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Integrating LIDAR and forest inventories to fill the trees outside forests data gap

Kristofer D. Johnson · Richard Birdsey · Jason Cole · Anu Swatantran · Jarlath O'Neil-Dunne · Ralph Dubayah · Andrew Lister

Abstract Forest inventories are commonly used to estimate total tree biomass of forest land even though they are not traditionally designed to measure biomass of trees outside forests (TOF). The consequence may be an inaccurate representation of all of the aboveground biomass, which propagates error to the outputs of spatial and process models that rely on the inventory data. An ideal approach to fill this data gap would be to integrate TOF measurements within a traditional forest inventory for a parsimonious estimate of total tree biomass. In this study, Light Detection and Ranging (LIDAR) data were used to predict biomass of TOF in all "nonforest" Forest Inventory and Analysis (FIA) plots in the state of Maryland. To validate the LIDAR-based biomass predictions, a field crew was sent to measure TOF on nonforest plots in three Maryland counties, revealing close agreement at both the plot and county scales between the two estimates. Total tree biomass in Maryland increased by 25.5 Tg, or 15.6 %, when biomass of TOF were included. In two counties (Carroll and Howard), there was a 47 % increase. In contrast,

counties located further away from the interstate highway corridor showed only a modest increase in biomass when TOF were added because nonforest conditions were less common in those areas. The advantage of this approach for estimating biomass of TOF is that it is compatible with, and explicitly separates TOF biomass from, forest biomass already measured by FIA crews. By predicting biomass of TOF at actual FIA plots, this approach is directly compatible with traditionally reported FIA forest biomass, providing a framework for other states to follow, and should improve carbon reporting and modeling activities in Maryland.

Keywords Trees outside forest · Carbon management · Nonforest biomass · LIDAR · Forest inventory

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Introduction

Forest inventories provide valuable datasets for monitoring forests, including biomass stock and stock changes that are periodically reported to the Intergovernmental Panel on Climate Change (IPCC), the Food and Agriculture Organization (FAO), and domestic outlets. Additionally, process-based and geospatial models of aboveground biomass frequently rely on forest inventory data to both calibrate and validate model results (Blackard et al. 2008; Wilson et al. 2012; Zhang et al. 2012). However, when forest inventories are assumed to represent total tree biomass in an area, the trees outside of forests (TOF) are ignored, potentially underestimating the total biomass. Unmeasured biomass of TOF may be

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a substantial, especially in areas with highly fragmented forests or urban and suburban development. Besides underestimating carbon stocks over a landscape or region, other potential consequences of ignoring this data gap include the following: overestimating carbon losses from land use changes, incorrectly calibrating process-based models, and incorrectly assuming error or bias in model outputs when compared with forest inventory data (Houghton 2003; Johnson et al. 2014). As populations increase and developed areas expand, TOF will likely become increasingly important.

There are many definitions of "forest" and "nonforest" used by the natural resource community. Most definitions include some measure of tree stem or cover abundance such as percent stocking or percent canopy cover (Konijnendijk et al. 2006). The definition of the USDA Forest Service also includes the size and shape of the treed patch, the presence of developed land uses, and the ability of the understory to provide tree regeneration. Under this definition, areas where trees may be present, such as orchards, city parks, residential yards, and rural areas, may be considered nonforest (Fig. 1) (Bechtold and Patterson 2005; de Foresta et al. 2013).

We know from previous TOF inventories that the TOF biomass pool is substantial (Guo et al. 2014; Nowak et al. 2013; Riemann 2003), but there is still a considerable uncertainty about its actual contribution to total above-ground carbon stock, especially in highly fragmented

forested landscapes (Jenkins and Riemann 2003; Nowak and Crane 2002; Nowak et al. 2013). Ground measurement inventories are the most direct way to estimate the TOF biomass pool (Lister et al. 2012; Nowak et al. 2013; Riemann 2003). Such inventories, however, are often expensive, difficult to implement (e.g., denied access from private land-owners), and rarely extend beyond urban borders. Furthermore, urban and other nonforest inventories are often not part of the design objectives for existing forest resource inventories and thus require establishment of a new network of field measurement plots (Cumming et al. 2008; Lister et al. 2012). Additionally, inventories that are spatially limited are sometimes extrapolated to larger polygons of urbanized areas that overlap forest inventories (Nowak et al. 2013; Riemann 2003). To measure total tree biomass in an area, a parsimonious approach is most ideal; i.e., one that leverages the data already collected in traditional forest inventories and simply fills the TOF data gap within the same inventory.

