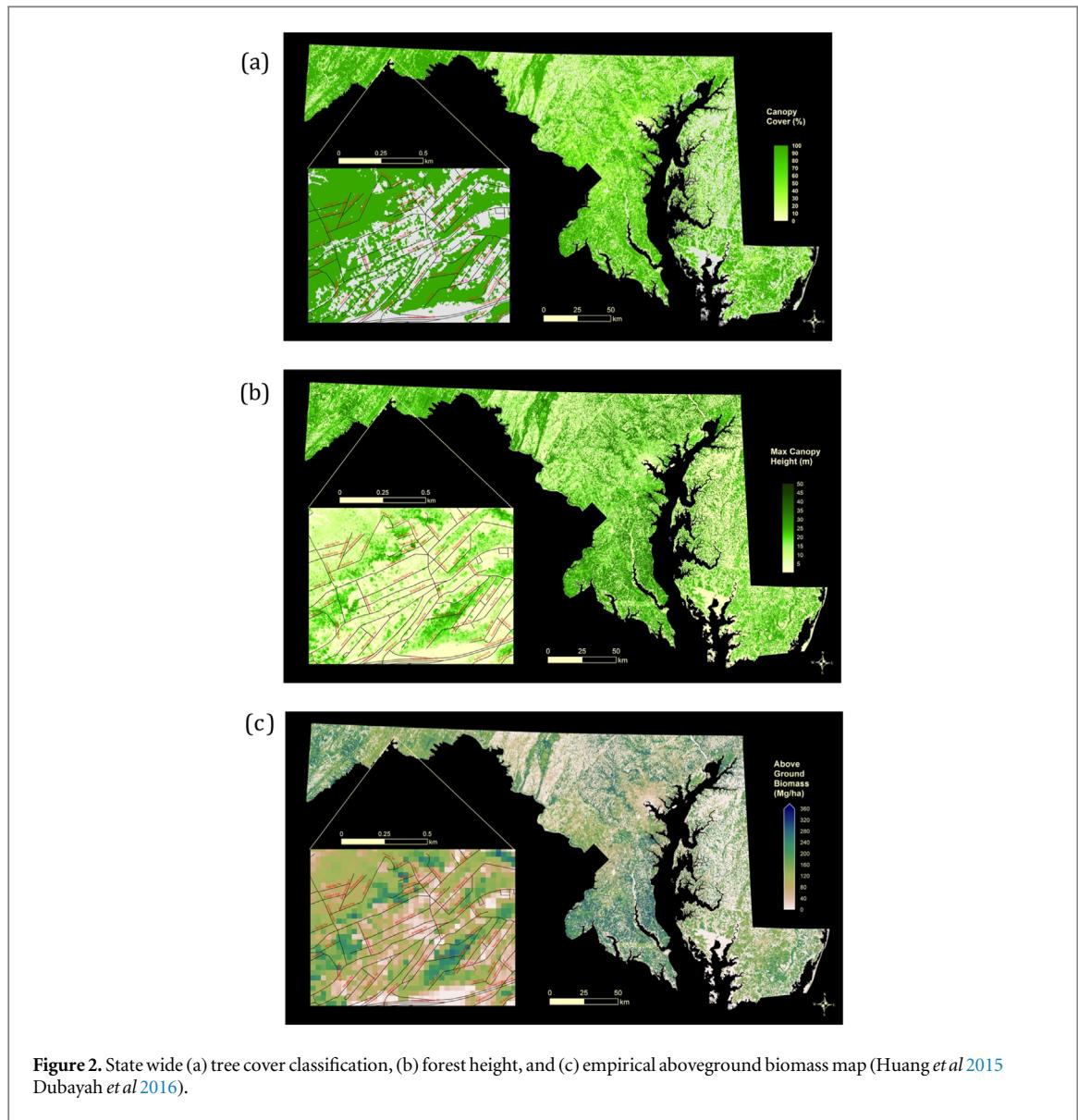
For soils, data on depth to bed rock, soil texture, and hydraulic conductivity were taken from the Soil Survey Geographic Database (SSURGO, version 2.2) with the aid of an ArcMap extension tool, Soil Data Viewer, developed by the USDA and rasterized to 90 m. For each grid cell, the dominant component method was applied if more than one component existed within a grid cell. ED uses a single soil-layer bucket model to simulate water percolation through the soil as mediated by the saturated conductivity of the soil (Klute *et al* 1986). Based on soil textural classes defined by the USDA soil triangle (Cosby *et al* 1984), the dominant soil types were loam and sandy loam, and the average soil depth was 170.95 cm. Statewide averages of texture were 46%, 17% and 37%, for sand, silt and clay, respectively.

For land cover, data were used from the National Agriculture Imagery Program (NAIP), airborne lidar, and National Land Cover Database (NLCD). Tree cover and forest height maps were initially generated at 1 m resolution from NAIP and lidar data (figure 1) and then aggregated at 30 m resolution to match

NLCD data for estimating forest cover, forest height and forest biomass statewide (Huang *et al* 2015, figure 2). The same data sets were then aggregated to 90 m resolution in order to define the forested fraction of each grid cell, and corresponding vegetation mean height of the forested fraction. We used NLCD 2011 land cover data (Jin *et al* 2013) to exclude inland water, barren land, imperviousness, and wetland from our analysis. Woody wetland and herbaceous wetland account for 9.4% and 3.4% of land areas in Maryland, respectively. NLCD 2011 Percent Developed Imperviousness (Xian *et al* 2011) accounted for 9.8% of the state and was excluded from carbon sequestration potential estimates.

