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Predicting downed woody material carbon stocks in forests of the conterminous United States

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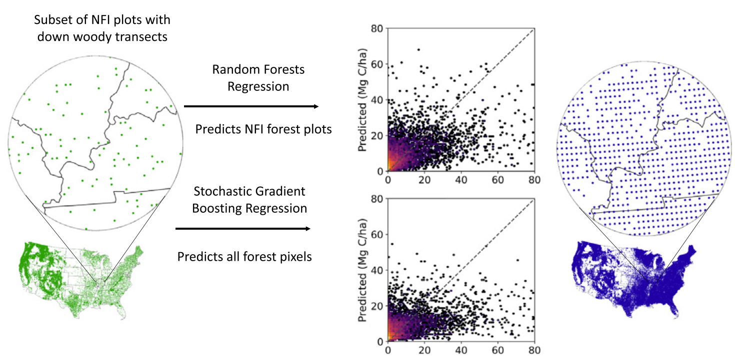
HIGHLIGHTS

- New regression models developed to predict forest downed woody material (DWM) stock.
- National forest inventory (NFI) data used to train non-parametric regression models.
- New model predictions of DWM carbon stocks outperformed previous model predictions.
- Important predictors: dead trees, long-term precipitation and summer temperature
- Updated predictions show a 15% decrease in DWM carbon stocks over Continental US.

GRAPHICAL ABSTRACT



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ABSTRACT

Downed woody material (DWM) is a unique part of the forest carbon cycle serving as a pool between living biomass and subsequent atmospheric emission or transference to other forest pools. Thus, DWM is an individually defined pool in national greenhouse gas inventories. The diversity of DWM carbon drivers (e.g., decay, tree mortality, or wildfire) and associated high spatial variability make this a difficult-to-predict component of forest ecosystems. Using the now fully established nationwide inventory of DWM across the United States (US), we developed models, which substantially improved predictions of stand-level DWM carbon density relative to the current national-reporting model ('previous' model, here). The previous model was developed from published DWM carbon densities prior to the NFI DWM inventory. Those predictions were tested using NFI DWM carbon densities resulting in a poor fit to the data (coefficient of determination, or $R^2 = 0.03$).

We present new random forest (RF) and stochastic gradient boosted (SGB) regression models to prediction DWM carbon density on all NFI plots and spatially on all forest land pixels. We evaluated various biotic and abiotic regression predictors, and the most important were standing dead trees, long-term annual precipitation, and long-term maximum summer temperature. A RF model scored best for expanding predictions to NFI plots ($R^2 = 0.31$), while an SGB model was identified for DWM carbon predictions based on purely spatial data (i.e., NFI-plot-independent, with $R^2 = 0.23$). The new RF model predicts conterminous US DWM carbon stocks to be 15% lower than the previous model and 2% higher than NFI data expanded according to inventory design-based inference. The new NFI data-driven models not only improve the predictions of DWM carbon density on all plots, they also provide flexibility in extending these predictions beyond the NFI to make spatially explicit and spatially continuous estimates of DWM carbon on all forest land in the US.

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1. Introduction

The role of downed woody material (DWM) in forest ecosystem dynamics and terrestrial carbon cycles is the basis for its separation as a distinct carbon pool summarized at scales from state (Domke et al., 2021; USDA, in press), to national (U.S. EPA, 2021), to international reporting of greenhouse gas inventories (IPCC, 2006, 2019). The DWM component of forest ecosystems serves numerous functions including wildlife habitat (Nordén et al., 2004), wildfire fuel (Schoennagel et al., 2004), substrate for tree regeneration (Bolton and D'Amato, 2011), biodiversity of deadwood-dependent organisms (Stokland et al., 2012), component of nutrient cycling (Harmon et al., 1986), and store of carbon (Bradford et al., 2008). Down woody material is estimated to represent 5 to 27% of the total terrestrial carbon stock over forest biomes (tropical to boreal, respectively) (Pregitzer and Euskirchen, 2004; Bradford et al., 2008; Pan et al., 2011; Woodall et al., 2013) and may be quite dynamic (Russell et al., 2015) given expected future influences of global change (Harmon et al., 2020). Refining the monitoring of DWM should enable more accurate assessment of the effect of future global change events (e.g., tree mortality from insect outbreaks, droughts, or wildfires) (McDowell and Allen, 2015) on the terrestrial carbon cycle with substantial implications for climate change trajectories.

Several nations conduct systematic inventories of DWM (Woodall et al., 2008, 2009) in forest biomes ranging from boreal (Fridman and Walheim, 2000) to temperate (Rondeux et al., 2012; Woodall et al., 2013; Crecente-Campo et al., 2016; Alberdi et al., 2020; Moreno-Fernández et al., 2020) to tropical (Gora et al., 2019). Costs and uncertainties associated with DWM inventories (Campbell et al., 2019) often require the inclusion of auxiliary information and modeling to produce robust estimates across large scales. Crecente-Campo et al. (2016) used zero-inflated Poisson models to predict DWM across forest inventory plots for Spain. Other approaches have used DWM empirical assessments to parametrize ecosystem process models (Verkerk et al., 2011) with promising results. Additional approaches include structural equation modeling (Richardson et al., 2009) and non-parametric techniques, such as component-wise gradient boosting (Doerfler et al., 2017). The predictive ability of remotely sensed variables, including LiDAR or radar (Scaranello et al., 2019; Bae et al., 2019) underscores the potential role of machine learning approaches, which can incorporate a range of potentially predictive data (López-Senespleda et al., 2021).

National DWM inventories are frequently based on subsets of inventory plots; that is, intensive sampling of a few plots with the goal of predicting all. This is the case for the United States (US) national forest inventory (NFI; Woodall et al., 2019), and appropriate expansion of sparse samples will increase spatial resolution and meet reporting requirements (e.g., IPCC, 2006, 2019). The US Department of Agriculture (USDA) Forest Service began implementing a nation-wide inventory of DWM using line transects on a subset of NFI plots in the early 2000s (Woodall et al., 2019). The definition of forest DWM is typically based on size of individual pieces (e.g., fine woody materials versus larger logs) and orientation (e.g., downed dead versus standing dead) in order to delineate DWM classification with inherently different decay trajectories or risks of combustion (Woodall et al., 2009; Woodall et al., 2019). For the purpose of this study, which is aligned with refining the DWM component of the US national greenhouse gas reporting (US NGHGI), DWM (otherwise termed coarse woody debris) is defined as dead and downed wood in forests with a lean angle greater than 45° from vertical and a minimum transect diameter of 7.62 cm (Woodall et al., 2019).