The goals of this study were to estimate and separate the contribution of biomass of TOF to the total tree biomass pool in Maryland, using Forest Inventory and Analysis (FIA) and Light Detection and Ranging (LIDAR) data sets. We used LIDAR to estimate mean canopy height and spatial occurrence of trees at unmeasured forest inventory plots. In addition to analyzing results at the plot scale, we also estimated biomass of TOF at the county scale because this is a common

Fig. 1 An example of an FIA plot (made up of four subplots) located in fragmented forest cover in Maryland. *Brighter colors* are higher canopy heights of the 1-m canopy height model. *Inset*: a zoomed-out view of the same plot showing as an example of a "nonforest" condition. The traditional FIA inventory will not visit this plot because it does not meet the requirements of "Forest land," even though it is highly probable that trees are in the plot
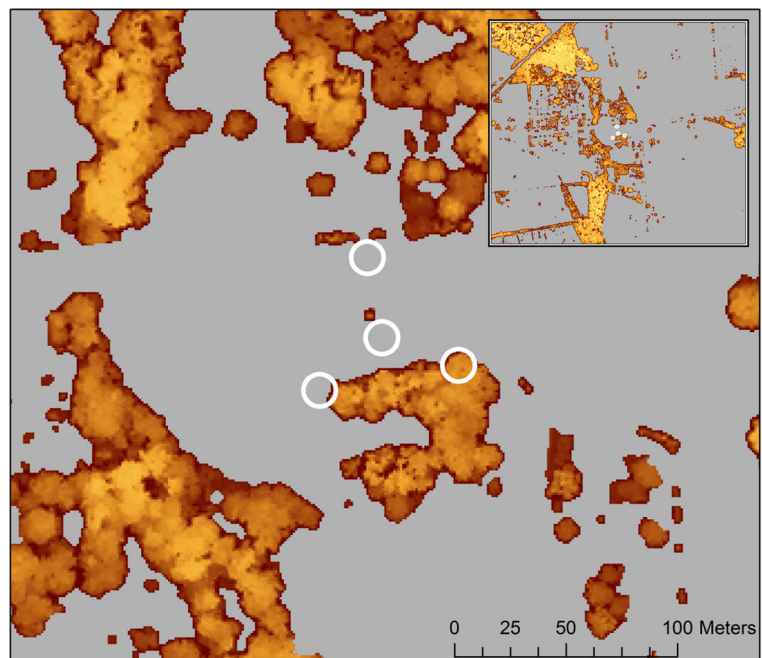
estimation unit of the FIA program. Prediction estimates were validated in three Maryland counties at the plot and county scales by directly measuring TOF in "nonforest" FIA plots.

Data sets and methods

Tree canopy was extracted from high-resolution imagery and LIDAR using an object-based approach described in O'Neil-Dunne et al. (2014). The imagery consisted of leaf-on, 4-band, 1-m resolution aerial data acquired as part of the National Agricultural Imagery Program (NAIP) in the summer of 2011. LIDAR data were obtained from individual counties and the Maryland Department of Natural Resources (DNR). The LIDAR datasets met established USGS mapping standards (e.g., either a 1/9 or 1/27 arc second required posting). The LIDAR collection was processed to create various raster surface models that were integrated with the imagery and where available, existing vector datasets (e.g., roads and buildings), to automatically map tree canopy features through the application of segmentation, classification, and morphology algorithms in an object-based expert system. The final output consisted of a 1-m resolution tree canopy raster dataset for the entire state of Maryland (O'Neil-Dunne et al. 2014).