#### 2.4. Model initialization and validation

Field data over the domain were gathered from US Forest Service Forest Inventory and Analysis (FIA) (USDA 2000) plots from 1990 to present within the study area. The FIA plot data were sorted by species and used to calculate importance value indices (Curtis and McIntosh 1951, Kent and Coker 1994) to provide background information on species abundances for the state. Allometric comparisons were then made between the model equations and equations found in Ter-Mikaelian and Korzukhin (1997) per species. Modifications were made to the ED model's existing evergreen and deciduous tree PFT equations to ensure that the height and biomass relationships fell within the ranges of the regionally most important deciduous and evergreen tree species. To constrain dynamics, model estimates of net primary production (NPP) and disturbance rate were compared to independent literature values. Statewide average estimates of NPP 0.57 kg C m<sup>-2</sup> yr<sup>-1</sup> and disturbance rate 1.2% yr<sup>-1</sup>



**Figure 2.** State wide (a) tree cover classification, (b) forest height, and (c) empirical aboveground biomass map (Huang *et al* 2015 Dubayah *et al* 2016).

were both close to and within range of independent estimates for these variables (Turner *et al* 2006, Masek *et al* 2008, Seagle 2008, Masek *et al* 2013, Dolan *et al* 2017).

Next, three alternative strategies were evaluated to obtain canopy height metrics for initialization of forest structure in ED (see supplemental material). The linkage of these canopy height metrics to the ED model was made through a lookup table approach, whereby the canopy height metrics were used to index associated model state variables (Hurtt *et al* 2004, Thomas *et al* 2008, Fisk 2015). To establish the look-up table, ED was run for each grid cell from initial seedlings for 500 years of succession, storing all model state variables and associated canopy height metrics. The optimum initialization strategy was selected based on validating ED-derived biomass estimates with corresponding empirically determined above ground biomass estimates. Using the optimal approach, we aggregated ED-lidar estimates county wide, and performed direct comparisons to FIA-

based county estimates. Uncertainties associated with potential height/biomass saturation in the tallest patches were quantified using three alternative assumptions (see supplemental material).

## 2.5. Future projections

Future projections were first computed using the ED model under contemporary climate conditions outlined in section 2.3. Carbon sequestration potential (CSP) was defined as 95% of the maximum above ground biomass a site reaches during succession. Carbon sequestration potential gap (CSPG) was defined as the difference between CSP and current carbon stocks. Carbon sequestration potential time gap (CSPTG) was defined as the number of years it is estimated to take to go from the current carbon stock to the CSP. In computing these potentials, all non-forest could theoretically be reforested excluding barren, wetland, and impervious surface. Gridded estimates of CSP were compared to current maximum

values of biomass over the state to ensure precedence. Finally, to assess the sensitivity of modeled results to potential changes in climate, statewide analyses were repeated for 9 combinations of alternative plant growth and disturbance rates chosen to encompass a broad range of possible future responses. Specifically, plant NPP and disturbance rates were altered by the factors 0.5, 1.0 and 1.5, respectively. For computational efficiency in these calculations, the state was subsampled using one ninth of the cells by running the center cell for each  $3 \times 3$  window, and aggregate results were assessed for representativeness for state wide totals.

Mapped estimates of AGB, CSP, CSPG, and CSPTG at 90 m resolution were archived at the Oak Ridge National Laboratory Distributed Active Archive Center (Hurtt *et al* 2019; <https://doi.org/10.3334/ORNLDAAAC/1660>).

### 3. Results

Initialization of the ED model with tree cover and tree height data was a critical first step to this research. figure 3 illustrates the results of lidar initialization compared to corresponding empirically based estimates, and FIA data. Of the three alternative initialization strategies tested, the strategy of calculating the maximum lidar canopy height for trees within each 10 m window and then averaging the maxima to 90 m scale was determined to be the best with the highest  $R^2 = 0.94$  and lowest RMSE = 20.32 Mg ha $^{-1}$  and slope closest to 1. This strategy also matched ED's native 10 m diameter canopy scale. For additional validation we aggregated model estimates to the county scale and compared to FIA-based estimates at that scale (figure 4). The correlation between the two estimates was high ( $R^2 = 0.85$ ) and error was low (RMSE = 23.87 Mg ha $^{-1}$ ). Despite very good agreement, regression statistics indicate an initial offset with intercept of 18.34 Mg ha $^{-1}$ , and a very slight underestimate of FIA with slope of 0.98.