The reporting of DWM as a component of the total forest ecosystem carbon pool began for the US with the 2001 NGHGI (U.S. EPA, 2001; Heath, 2013). As field-based measurements of DWM from the NFI were not available at that time (i.e., for U.S. EPA, 2001), estimates of DWM pools were from simulations developed from available published estimates. With some modifications over time (e.g., Smith et al., 2006), that original model remains in use as the DWM model for US forest carbon reporting and model predictions are included in the publicly available NFI database. In 2012, preliminary NFI-design-based estimates of DWM carbon stocks were developed, and the existing model was further modified according to prediction errors identified by state (Domke et al., 2013; U.S. EPA, 2013). This previous DWM model remained in use for the NFI and NGHGI for US forests through U.S. EPA (2021); hereafter, we refer to this model as the 'previous' DWM model in order to avoid confusion with the new DWM model predictions developed herein.

The goal of this study is to utilize the accumulated NFI transect observations of DWM to replace the previous empirical model by developing machine learning (ML) regression models to predict plot-level DWM, which then allows flexibility in defining forest subsets of interest for developing forest ecosystem carbon estimates where sample intensity associated with the DWM NFI may be low. This is consistent with ongoing updates of the US NGHGI reporting (Domke et al., 2021). This report follows similar modeling of other forest carbon stocks based on NFI data, which have demonstrated success for nationwide carbon reporting. Specifically, recent ML regression models were developed and trained on NFI data to predict forest carbon stocks for litter and soil organic carbon (Domke et al., 2016; Domke et al., 2017; Cao et al., 2019).

Our objectives for this study are to: (1) evaluate the previous DWM model relative to the new NFI plot transect observations; (2) train ML regression models (random forests [RF] and stochastic gradient boosting [SGB]) with the limited set of DWM data and then broadly apply to predict carbon density on all current NFI forest plots; (3) train and test models using input data applicable to making predictions on all NFI plot data 1990-present; and (4) extend this approach by training and testing similar ML models to make spatial predictions of DWM independently from NFI plot data. The purpose of two different regression approaches – RF and SGB – is to identify the more-accurate model for a given set of predictor variables. The second through fourth objectives are expected to include differing sets of predictive features among the six models (i.e., scope of predictions by RF or SGB).

2. Methods

2.1. The down woody material component of the NFI

The USDA Forest Service conducts systematic and continuous inventories of multiple forest attributes on forest land. The Forest Inventory and Analysis (FIA) program within the Forest Service is responsible for the NFI design, data collection, and information management (Bechtold and Patterson, 2005). A portion of the permanent NFI plots visited by field crews for inventory data collection each year are also sites for measurement of DWM. Sampling of DWM on these plots varies by political boundaries (e.g., state or National Forest) according to levels of resources or information needs. In the current NFI, approximately 59% of forest plots in the West include DWM observations while in the East the proportion is approximately 12%. On these plots, various sizes and configurations of DWM are measured as part of the FIA dead wood inventory program (e.g., slash piles or fine woody materials), but for the purposes of this study, DWM includes only larger pieces observed along line intersect sampling transects. Specifically, down woody pieces with a diameter of at least 7.62 cm along a length of at least 0.15 m, or at least 12.7 cm above the duff layer along a length of at least 1.52 m for those most-decayed pieces (USDA Forest Service, 2016; Woodall et al., 2013, 2019). Pieces detached from the bole of a standing live or dead tree but still partly rooted are included if the lean angle is more than 45° from vertical (to distinguish from snags, USDA Forest Service, 2016). These pieces constitute the pool of DWM as used here and in NGHGI reporting by the United States (Domke et al., 2013; U.S. EPA, 2021).

The DWM data and all associated NFI data used in this study were downloaded from the FIA Datamart (USDA Forest Service, 2020). We selected a large consistently sampled subset of all DWM records, which are characterized by data observed along horizontal line intersect sampling transects and collected over the interval 2012–2020 (Woodall et al., 2019). The target prediction for regressions (i.e., dependent variable) is forest DWM carbon density. These values are directly obtained as the CWD_CARBON_COND field of the Condition Down Woody Material Calculation Table of the NFI database (USDA Forest Service, 2018; Burrill et al., 2018). The geographical extent of the analysis is all forest land within the set of conterminous states (CONUS). "Forest" is defined according to land use, which includes all silvicultural systems such as even-aged plantations. See Reams et al. (2005) and USDA Forest Service (2018) for additional information on forest land as applied here and the US NFI in general; Woodall et al. (2013, 2019) for more specific information on the DWM inventory; and Burrill et al. (2018) regarding database information.

2.2. Non-parametric regression models

The two ML approaches are ensemble methods, which combine the predictions of multiple trees, and both have established records for applications such as these. For background information, see, for example, Breiman (2001) or Belgiu and Dragut (2016) for RF and De'ath and Fabricius (2000) or Elith et al. (2008) for SGB. The use of the two alternate approaches (RF and SGB) is because (1) prediction accuracy is likely to vary between the two, and (2) predictive features (the X values of the regressions) are likely to differ somewhat (Dube et al., 2014; Freeman et al., 2015; Yang et al., 2016; Zhang et al., 2020). That is, our purpose is not to evaluate the models so much as to find the better predictor. For this reason, we use the same set of features for each pair of RF and SGB regressions. The presence of some additional, redundant or correlated features does not adversely affect RF or SGB model performance or accuracy (Elith et al., 2008; Genuer et al., 2010).

A large set of potentially useful features (predictor variables) focused on processes or conditions affecting DWM were included in model development (Harmon et al., 1986; Woodall and Westfall, 2009). These include forest stand characteristics from NFI plots, soils data, and abiotic site characteristics; where possible, we included indicators of productivity, recent disturbance, or changes in vegetation (see Appendix for details). Selection was primarily through determining importance of features to model predictions; this is specifically Gini importance (aka, mean decrease in impurity) in this analysis (Pedregosa et al., 2011). As a part of developing these models, we include two basic steps to identify and avoid possible overfitting (Elith et al., 2008, Mayr et al., 2012, López-Serrano et al., 2020). First, we use cross validation to select hyperparameter values (see supplementary material) and for feature selection. Second, we randomly select 20% of the DWM records that are then set aside for later testing only; that is, not a part of the iterative tuning or feature selection.