Data from the most recently completed inventory (2008–2012) was used to calculate forest biomass (FB) density (Mg/ha) at standard FIA plots and subplots (one of several sample points in a cluster), and total biomass (Tg) at the county scale in Maryland with the EVALIDATOR tool (Miles 2014). The allometric models used for biomass estimations were volume-based, following the standard component ratio method used by FIA (Heath et al. 2008). Since FIA data systematically samples all lands, we assumed that combining LIDAR-based TOF biomass from nonforest FIA plots with those from ground measured forested plots provided a holistic characterization of the biomass resource in Maryland.

TOF models and validation process

Subplot level model in Maryland

In Maryland, biomass of TOF was predicted from the relationship between aboveground biomass in live trees at least 2.54 cm in diameter (AGB) and the mean canopy height from LIDAR (H) within "forested" FIA subplots (Fig. 1). We selected a simple one parameter model (mean canopy height) as opposed to a more sophisticated model because we strove for general applicability to other large datasets and it was unclear whether additional metrics would significantly improve the model (c.f. Asner et al. 2014). Twenty of the 23 counties in Maryland were used to develop the relationship and three counties were left out for validation purposes. In the training dataset, a few plots were affected by biomass removals or other perturbations between the time of the data collection in the field and the time of the LIDAR flight, so these plots were excluded. The ordinary least squares linear regression model for the training data was ($r^2 = 0.25$, RMSE = 1753 kg, $P < 0.0001$, $n = 704$):

$$TOF_{subplot}\,biomass\,(kg) = AGB_{subplot}(kg)$$

$$= 167.95 * H_{subplot}(m) \qquad (1)$$

where TOF biomass is the biomass of an FIA nonforest condition, AGB is the aboveground living biomass calculated from tree diameters and heights using the component ratio method, and H is the mean canopy height of the subplot. It was necessary to predict biomass of TOF at the subplot level because of some few instances when there were two land types within the same subplot (i.e., a subplot with a forest/nonforest split mapped by FIA). Nonetheless, a plot level version of this model is somewhat better in terms of fit ($r^2 = 0.35$, RMSE = 271 kg) and all model assessments were conducted at the plot level instead of the subplot level. Although Eq. 1 had a poor fit, we relied on the validation data to assess bias and the accuracy of the model.

Although Eq. 1 does not predict for specific species groups or forest types, we note that the species composition of the training dataset was very similar to the validation dataset collected for nonforest conditions (for the top 10 species occurrence of both datasets, 9 of the 10 were the same). This suggests that Eq. 1 was developed from essentially the forest conditions as it was applied to in the prediction of TOF biomass.

After applying the TOF biomass model, we noticed that biomass was occasionally predicted at subplots where it was known that no biomass occurred. This occurred in mainly two situations: (1) the subplot had both forest and nonforest conditions ("split condition plot") but it was clear that FIA crews

measured every tree in the subplot, and (2) trees adjacent to the plot that were detected by LIDAR but the stems actually fell outside the subplot (common on the edge of agriculture fields). To remove these false-positive estimates and avoid double counting tree biomass, all subplots potentially affected by these situations (9 % of all nonforest plots) were visually checked with aerial imagery to determine which subplots should be given a zero value in terms of their TOF biomass.

The TOF biomass predictions at the plot and county scales were validated against field data collected in the summer of 2012 in actual nonforest FIA plots in three Maryland counties—Allegany, Baltimore, and Dorchester. These three counties are representative of the major physiographic provinces found in Maryland (Appalachian, Piedmont, and Coastal Plain) and also a gradient of TOF occurrence.

County level estimates in Maryland

After confirming that Eq. 1 gave accurate results for the validation datasets (see "Results"), the model was applied to all nonforest FIA subplots in Maryland to estimate county level biomass of TOF. County level TOF biomass was calculated by adding the additional TOF biomass to original inventory data with the EVALIDATOR tool, resulting in total tree biomass for both forest and nonforest conditions. The county level biomass of TOF was the difference between the new EVALIDATOR estimate and the original forest-only estimate. We used the EVALIDATOR tool because one of our goals was to compare against traditionally reported FIA estimates of biomass stocks as estimated by EVALIDATOR (Miles 2014).