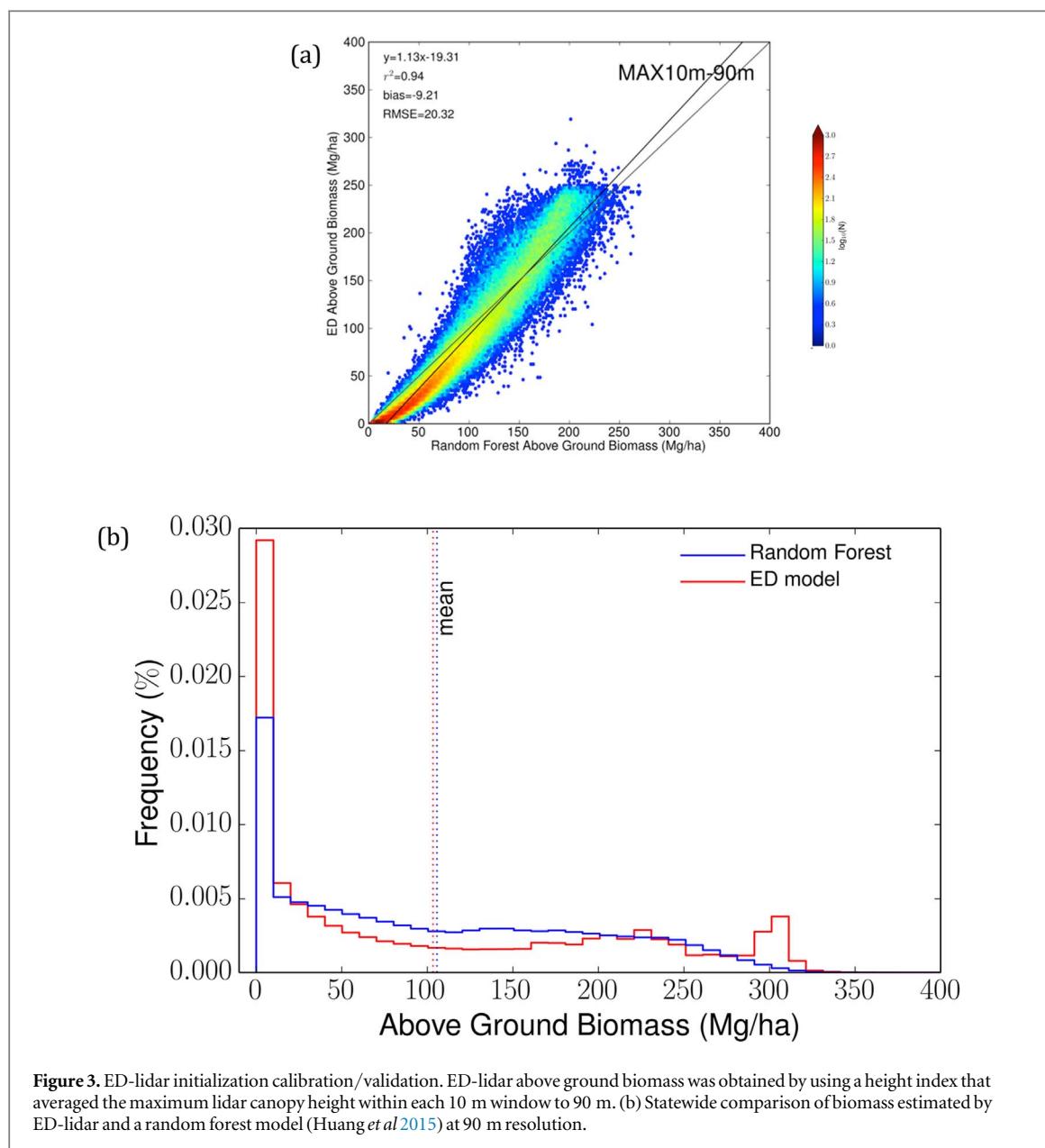
The spatial pattern of the lidar initialized ED biomass is shown in figure 5(a). The map shows a more detailed depiction of forest biomass and the impacts of land cover and land use change on forest biomass at 90 m resolution. Eastern Maryland has high human population densities and thus a greater area of human-dominated land cover types, such as urban, cropland and grassland; whereas in the west, large areas of continuous forest remain in mountainous areas. For the entire state, the average forest aboveground biomass (AGB) density was 103.7 Mg ha $^{-1}$  and total above ground carbon stock was 110.8 Tg C (100.3–125.8 Tg C). These estimates compare favorably to corresponding empirically based estimate of 105.9 Mg ha $^{-1}$  (Huang *et al* 2015). Figure 5(b) shows the spatial pattern of CSP. At the state level, the average CSP density was 293.5 Mg ha $^{-1}$  and total CSP stock was 314.8 Tg C. Maximum gridded values of CSP did not

exceed the maximum observed biomass densities in the state, suggesting these estimates are not unreasonable. The spatial pattern of CSP reflects the effects of both climate and soil properties on potential biomass. A warmer and longer growing season in Eastern Maryland leads to a higher potential biomass in the area. In the Northern and Western mountain areas of the state, colder average temperatures and a shorter growing season result in a lower CSP. Soil depth and texture further increase the spatial heterogeneity of carbon sequestration potential as they influence soil water stress and NPP, and thus CSP.

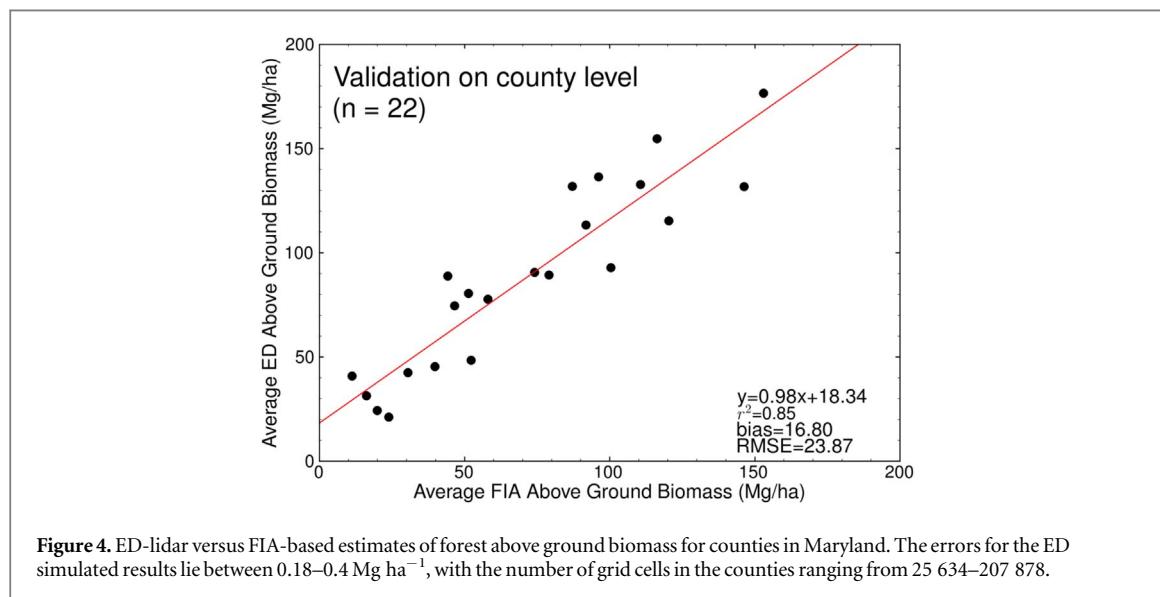
The CSPG (potential-current) was mapped in figure 5(c). As expected, the gap was greater over most of the area of Eastern Maryland, and generally lower over the Western portion of the state. This pattern was generally the result of both more intensive human-induced land cover change, and higher values of CSP, in the East. At the state level, average CSPG was 190.2 Mg ha $^{-1}$  and the total CSPG was 204.1 Tg C (table 1). Finally, the time required to reach the CSP from the current biomass (CSPTG) was mapped in figure 5(d). As expected, there is a complex pattern of CSPTG affected by both growing conditions and current and potential stocks, with Eastern Maryland having typically larger values than the West due to the higher CSPG in that area. For the entire state, the average age gap was 228 years.