Preliminary analyses of these data identified that approximately 30% of the DWM records are 0 Mg C ha^{-1} and another 30% are under 3 Mg C ha^{-1}. Despite this skewing of the DWM observations, preliminary regressions suggested no specific need to modify models for the zero records (i.e., zero-inflated models, Garcia-Marti et al., 2019, Mathlouthi et al., 2020). Additionally, infrequent high carbon density records did adversely affect model training and scoring as outliers with no features identified as useful for predicting these extreme values. The 99.9th percentile was 150 Mg C ha^{-1} with records exceeding this value excluded from model training. Similarly, we dropped model training records with a low proportion of forest on plot area (<25%), which may reduce accuracy of plot level predictions (Bechtold and Patterson, 2005). However, all the test records were retained for testing and scoring.

Analysis and modeling are based on Python 3 and various Python libraries, including the machine learning libraries in Scikit-learn (Pedregosa et al., 2011) for RF and SGB regressions. The previous DWM model is described, with all necessary coefficients to make predictions, in the forest methods annex of U.S. EPA (2021) and predicted values on NFI plots are available as a part of the NFI data (Burrill et al., 2018 as CARBON_DOWN_DEAD).

3. Results

Downed woody material density estimates ranged from 0 to 847 Mg C ha^{-1} with a mean of 6.8 Mg C ha^{-1} and median of 1.8 Mg C ha^{-1} on 47,591 forest-condition transect plot records available for this analysis. The data were positively skewed. Regionally (Fig. A1), the median and maximum carbon density estimates on NFI plots with DWM observations were 5.5/277, 1.5/142, 2.0/450, and 0.3/847 Mg C ha^{-1} for Pacific Coast, Rocky Mountain, North, and South, respectively (i.e., summaries of transect plots, not regions). Individual plot predictions from the previous DWM model relative to the observed plot densities are shown in Fig. 1 (figure bounds of 80 Mg C ha^{-1} include 99.5% of the data). The plot level prediction errors (previous prediction minus DWM observations) have a median of 1.7 Mg C ha^{-1}, and distributions of plot-level differences suggest that the model overestimates DWM carbon for most plots. These differences by region (Fig. 2) have medians of 2.9, 0.6, 1.5, and 3.1 Mg C ha^{-1} for Pacific Coast, Rocky Mountain, North, and South, respectively. The largest regional difference (overestimation) in the previous model is in the South. Overall, 90% of paired differences are between −18.3 and 16.3 Mg C ha^{-1}. The previous DWM model coefficient of determination was 0.03 and the relative root mean square error was 200%.

Predictions via the RF and SGB models using test records across the full set of 21 features are illustrated in Fig. 3. The two recent-NFI models (Table 1) were similar for R^2, RMSE%, and Spearman correlation in predictions; there was greater relative bias in the RF model. Overall, these regression models showed a better fit to the DWM data than the previous model, but Spearman correlations were similar, which may suggest similar level of site specificity, or lack of, between current and previous models.

Feature selection was primarily through determining importance of features to model predictions. The most important predictor features for both models are standing dead trees followed by 30-year mean precipitation and 30-year summer high temperature (Fig. 4). Two standing

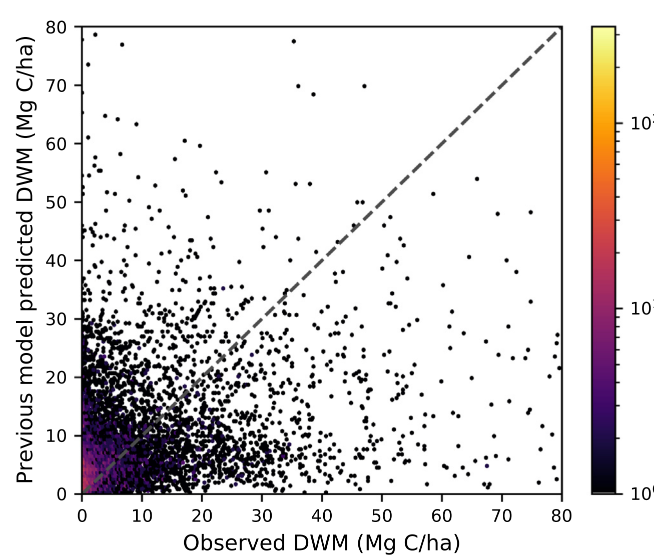


Fig. 1. Predicted plot level DWM for the previous DWM model relative to the observed transect values in the test dataset. Note that 80 Mg C ha^{-1} represents the 99.5th percentile of the DWM records. Brighter points represent greater number of plots predicted at that point, on a logarithmic scale.