To approximate the 95 % confidence limits, the sampling error of predicted biomass of TOF by county was doubled. Sampling errors (half widths of the 68 % confidence interval) were calculated with EVALIDATOR using the post-stratified estimator described in Bechtold and Patterson (2005). This assumes that the TOF biomass error distribution is normal and does not propagate the error from Eq. 1. More sophisticated methods that quantify uncertainty were not the focus of this analysis but we recognize that these methods may improve the uncertainty estimates (e.g., Monte Carlo and Bayesian approaches).

Results

TOF biomass model validation with field data in three counties

In the validation dataset of 33 nonforest plots in Allegany, Baltimore, and Dorchester counties, the relationship between measured biomass of TOF and predicted biomass of TOF was nearly 1:1 ($r^2 = 0.87$, RMSE = 1583 kg) (Fig. 2). The validation results were better than the training model results because of the ability of the LIDAR model to predict not only canopy height but also the presence or absence of TOF. In other words, the r^2 was inflated in the validation results because of the weight of many zero values that were included compared to the training model.

Comparison results at the county level were also close. Combined TOF biomass predictions and traditional FIA estimates were similar to estimates derived from the joint FIA and TOF ground inventory conducted in the three counties used for validation. The predicted estimates of total nonforest biomass from Eq. 1, and the percent increase from the traditional FIA estimate (i.e., without gap-filling TOF), were well within the 95 % confidence intervals of the validation measurements (Table 1).

Predicted biomass of TOF in Maryland

For the state of Maryland, there was 25.5 Tg of biomass in TOF accounting for an estimated 13.5 % of the total
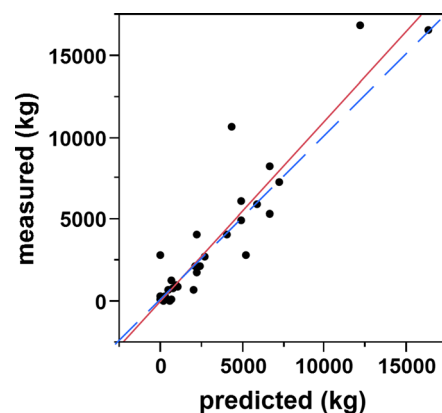
Fig. 2 Measured vs. predicted biomass of TOF from the LIDAR mean canopy height model for 33 nonforest plots in Allegany, Baltimore, and Dorchester counties. The *solid line* is the regression line ($r^2 = 0.87$, RMSE = 1583 kg) and the *dashed line* is the 1:1 line

Table 1 Biomass of trees outside forest (TOF) estimates for three counties

County	TOF biomass, Tg		% increase	
	Predicted (95 % CI)	Measured (95 % CI)	Predicted	Measured
Allegany	0.56 (0.39, 0.74)	0.52 (0.36, 0.69)	5.7	5.3
Baltimore	3.30 (2.15, 4.46)	3.51 (2.27, 4.74)	26.8	28.4
Dorchester	0.57 (0.34, 0.80)	0.60 (0.35, 0.84)	6.7	7.0

Predicted estimates represent those predicted from LIDAR using Eq. 1. Measured estimates represent a ground inventory of all trees in FIA plots, both forest and nonforest. The % increase is the increase of total biomass in a county when TOF biomass is added to the traditionally reported FIA estimate. All estimates and 95 % confidence intervals were calculated using the EVALIDATOR tool

biomass (Table 2). Predicted TOF biomass was highly variable among Maryland counties, with some counties having essentially none and others with substantial biomass in TOF. In terms of total biomass added by county, TOF biomass ranged from 0.02 Tg in Somerset to 1.7 Tg in Baltimore County. In terms of the percent increase in biomass from the traditionally reported FIA value, 13 of the 23 counties increased by 10 % or more.