To augment the mapped results presented above, the results were aggregated both statewide and by county, and quantified as a time series of carbon sequestration from current conditions to potential in figure 6. County level diagnostics are provided to illustrate patterns within the state, and to inform the current operational scale of many land-use decisions, as each county has direct influence over local land planning and development within their respective jurisdictions. Statewide, while CSPTG was >220 year, 50% of the carbon sequestration potential gap could be realized in 80 years. Within the state, the carbon sequestration potential and rate varied by county due to county size and local edaphic and climate conditions, with the highest potential in Frederick and Baltimore counties (>20 Tg C each). For each of these political units, we also stratified CSPG by landcover forest/non-forest conditions (figure 7). Statewide, and for many counties, the majority of CSPG is on non-forest areas as these areas have low biomass, typically due to land use, and therefore contain the largest potential to regrow.

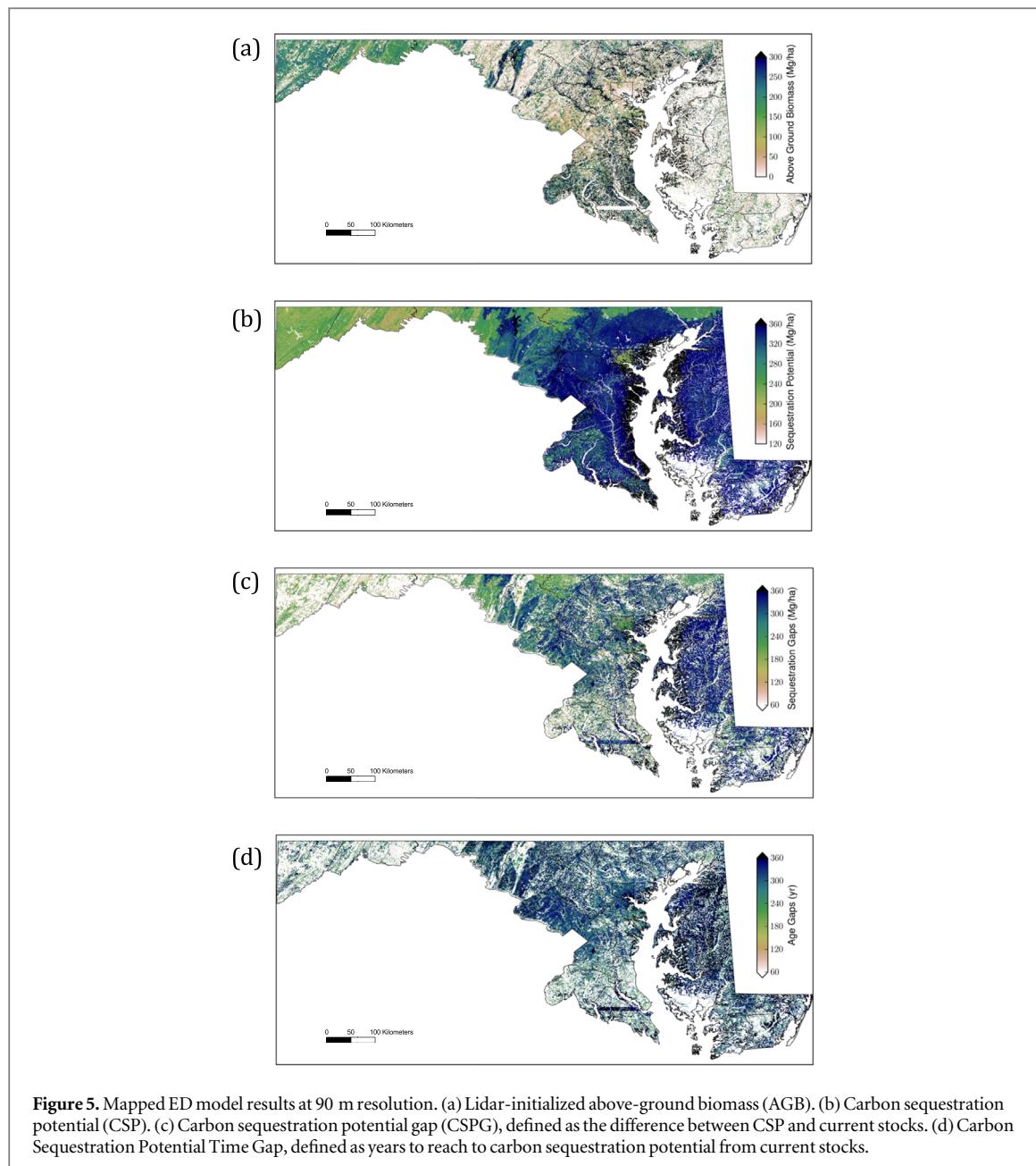
Figure 8 illustrates the sensitivity of CSPG and CSPTG to potentially altered NPP and disturbances rates. As expected, CSP and CSPTG were highly sensitive to these rates. Low disturbance and high NPP rates are associated with large CSP and CSPTG values, and high disturbance and low NPP rates are associated with smaller CSP and CSPTG values. CSP was generally proportional to NPP and inversely proportional to the disturbance rate. Changes in CSPTG were most



**Figure 3.** ED-lidar initialization calibration/validation. ED-lidar above ground biomass was obtained by using a height index that averaged the maximum lidar canopy height within each 10 m window to 90 m. (b) Statewide comparison of biomass estimated by ED-lidar and a random forest model (Huang *et al* 2015) at 90 m resolution.