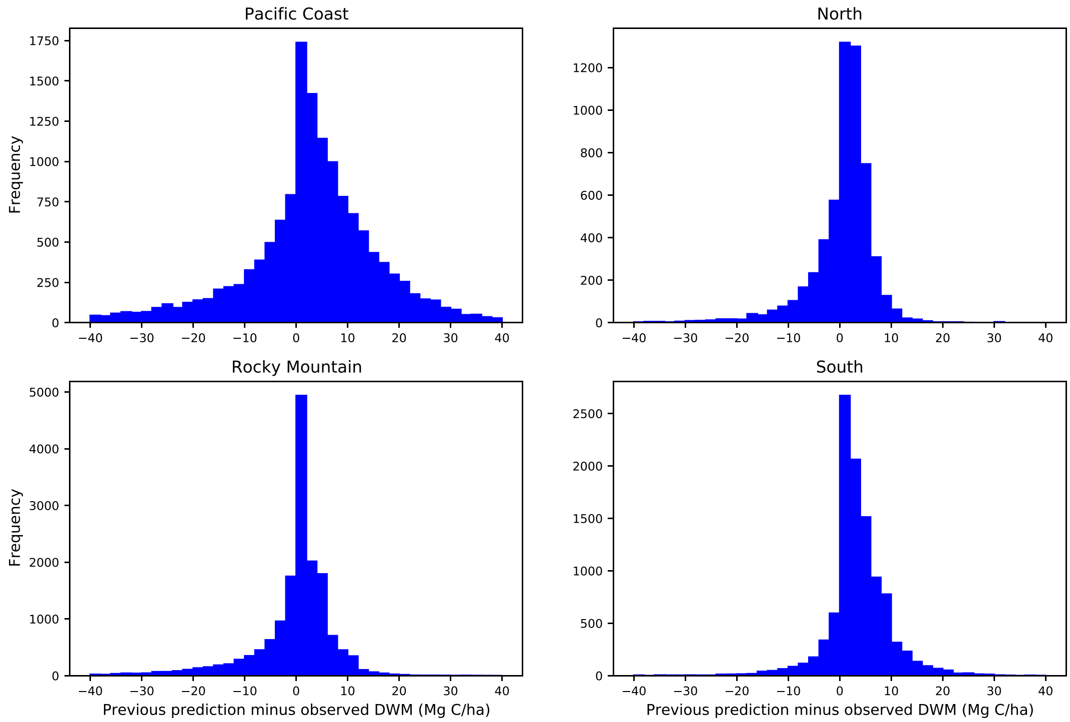


Fig. 2. Regional summaries of prediction error at plot level for previous DWM model relative to observed values. That is, frequency of the previous model prediction minus transect observations.

dead tree features are included because while standing dead trees that were also identified in the previous NFI cycle are more important than the full set from the most recent cycle, the older dead tree data are less generally available in the older NFI data back through 1990. The Gini index is the second most important of the four features associated with the recent NFI, but these remaining recent-NFI features are relatively low on the lists (Fig. 4, i.e., in bottom 5 for RF and lower half of list for SGB). Importance values or rank of features are not necessarily consistent between models, which underscores the potential of the two approaches to use different data to build trees. For example, the SGB recent-NFI model ranks large live trees and site class code (both NFI features) as relatively important for predicting DWM, but both of those features are ranked lower for the corresponding RF model.

Partial dependence plots, or marginal effects of features on predictions (Friedman, 2001; Elith et al., 2008; Natekin and Knoll, 2013) are provided for the 8 most important features in each of the two models (Fig. 5). In general, greater predicted DWM is associated with higher precipitation and lower maximum summer temperatures in the RF model; the SGB model shows the same summer temperature effect but not so clearly with precipitation. The two models are similar with respect to longitude (higher DWM in the West) and stand age (minimum at about 50 years, with higher DWM in younger and older stands).

In order to predict DWM on all-NFI plots (past and current), models were trained on 17 features. The observation-prediction pairs, ranked feature importance, and feature partial dependence are provided in Appendix Figs. A.2, A.3, and A.4. Again, importance rankings are not consistent between the two models; for example, the relative importance of elevation and large live trees are reversed in SGB relative to RF (Fig. A.3). Also note that the relative ranking of features is not always the same between the recent- and all-NFI models. For example, the 30-year summer maximum temperature in the SGB recent-NFI model (Fig. 4) ranks higher than large live trees or stand age, but in the SGB all-NFI model (Fig. A.3) it is less important than either large live trees or stand age. Scoring for the two models was similar; R^2 were slightly lower and RMSE as a percentage were slightly greater than the recent-NFI versions (Table 1).

Spatial models, independent of any features unique to NFI plots, were trained on the 12 spatial features (see Appendix Figs. A.2, A.3, and A.4). Here, an example of importance rankings changing between the RF and SGB models are Modis net primary productivity and topographic position (Fig. A.3). Soil bulk density, an NFI-independent feature, ranks relatively high in the four NFI-linked models, yet ranks relatively lower in both the spatial models. Scoring of these two models was clearly lower relative to the four NFI-linked models but also remains higher than the previous DWM model. The spatial R^2 were lower and RMSE as a percentage were greater than the NFI versions, and for this pair, the SGB model scored slightly better than RF (Table 1).

The plot level prediction error for the RF recent-NFI model has a median of 1.4 Mg C ha^{-1} and 90% of paired differences are between −15.2 and 11.8 Mg C ha^{-1} (Fig. 6 and see Fig. 2 for contrast with previous DWM model). Regionally, medians are 3.2, 1.2, 1.9, and 0.9 Mg C ha^{-1} for Pacific Coast, Rocky Mountain, North, and South, respectively. At the regional level, the interquartile ranges provides a simple measure of improved predictions of the RF recent-NFI model relative to the previous model (i.e., Fig. 6/Fig. 2), which are 10.3/13.4, 3.9/5.5, 4.2/5.1, and 2.2/5.1 for Pacific Coast, Rocky Mountain, North, and South, respectively. For the SGB spatial model, the median is 1.8 Mg C ha^{-1} and 90% of paired differences are between −17.8 and 10.8 Mg C ha^{-1}. Regionally, medians are 3.6, 1.5, 2.3, and 1.5 Mg C ha^{-1} for Pacific Coast, Rocky Mountain, North, and South, respectively (data not shown).

A CONUS-wide and regional comparison of model predictions (previous plus six new) with the NFI design-based population estimates shows that the new regressions better reflect population totals than the previous model (Table 2). The previous DWM model overestimated Pacific Coast and South regional totals relative to all new regressions. Similarly, previous Rocky Mountain estimates appear low, while North were comparable to new models.

4. Discussion

Downed woody material model predictions presented here represent clear improvements relative to the previous model for individual