Table 2 The traditionally reported county and state FIA estimates, the predicted biomass of TOF, and the total tree biomass estimates in Tg biomass

County/state	FIA traditional, Tg	TOF biomass, Tg	Total tree biomass (FIA + TOF), Tg	Increase, %	TOF, Mg/ha
Worcester	9.14 (5.45, 12.83)	0.05 (0.04, 0.06)	9.19 (5.5, 12.9)	0.6	0.3
Somerset	4.03 (1.73, 6.33)	0.04 (0.03, 0.05)	4.07 (1.77, 6.39)	1.0	0.5
Wicomico	7.16 (3.78, 10.54)	0.36 (0.31, 0.41)	7.52 (4.12, 11.07)	5.1	3.6
Allegany	9.88 (6.73, 13.02)	0.56 (0.48, 0.65)	10.44 (7.13, 13.76)	5.7	4.8
Caroline	3.21 (0.88, 5.53)	0.18 (0.14, 0.22)	3.39 (1.05, 5.84)	5.7	2.0
Dorchester	8.5 (4.84, 12.17)	0.57 (0.49, 0.65)	9.07 (5.36, 12.98)	6.7	3.3
Kent	3.78 (1.06, 6.49)	0.31 (0.25, 0.37)	4.09 (1.35, 7.03)	8.2	4.3
Charles	12.72 (8.24, 17.21)	1.08 (0.97, 1.18)	13.8 (9.24, 18.66)	8.5	8.8
Washington	8.26 (4.46, 12.07)	0.78 (0.71, 0.86)	9.05 (5.21, 13.21)	9.5	6.4
St. Mary's	8.25 (4.12, 12.38)	0.81 (0.71, 0.92)	9.06 (4.85, 13.59)	9.8	7.4
Queen Anne's	4.55 (1.48, 7.62)	0.5 (0.43, 0.58)	5.06 (1.91, 8.47)	11.1	4.7
Garrett	14.35 (10.19, 18.51)	1.62 (1.49, 1.74)	15.97 (11.76, 20.6)	11.3	9.8
Montgomery	6.63 (2.97, 10.28)	0.76 (0.71, 0.81)	7.38 (3.68, 11.46)	11.4	6.0
Frederick	10.87 (6.51, 15.23)	1.38 (1.3, 1.47)	12.25 (7.73, 17.16)	12.7	7.6
Baltimore	12.34 (7.31, 17.37)	3.3 (3.09, 3.52)	15.64 (10.16, 22.02)	26.8	19.9
Pr. George's	8.57 (4.4, 12.75)	2.32 (2.14, 2.49)	10.89 (6.51, 16.2)	27.1	18.5
Talbot	2.09 (0.4, 3.78)	0.58 (0.45, 0.71)	2.67 (0.81, 4.83)	27.6	6.7
Calvert	6.31 (2.13, 10.48)	1.79 (1.42, 2.16)	8.1 (3.42, 13.46)	28.4	28.2
Cecil	4.9 (2, 7.79)	1.39 (1.28, 1.5)	6.28 (3.14, 10)	28.4	13.3
Harford	7.12 (3.22, 11.01)	2.25 (2.03, 2.46)	9.36 (5.17, 14.49)	31.5	18.6
Anne Arundel	3.23 (0.94, 5.52)	1.15 (1.04, 1.27)	4.38 (1.96, 7.49)	35.6	11.3
Howard	4.81 (1.49, 8.14)	2.24 (1.95, 2.53)	7.05 (3.27, 11.93)	46.5	32.6
Carroll	3.18 (0.84, 5.53)	1.5 (1.36, 1.63)	4.68 (2.08, 8.13)	47.0	13.3
Maryland	163.88 (153.75, 174)	25.52 (25.46, 25.58)	189.39 (179.47, 201.1)	15.6	25.9

All estimates were calculated using the EVALIDATOR tool. The % increase refers to the increase in biomass from the traditional FIA estimate. TOF biomass density in Mg/ha is the TOF biomass divided by the county area reported by FIA

Worcester and Somerset counties only increased by 1 % or less, but there was as much as a 47 % increase in Howard and Carrol counties. In terms of TOF biomass density per county (in Mg/ha), the counties located closer to the I-95 corridor generally had higher biomass in TOF (Fig. 3). There was also a strong positive Pearson's correlation between the TOF biomass density per county and the proportion of county area sampled as nonforest ($r = 0.81$, $P < 0.0001$).