**Figure 4.** ED-lidar versus FIA-based estimates of forest above ground biomass for counties in Maryland. The errors for the ED simulated results lie between  $0.18\text{--}0.4 \text{ Mg ha}^{-1}$ , with the number of grid cells in the counties ranging from 25 634–207 878.



**Figure 5.** Mapped ED model results at 90 m resolution. (a) Lidar-initialized above-ground biomass (AGB). (b) Carbon sequestration potential (CSP). (c) Carbon sequestration potential gap (CSPG), defined as the difference between CSP and current stocks. (d) Carbon Sequestration Potential Time Gap, defined as years to reach to carbon sequestration potential from current stocks.

strongly inversely proportional to changes in disturbance rate.

#### 4. Discussion

Forests are important ecosystems that globally store a large amount of carbon yet have lost significant area and carbon storage in response to previous land-use changes (Turner *et al* 1990, Vitousek *et al* 1997, Waring and Running 1998, Hurt et al 2006, 2011). Consequently, afforestation, reforestation, and forest management activities represent important contributions to climate mitigation efforts (Bonan 2008, Canadell and Raupach 2008). To inform planning, high resolution forest MRV frameworks are needed that not only quantify current forest extent and carbon stocks, but also estimate the amount of carbon that

could be stored in the future. To be most useful, model estimates should seamlessly connect to maps of present conditions and be of sufficiently high spatial resolution and accuracy for application.

This work moved beyond traditional MRV to provide high resolution model estimates of forest carbon sequestration potential. Aggregated statewide, Maryland is currently at ~1/3 of its above ground carbon sequestration potential. Future projections indicate it would take ~80 year to double aboveground carbon storage, and ~228 year to reach 95% of full potential under current conditions. With ~200 Tg C to potentially gain above ground through reforestation, these aggregate results suggest there is significant potential for additional carbon sequestration. Extending the approach to include estimates of total forest carbon sequestration potential (i.e. above ground + below