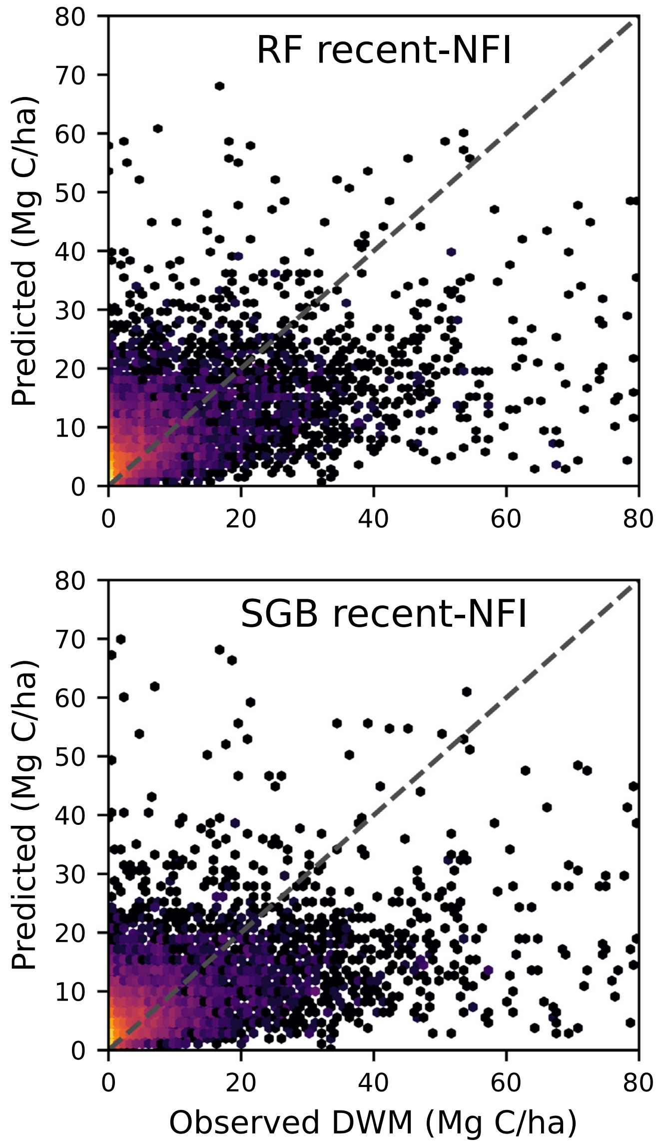


Fig. 3. Predicted plot level DWM for the recent-NFI models relative to the observed transect values for the test data.

plots (Table 1) or aggregations thereof up to regional or national population totals (Table 2). The trajectory of field inventory-based monitoring of DWM attributes (e.g., biomass, carbon, or fuel loadings) across US forests has progressed from purely predicting such attributes based on stand or site attributes (Smith et al., 2006) to models constrained by field-observations (Domke et al., 2013) to the current potential improvements explored in this study. These results underscore the potential role of ML approaches in efficiently adapting emerging NFI data to provide and update policy-relevant information, which are forest carbon estimates at various scale, in this case.

Although population estimates of DWM can be obtained using a design-based inference approach (Woodall et al., 2019), predicting DWM attributes for every plot in a NFI is often needed to enable more comprehensive forest carbon assessments, or downscaling estimates to operational scales. The ML-based DWM predictions presented here represent such an alternative approach to producing population-level estimates (e.g., by state or CONUS) of DWM attributes based on a subset of NFI plots where DWM was empirically observed (Bechtold and Patterson, 2005; Woodall et al., 2019). The RF model predicts CONUS DWM carbon stocks to be 15% lower than the previous NGHGI model and 2% higher than NFI transect data expanded according to inventory design-based estimates (Woodall et al., 2019). Forests DWM varies regionally but also from stand to stand, with CONUS DWM averaging 7% of non-soil forest carbon stocks (U.S. EPA, 2021). The resulting effect of the ML model predictions on total CONUS forest carbon stocks are a relatively small proportion of total stocks, but this represents improved reporting accuracy.

Extending DWM predictions to all forest NFI plots is the primary purpose of these models, which facilitates selection of specific subsets of plots according to reporting needs. Similarly, the spatial versions provide for forest selection according to geographic attributes without the need to rely on potentially limited NFI plot locations. The new regression models approximate the design-based totals for CONUS (Table 2) as well as regional totals. This approach to coverage is a part of the forest carbon reporting approaches developed by the US Forest Service (Domke et al., 2016, 2017).

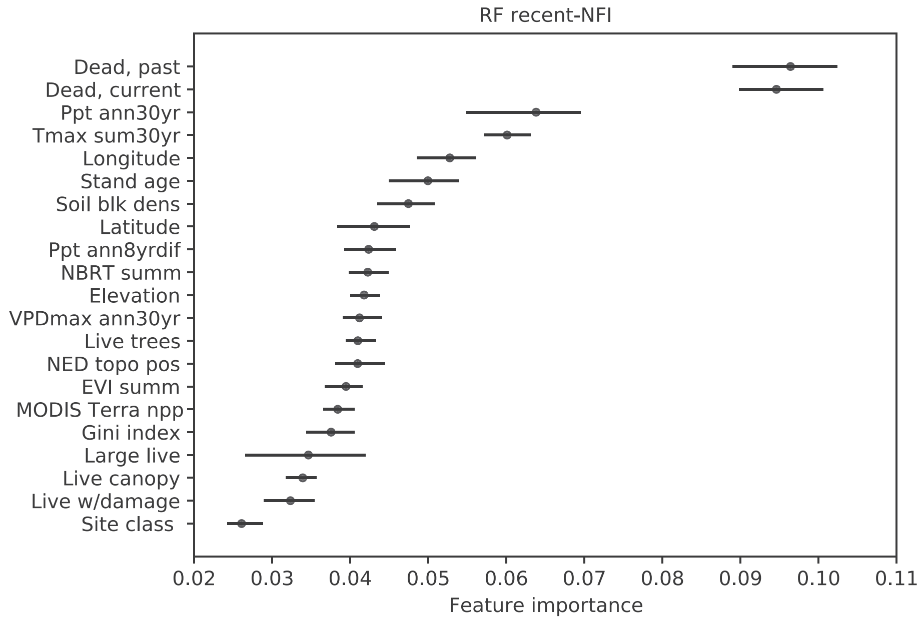
Evaluation of the previous DWM model used to predict and report carbon totals indicates greater model bias while explaining very little of the variation in the empirically observed DWM estimates relative to the models presented here. This was expected given that the model was not developed with DWM estimates from the NFI. With these new ML regressions, plot level errors are reduced for all models with population totals conforming more closely to the NFI design-based estimates. Results exhibited very similar model scoring between the RF and SGB models with no clear best, or prescribed, model. The RF scored slightly better for NFI plots while SGB was slightly better for spatial predictions. The use of the strongest predictor data for the respective models suggests retaining the recent-NFI, all-NFI, and spatial models depending on the application. The ML applications and resulting models here demonstrates the value of including both the RF and SGB approaches with the expectation that model scoring can differ (Dube et al., 2014; Freeman et al., 2015; Yang et al., 2016; Zhang et al., 2020).

A variety of stand and site variables can be considered when trying to model DWM attributes which often are the result of gradual stand

Table 1
Model scoring summaries for previous DWM model and the six regression models, with predicted values relative to observed DWM.