Discussion

Comparing approaches for analyzing the impact of biomass of TOF in Maryland

Jenkins and Riemann (2003) estimated biomass of TOF in Maryland based on an additional inventory of nonforest areas in several Maryland counties, mostly along the I-95 corridor. Their estimate was 52 Tg, or 25 % of the total biomass, roughly double our estimates of 26 Tg and 14 %. As much as 30 % of this difference may be due to a difference in the allometric equations applied (i.e., "Jenkins" equations vs. component ratio method) (Johnson et al. 2014). The reason for the rest of the difference is unclear, but we note that the TOF

biomass density of the five counties in their study (35.6 Mg/ha) was higher than the predicted density for the same counties in this study (18.3 Mg/ha).

This study's estimate for Maryland is closer to another estimate from Nowak et al. (2013), reporting 23.8 and 31.2 Tg of biomass for "urban" and "urban communities," respectively. However, the results are not exactly comparable because in that study, "urban" areas were defined by polygons from the US Census Bureau (2007) and large areas overlap forest FIA plots. Thus, with the "urban" polygon approach, there is a double counting of biomass when "urban" area biomass is combined with FIA forest biomass, and the separation of the two components is not straightforward (Nowak et al. 2013). In contrast, this study estimated total tree biomass parsimoniously by filling in biomass estimates where they were missing within the same inventory.

Filling the TOF data gap

Biomass in TOF accounts for a substantial proportion of the total biomass, but the distribution of TOF biomass density is variable and depends on the degree of forest fragmentation and nonforest land use in counties. The current results for Maryland indicate that FIA reporting of forest biomass for nearby states may also be
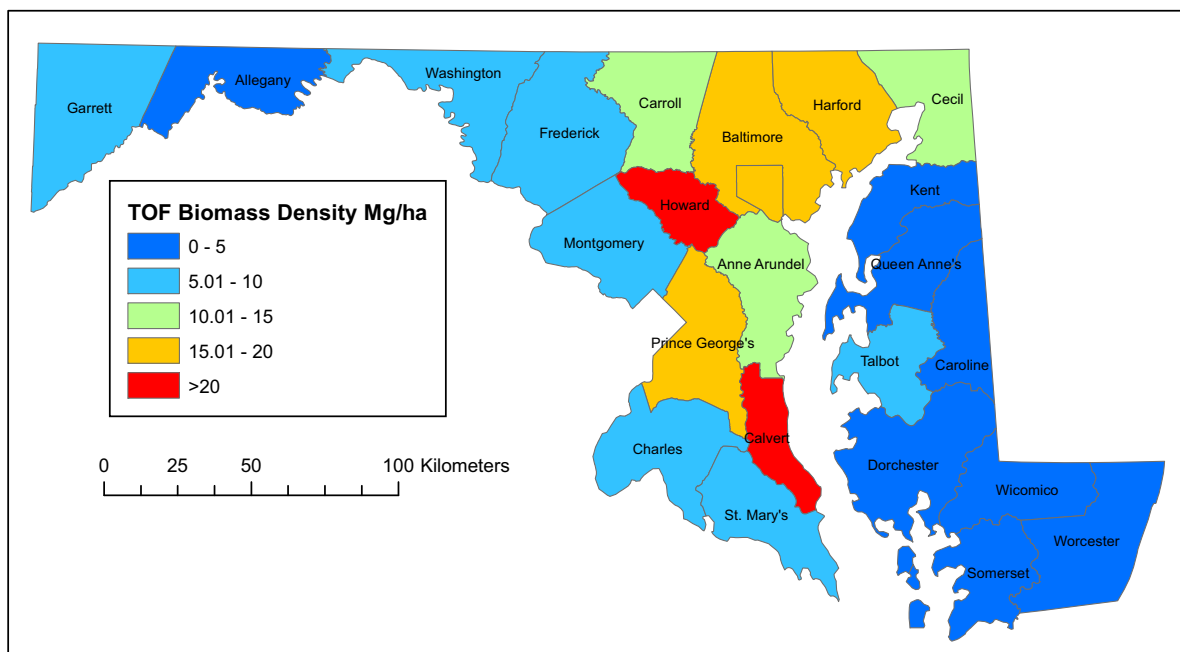
Fig. 3 The biomass density of TOF by county in Maryland. Higher densities generally correspond to counties closer to Interstate 95, which divides the Howard and Anne Arundel counties