**Table 1.** ED simulated forest biomass and age metrics for each county in Maryland.

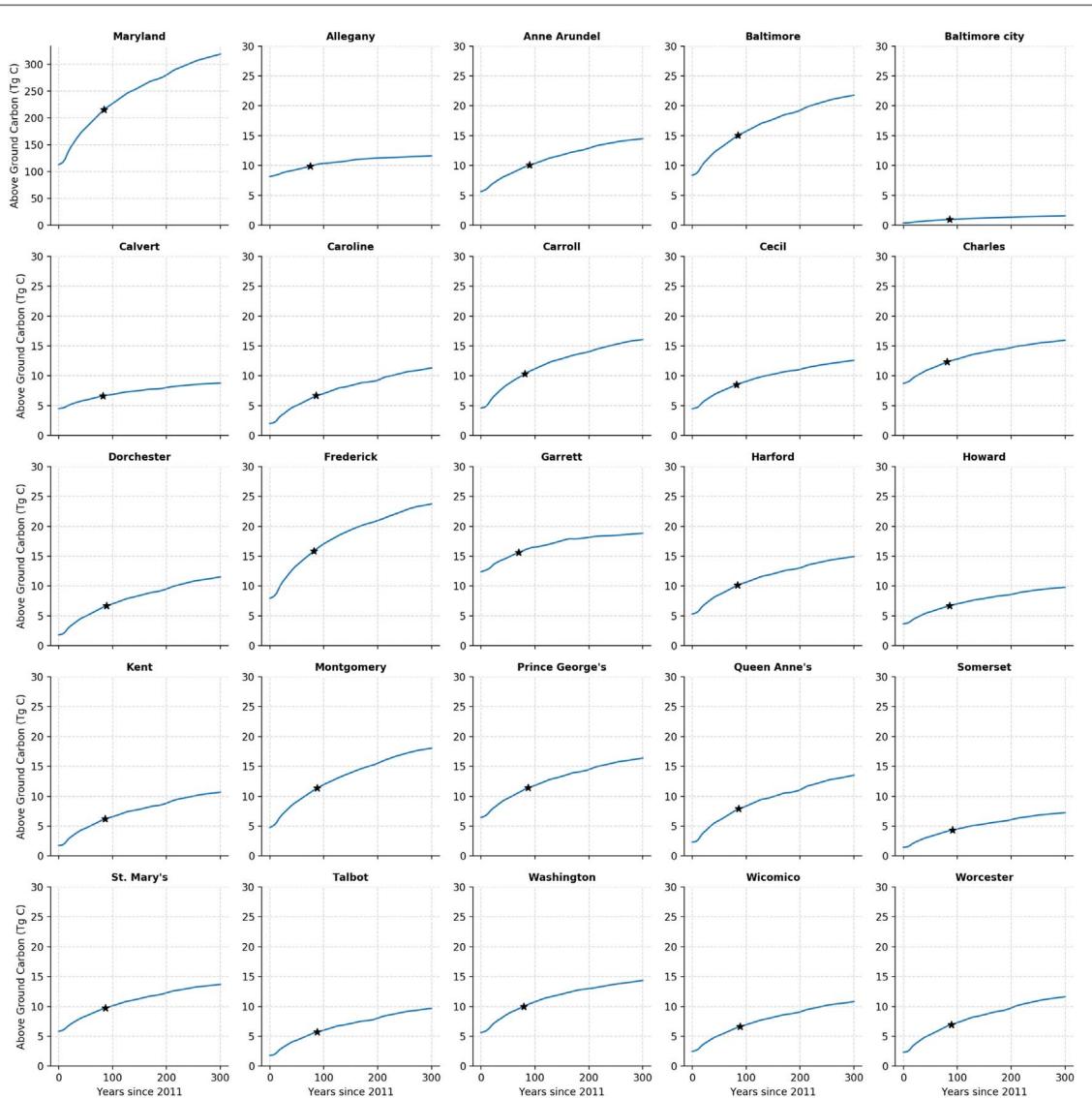
	Area <sup>a</sup> km <sup>2</sup>	AGB density <sup>b</sup> Mg ha <sup>-1</sup>	AGB stock <sup>c</sup> Tg C	CSP <sup>d</sup> Mg ha <sup>-1</sup>	CSPG <sup>e</sup> Mg ha <sup>-1</sup>	CSPTG <sup>f</sup> Years	Total CSP <sup>g</sup> Tg C	Total CSPG <sup>h</sup> Tg C
Allegany	1114	149.1	8.1	208.9	59.8	117.2	11.4	3.3
Anne Arundel	1523	120.6	5.6	308.0	187.4	213.5	14.3	8.7
Baltimore	1766	115.7	8.3	298.6	182.9	212.0	21.5	13.2
Baltimore city	238	36.9	0.4	153.0	116.1	165.2	1.6	1.2
Calvert	894	179.8	4.5	344.7	164.9	164.3	8.6	4.1
Caroline	844	55.2	1.9	336.7	281.5	310.4	11.5	9.6
Carroll	1171	79.9	4.6	287.2	207.3	262.3	16.5	11.9
Cecil	1083	104.8	4.4	296.7	191.9	234.4	12.5	8.1
Charles	1665	170.7	8.6	306.3	135.6	159.1	15.5	6.9
Dorchester	1399	49.9	1.7	335.2	285.4	312.4	11.3	9.6
Frederick	1728	93.9	7.9	286.2	192.3	243.3	24.1	16.2
Garrett	1699	151.6	12.3	226.4	74.8	125.9	18.4	6.1
Harford	1365	111.6	5.3	315.3	203.7	232.3	15.0	9.7
Howard	658	114.0	3.6	307.5	193.5	222.8	9.8	6.2
Kent	1072	52.9	1.6	351.4	298.5	307.5	10.8	9.2
Montgomery	1313	76.1	4.7	293.3	217.2	269.5	18.2	13.5
Prince George's	1290	112.1	6.4	283.7	171.6	206.2	16.2	9.8
Queen Anne's	1321	53.0	2.1	339.5	286.4	306.9	13.6	11.4
Somerset	1582	71.1	1.4	335.0	263.8	293.7	6.4	5.1
St. Mary's	1582	152.6	5.3	330.8	178.2	189.8	11.4	6.2
Talbot	1235	59.9	1.7	339.6	279.6	298.3	9.7	8.0
Washington	1212	95.8	5.6	247.7	151.9	221.3	14.5	8.9
Wicomico	1036	70.9	2.4	321.1	250.2	291.4	10.9	8.5
Worcester	1800	59.6	2.2	302.4	242.8	262.9	11.0	8.8
<b>Maryland</b>	<b>30590</b>	<b>103.7</b>	<b>110.8</b>	<b>293.5</b>	<b>190.2</b>	<b>228.13</b>	<b>314.8</b>	<b>204.1</b>

<sup>a</sup> Area: Area of county.<sup>b</sup> AGB density: Above-ground biomass simulated by ED model.<sup>c</sup> AGB stock: Above-ground carbon stock in 2015 estimated by ED model.<sup>d</sup> CSP: Carbon sequestration potential estimated by ED model.<sup>e</sup> CSPG: Gap to carbon sequestration potential.<sup>f</sup> CSPTG: Gap of years to reach carbon sequestration potential.<sup>g</sup> CSP: Carbon sequestration potential.<sup>h</sup> Total CSPG: Gap to total carbon sequestration potential.

ground + soil) resulted in an estimated total more than double the above ground value. In terms of annualized total CO<sub>2e</sub>, the units used for state carbon budgeting, existing forests together with statewide reforestation could therefore yield as much as 12 Tg CO<sub>2e</sub>/year, with reforestation potential per se comprising nearly 2/3 this amount. In practical terms, it is likely only a portion of this potential could actually be realized given the economic importance of other land uses and the relatively long-time scale of recovery. These considerations suggest placing even greater importance on preserving existing forests, reducing remaining uncertainties, and prioritizing areas to be reforested.

This approach, based on initializing a 3D forest model with ‘wall-to-wall’ high-resolution lidar and optical remote sensing data, provided an unparalleled opportunity for initialization and calibration/validation with corresponding empirically based maps and FIA data. However, evaluating spatio-temporal dynamics was much more challenging, as the modeling effort involved hundreds of years of dynamics across millions of grid cells—a domain for which data

simply do not exist. While future climate conditions are not yet known, several lines of evidence suggest the major spatio-temporal results were not unreasonable given current climate conditions. First, in addition to the extensive spatial validation, the key dynamic rates of NPP and disturbance were verified to be within range of prior estimates. Second, mapped estimates of CSP did not exceed maximum observed biomass values in the state. Third, statewide estimates of CSP were broadly consistent with the state’s >50% loss of original forest area to agriculture and development (Weber *et al* 2006) and the status of remaining forests as still recovering from prior land-use history (Pan *et al* 2013). Finally, the estimated nonlinear rates of recovery, involving decades to double above ground biomass and centuries to reach maximum carbon sequestration potential, were consistent with the long time-scales of forest recovery shown from experimental forest plots in Maryland and New England (McMahon *et al* 2010, Eisen and Plotkin 2015). Taken together, these results suggest that the extensive initialization and calibration/validation of the model was