Model	R^2		RMSE %		Bias %		Spearman	
	100× train	Test	100× train	Test	100× train	Test	100× train	Test
Previous model		0.031		199.8		10.9		0.66
RF recent-NFI	0.307 (0.015)	0.312	162 (3.5)	156	7.6 (1.9)	7.6	0.64 (0.006)	0.66
SGB recent-NFI	0.299 (0.016)	0.310	163 (3.4)	160	0.2 (1.8)	0.0	0.63 (0.006)	0.65
RF all-NFI	0.299 (0.016)	0.302	163 (3.8)	161	7.2 (2.2)	7.5	0.64 (0.005)	0.65
SGB all-NFI	0.292 (0.016)	0.298	164 (3.4)	161	0.5 (2.0)	0.1	0.63 (0.006)	0.64
RF spatial	0.185 (0.015)	0.194	176 (3.3)	173	6.4 (2.1)	6.1	0.57 (0.006)	0.58
SGB spatial	0.211 (0.013)	0.230	173 (3.7)	169	0.4 (2.1)	0.2	0.56 (0.006)	0.58

Note: Summaries under '100× train' are mean and standard deviation (parentheses) from sampling and training models 100 times (with training data). The additional columns, under 'test' are scores from applying models to the test data. Scores are the coefficient of determination (R^2); root mean square error as a percentage of test mean (RMSE%); bias as a percentage of test mean; and Spearman's rank-order correlation between observations and predictions.



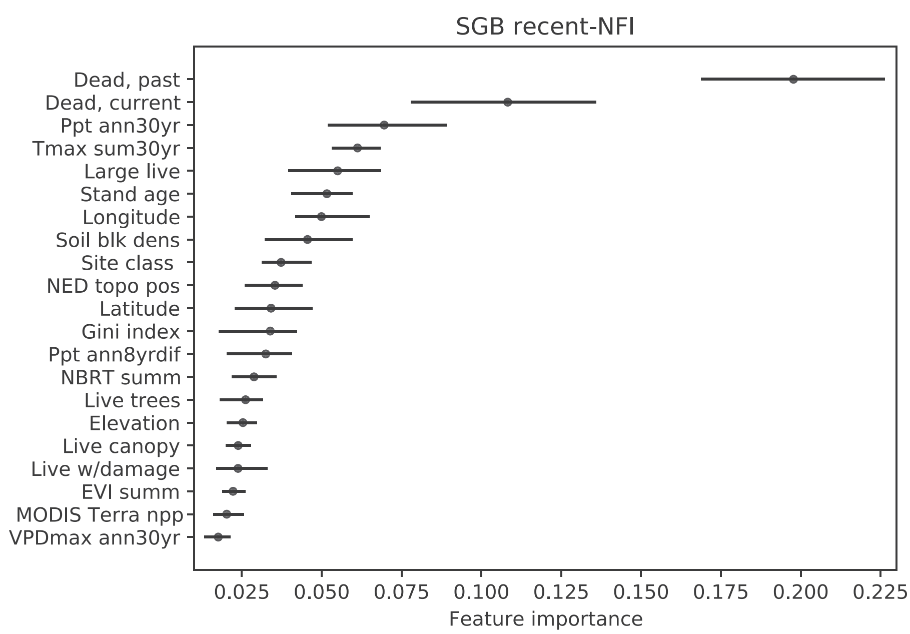


Fig. 4. Ranking and range for importance of features in the recent-NFI models. See Table A.1 for additional information on features.

processes (e.g., self-thinning mortality) and episodic disturbances (e.g., hurricanes). Precipitation and temperature are widely recognized as predictors of DWM (Harmon et al., 1986). Each of the precipitation and temperature features included for model development (see discussion of PRISM (PRISM Climate Group, 2012) data in Appendix) were summarized as 30-year means or recent differences from the long-term (30-year) mean. The 30-year means were consistently more-important than the differences from long-term for these models. While most studies identify precipitation and temperature as most-important (Garbarino et al., 2015; Zhu et al., 2017; López-Senespleda et al., 2021), this is not always the case (e.g., Oettel et al., 2020). Increasing precipitation and temperature are generally associated with increases in forest productivity contributing to greater DWM input, but the same gradients are associated with increases in decomposition, except for very wet sites which can inhibit decomposition (Harmon et al., 1986). Garbarino et al. (2015) found that intermediate levels of the two gradients were associated with maximum DWM in relatively arid forests of the US West. The clearest indicators of precipitation and temperature effects in our models are in the partial dependence plots that summarizes all of CONUS forest land; highest annual precipitation and lowest maximum summer temperatures predicted the greatest levels of DWM.

Standing dead, or snag, tree fall has been identified as the most important direct input to DWM (Hilger et al., 2012; Woodall et al., 2013; Oberle et al., 2018; Hararuk et al., 2020), and our models that included features based on individual tree data identified amount of standing