underestimating total tree biomass. Like many US states, some nearby states also have wall to wall LIDAR (Pennsylvania, Delaware, and New Jersey) that can be used to fill the TOF data gap. In other areas where forest fragmentation is common but wall to wall LIDAR is not available, it is possible that small areas, or transects, could be flown in a way that helps predict TOF occurrence. For example, LIDAR transects in the USA and Mexico have targeted national forest inventory plots for modeling and validating biomass maps at a much lower cost than wall to wall acquisitions (Cook et al. 2013).

The new biomass estimates for Maryland and its counties should be more comparable to remote sensing-derived biomass maps that are becoming increasingly important for carbon monitoring purposes. These maps have the advantage of representing biomass at high resolutions where no plot information is available (Huang et al. 2015). However, it is difficult to improve such maps by assessing if they are too high or too low at the county scale when they are compared against reference ground data that incompletely represents total tree biomass. For example, Johnson et al. (2014) showed that using both a nonforest inventory and FIA estimate in Anne Arundel County resulted in much better agreement with a biomass map than if only the FIA estimate was used. In contrast, in Howard County, they found that adding nonforest data actually resulted in a greater difference between the two estimates. This observation applies to larger scales as well - global biogeochemical models will benefit as reference data for aboveground biomass and other important terrestrial carbon pools become more accurate.

Limitations

Serviceable, yet basic, approaches were used in this study to estimate biomass of TOF and uncertainty but, more sophisticated methods could be applied. For example, more LIDAR metrics could be used in the step that predicts subplot level TOF biomass. Bayesian and Monte Carlo methods could be applied to propagate allometric model and LIDAR model errors to more accurately represent uncertainty. Additionally, although this approach complements FIA estimates by filling a data gap at the county and state scales, urban areas with few FIA plots (e.g., Baltimore City) will still be inadequately represented for TOF detection. Therefore, intensifying field collection in sub-county estimation units, such as highly urbanized areas (e.g., Nowak and Crane 2002), is still likely needed to account for biomass of

TOF at these smaller scales. Finally, we note that the TOF prediction equation does not explicitly include exotic and ornamental trees that are sometimes found within urban landscapes. Nonetheless, we believe these cases are few and mostly limited to urban areas that are relatively a small portion of TOF biomass.

Conclusions

Biomass of TOF is a substantial carbon pool that cannot be ignored in many areas of the world where populations and forests intersect to create highly fragmented landscapes. Yet, because the trees in these areas are not usually of economic interest and do not meet forest land definitions, most forest inventories do not include TOF. The consequences are that even well-designed spatial and ecosystem models of biomass stocks and changes will suffer from this lack of information in some areas. To fill this data gap, it is common to combine separate nonforest and forest inventories. However, this is usually less ideal because of the additional costs needed for field sampling a new inventory and accommodating for differences in sample intensity and plot designs. By utilizing available LIDAR data, no additional network of plots needed to be established and measured. As populations continue to grow and expand, the need to account for biomass in TOF will be even greater in the future.

Conflict of interest   The authors declare that they have no competing interests.

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