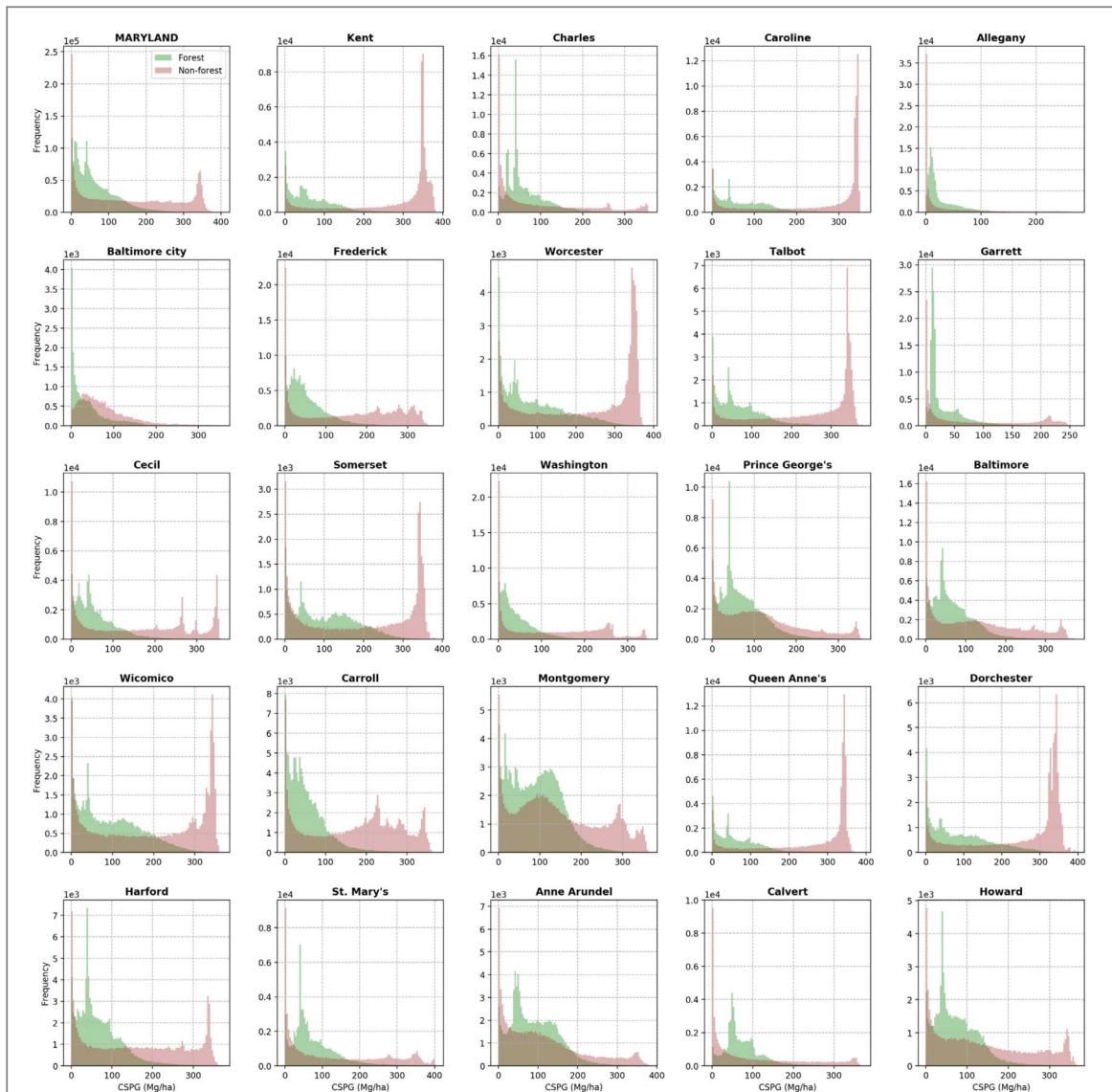


**Figure 6.** Carbon sequestration time-series at state scale (top left), and by county in Maryland. The star indicates the year at which half of the potential carbon total is reached.

sufficient to constrain the major predicted variables to reasonable values.

Two important uncertainties in this study involve climate change and wetlands. Perhaps most serious is the uncertainty associated with future climate change, its potential effects on forests, and how this in turn affects future carbon sequestration potential. Previous studies have shown that climate change can affect both forest growth rates and disturbance rates with implications for forest carbon and climate mitigation (Nemani *et al* 2003, McMahon *et al* 2010, Zhao and Running 2010, Fisk *et al* 2013, Le Page *et al* 2013, Murray-Tortarolo *et al* 2016, Dolan *et al* 2017). Predicting these effects over this domain was beyond the scope of this study, as the relevant global climate change scenarios were not available or harmonized at the resolutions required, and the links between future climate change and disturbance rates are not well understood. However, it is clear that plausible future climate conditions could either raise (e.g. through

enhanced growth rates and/or reduced disturbance rates) or lower (e.g. through depressed growth rates and/or increased disturbance rates) the default estimates for CSP, and affect the estimates of CSPTG. While the range assessed for sensitivity was wide by design, a narrower more practical range of concern can be inferred based on results from prior studies. Temperate deciduous forest NPP has been estimated to increase 4%–30% in response to a doubling of atmospheric CO<sub>2</sub> and associated climate change (Melillo *et al* 1993). In addition, recent results from an experimental forest in Maryland indicate significant net increases in forest growth rates already occurring (McMahon *et al* 2010). Together, these rising growth rates would imply our estimates for CSP based on current conditions may be conservative. However, changes in future forest disturbance rates, which are critically important and much less certain, are generally expected to increase (Frolking *et al* 2009, Dolan *et al* 2017), and have an opposite effect on CSP.