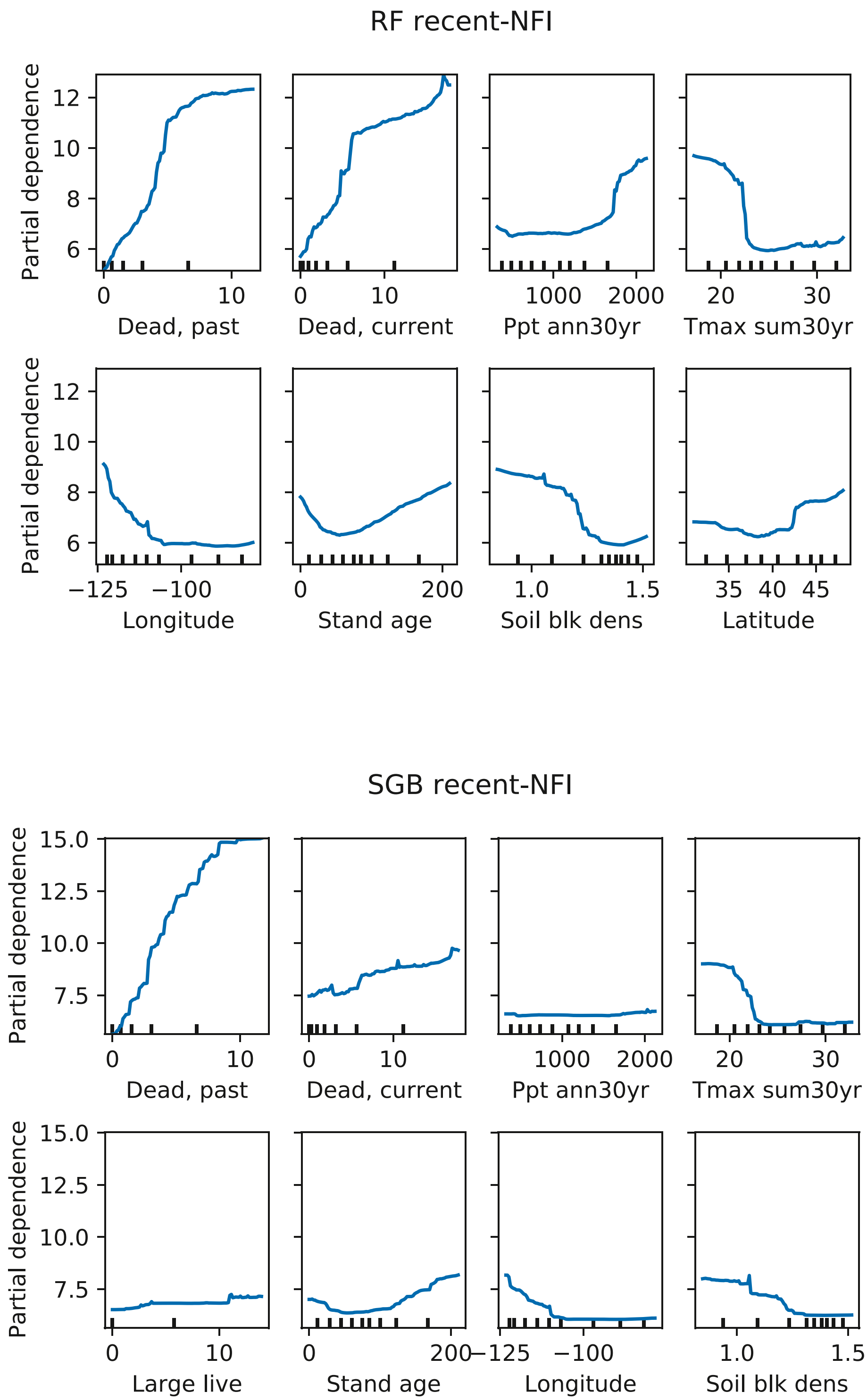


Fig. 5. Partial dependence plots for the eight most-important features the RF and SGB recent-NFI models. See Table A.1 for additional information on features. Note that the group of eight features in each panel are represented with relative marginal effect on the y-axis and the range and distribution of input values on the x-axis.

dead as the most important predictors. Older standing dead, as measured in both the previous (second most recent) and current inventory cycle was the more important of the two standing dead features. Fall rates are likely higher for these individuals identified as longer-standing snags. Features such as temperature, species, or size have been identified as predictors of standing dead fall rate, but results are not consistent (Hilger et al., 2012; Oberle et al., 2018; Hararuk et al., 2020). While fall of these dead trees is the proximate event adding to the DWM pool, the presence of standing dead, particularly older records, is clearly a useful predictor for DWM stock in our models. Note that while our feature list (e.g., Fig. 4) includes possible predictors of standing dead such as amount of live or large-live trees or stand age, we did not identify clear mortality or tree-fall related features.

The remaining features we identified for model inclusion are consistent with many of the long-accepted influences on DWM such as stand age or size, site, climate, or productivity (Harmon et al., 1986; Herrmann

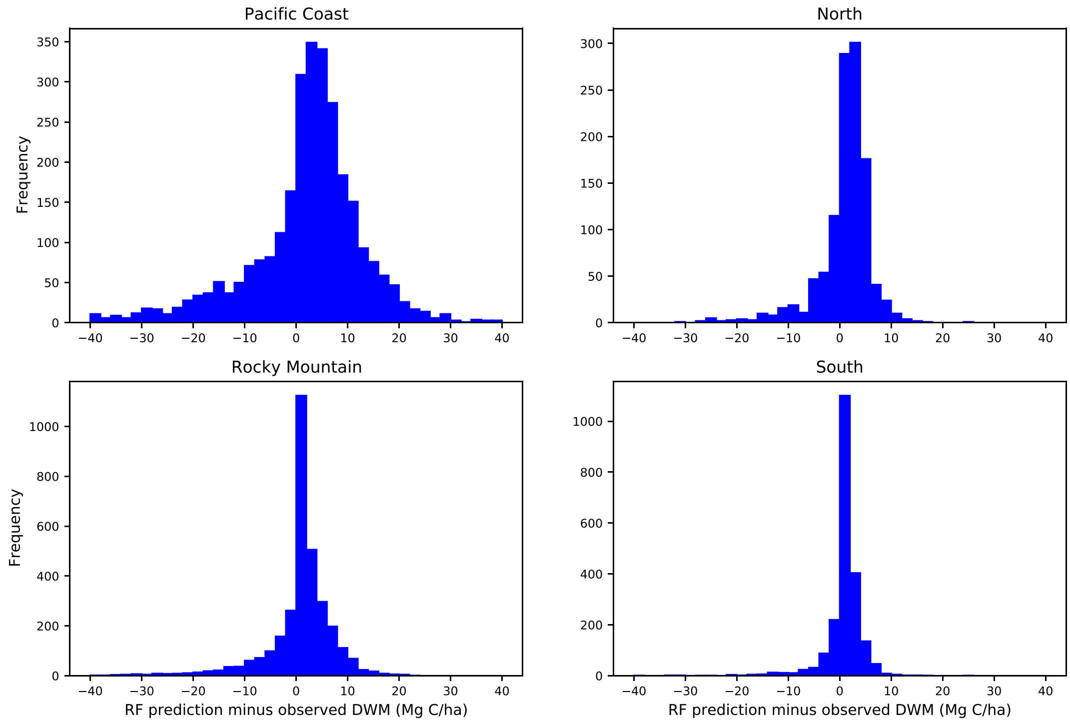


Fig. 6. Regional summaries of plot-level DWM prediction error for the RF recent-NFI model relative to observed values for the test data. That is, frequency of predicted minus transect observation.