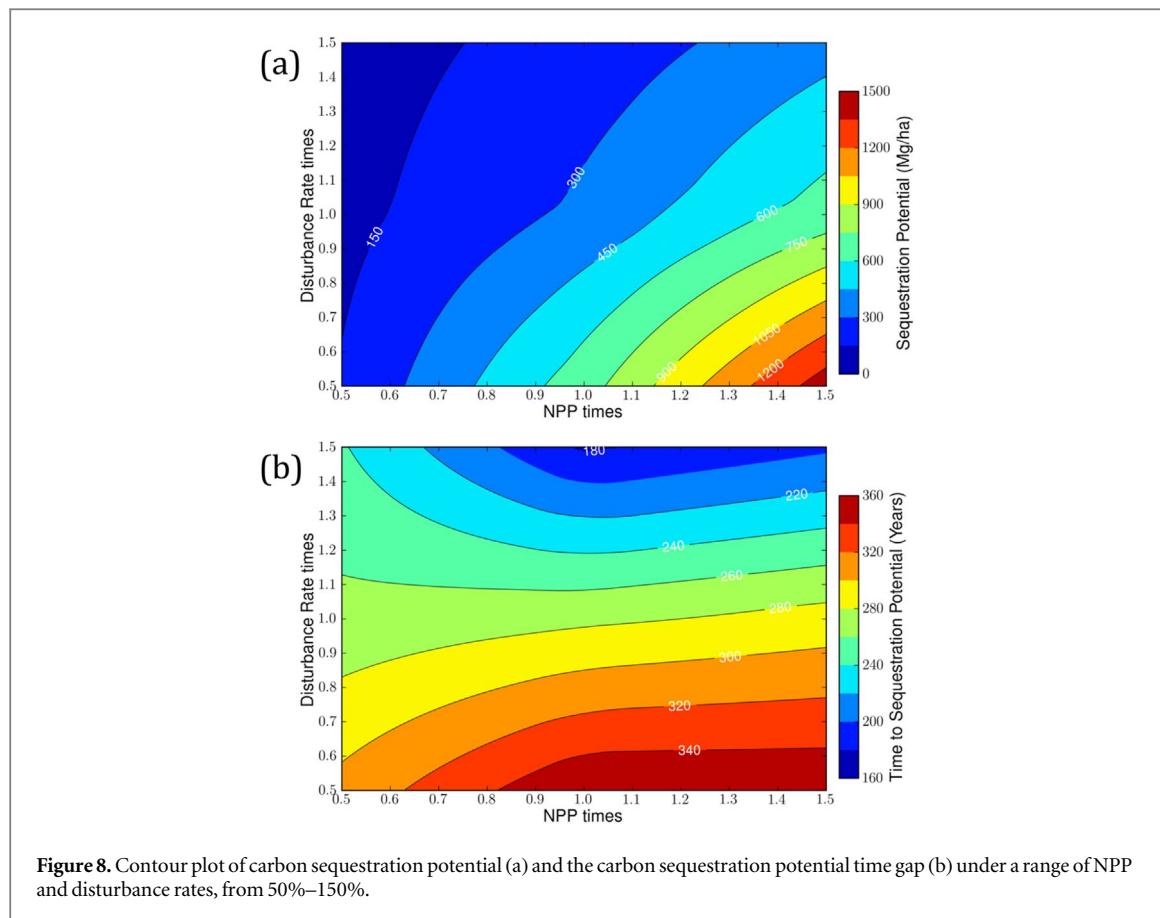
**Figure 7.** Carbon sequestration potential on forest versus non-forest conditions at state scale, and by county in Maryland.

Wetlands are particularly sensitive areas with unique species, biogeochemistry, and dynamics deserving focused attention (Melton *et al* 2013, Zhang *et al* 2018). This study excluded them from carbon modeling due to a relative lack of field data for calibration/validation. While critical to revisit in future studies, initial estimates suggest they may not be a large contributor to above ground carbon stocks statewide. Assuming an average biomass density of  $6.3 \text{ Mg ha}^{-1}$  for forested and  $1.34 \text{ Mg ha}^{-1}$  for herbaceous wetlands (Lister *et al* 2011, Riegel *et al* 2013), the state-wide totals in this study may underestimate above ground carbon stock by  $0.83 \text{ Tg C}$  or  $<1\%$ . Though not the focus of this study, the omission of wetland soil carbon and methane dynamics is likely much larger.

Additional technical uncertainties and opportunities for future research remain. Height-biomass saturation in tall forest patches resulted in uncertainty in the initial biomass estimate, suggesting that additional methods or data sources are needed to reduce this uncertainty. Furthermore, while this

study focused on the long-term potential for carbon sequestration using a minimum of plant functional types, high-spatial resolution transient dynamics are likely much more complex and may exhibit unpredictable successional pathways requiring additional research. Finally, the approach here for above ground forest carbon now far exceeds what is possible below ground, placing even greater urgency on developing new analogous approaches for below ground carbon monitoring and modeling.

Moving forward, results from this study are being used to update the afforestation and reforestation estimates in the state's greenhouse gas reduction plan for 2020–2030 reductions. Efforts are also underway to expand the domain of coverage of this work, first to the tri-state area of Maryland–Pennsylvania–Delaware, and next to an 11-state region encompassing the member states of the Regional Greenhouse Gas Initiative. A consistent high-resolution product for monitoring and modeling forest carbon will provide an important information base for policy makers in state



**Figure 8.** Contour plot of carbon sequestration potential (a) and the carbon sequestration potential time gap (b) under a range of NPP and disturbance rates, from 50%–150%.

and regional carbon mitigation planning. Finally, with the recent launch of the NASA-GEDI lidar mission (Dubayah *et al* 2014), and the use of larger and faster computational resources, these analyses should soon be possible over continental and global domains ushering in advances in both the ability to estimate current forest carbon stocks and to inform climate mitigation planning.

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