et al., 2015; Woodall and Westfall, 2009; Woodall et al., 2013). However, features classifying forest according to species, forest type, or ecoregion were not important for these DWM predictions; however, these are often cited as important (Garbarino et al., 2015; Lo Monaco et al., 2020; Oettel et al., 2020; Öder et al., 2021). We found that ecoregion, even when represented as a simple three-biome division (Cleland et al., 2007) or even as 'east-versus-west' were not useful for improved model score. Because descriptive location classifications proved unimportant, longitude and latitude are the remaining primary indicators of location. Similar results were seen with specifying forest type group (USDA Forest Service, 2020) or even very broad types such as softwood versus hardwood stands. In this case, rather than a generalized classification of type, quantities obtained on NFI plots such as age, cover, or live-versus-dead basal area served to characterize stands. Additionally, while the term 'management' is listed as important in many studies (Lo Monaco et al., 2020, Oettel et al., 2020, Öder et al., 2021), features flagging recent harvest or time since harvest were not identified as important for our models. Wisdom and Bate (2008) also point out that the term management can also include direct human removal of DWM from forests, not a part of harvest, but this level of detail is not addressed in our model features. It is possible that these class features may be important for DWM over CONUS if recast in a different modeling framework.

Disturbance events can potentially contribute significant amounts of DWM and standing dead, and the type of disturbance (e.g., fire, insects, wind, or disease) affects quantity (Harmon et al., 1986). Our model development explored the incorporation of various indicators of disturbance. Despite the emphasis on identifying disturbances, very few of the initial features associated with disturbance remain in the final set of 21 features used here. In addition to dead trees, which are potentially disturbance related, live trees with damage (also from NFI tree data) is the only other disturbance-linked feature. Note that the live tree with damage feature was near the bottom of the list (e.g., Fig. 4). While type and severity can determine DWM added to forest ecosystems, standing dead trees and DWM existing prior to stand reestablishment can influence DWM for years (Garbarino et al., 2015), which further emphasizes the value of site history in predicting current stocks. Future model development should continue to focus on indicators of disturbance type (e.g., harvest or wind-event), severity, and timing.

Table 2
DWM total stocks for four regions (Fig. A.1) and CONUS from multiple sources: (1) expansion of the NFI DWM transect plots (design based); (2) the previous plot level DWM model; and (3) the six ML plot level models.

Model	Pacific Coast		Rocky Mountain		North		South		CONUS	
	Mean	% ± CI	Mean	% ± CI	Mean	% ± CI	Mean	% ± CI	Mean	% ± CI
					DWM carbon (million Mg C)					
NFI transect plots	358	2.5	320	1.9	353	7.4	300	27.6	1331	6.6
Previous model	430		279		333		557		1599	
RF recent-NFI	391	10.6	362	9.6	362	11.2	243	14.9	1358	5.6
SGB recent-NFI	370	10.3	340	9.8	340	8.0	257	9.3	1308	4.8
RF all-NFI	385	10.8	349	9.7	357	11.8	246	17.2	1336	6.0
SGB all-NFI	364	10.6	329	10.2	336	8.2	254	9.5	1284	4.9
RF spatial	394	11.5	351	10.0	355	12.5	253	16.8	1353	6.2
SGB spatial	372	11.7	330	11.1	334	8.6	264	9.8	1301	5.3

Note: Confidence intervals with the transect plots represent sampling error, and intervals with the ML regressions are based on quantile regressions.

A characteristic common to all the models evaluated in this study is the tendency to overpredict the smaller DWM densities and underpredict the larger values, as seen in the scatter of points relative to the one-to-one line. This is sometimes a consistent trait of regressions and can reflect data with a large proportion of zero values as the dependent variable (Dube et al., 2014; Garcia-Marti et al., 2019; Mathlouthi et al., 2020). While this suggests the use of zero inflated models, preliminary model development indicated no benefit in accuracy with predictions based on a zero inflated model. Despite the high proportion of zero records, they do not represent a discontinuity in target (predicted) values as is sometimes the case with zero inflated models. The zeros are somewhat continuous with about 30% of records with zero and another 30% under 3 Mg C ha^{-1}. As such, additional approaches may be explored in future model development, including the use of two-step prediction (e.g., Savage et al., 2015) or model-assisted estimators to correct for estimated bias in predictions (Opsomer et al., 2007).

This study's DWM models predict carbon stocks and in the context of the entire NFI, predictions at a single site may inform a series of successive stock estimates. Predictions that reference past stand conditions are likely more reliable sequences of stock. Current feature sets include only limited information about past stand conditions (e.g., previous standing dead or stand age). Likely ongoing and future changes in forest, which are expected to accompany possible climate-related change, will affect both stocks of DWM as well as annual rates of DWM change. Accounting for change will figure prominently in future DWM modeling, but these models do not explicitly address changing climate or annual change in DWM stocks. Developing predictions related to DWM decay is perhaps an important first step toward including change. Decay of DWM affects stocks, with the measurement variable of decay class being an important attribute of pieces in field-based inventories world-wide (Woodall et al., 2009; Harmon et al., 2013). However, decay class is a piece-specific attribute, which does not fit with these current model structures. One broader implication for DWM inventories is that the spatial, NFI-independent, model exhibited satisfactory results, or scoring. This suggests that an NFI without specific widespread DWM sampling may be modeled following this approach if sufficient sample data and training plots are available.

5. Conclusion

The national-level DWM carbon stock models for US forests presented here represent improved predictions relative to the previous model, and these results can inform an implementation of DWM carbon estimates for NGHGI reporting and the NFI. Model scoring indicated the RF models as preferable for expanding predictions to all NFI plots while the SGB spatial model demonstrated applicability beyond NFI plots to continuous, large spatial domains (e.g., all forested pixels in an area of interest). The new RF model predicts CONUS DWM carbon stocks to be 15% lower than the previous NGHGI model and 2% higher than NFI transect data expanded according to inventory design-based estimates. Key characteristics of the predictive features used in these ML regression models is that they are readily available and relatively easily configured (i.e., minimal processing), with most available for CONUS over the span of the last 30 years facilitating use in NGHGI reporting. DWM pools are considered quite dynamic in response to global change events affecting tree mortality or disturbance across large scales. For this reason, continued refinement of DWM modeling should reflect influences that contribute to these dynamics such as changing decay rates and wind or combustion disturbance.

CRediT authorship contribution statement

James E. Smith: Conceptualization, Methodology, Software, Writing – original draft, Visualization. **Grant M. Domke:** Conceptualization, Writing – review & editing. **Christopher W. Woodall:** Conceptualization, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2021.150061.

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