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Deriving Biomass Models for Small-Diameter Loblolly Pine on the Crossett Experimental Forest

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Running Title: Biomass Models for Loblolly Pine on the Crossett Experimental Forest

Abstract

Foresters and landowners have a growing interest in carbon sequestration and cellulosic biofuels in southern pine forests, and hence need to be able to accurately predict them. To this end, we derived a set of aboveground biomass models using data from 62 small-diameter loblolly pines (*Pinus taeda*) sampled on the Crossett Experimental Forest in southeastern Arkansas. Of the 25 equations initially evaluated, we chose 17 that best fit our dataset and compared them using a suite of conventional test statistics, including pseudo-R^2, root mean squared error (RMSE), and bias. Because most of the 17 models varied little in pseudo-R^2 (ranging between 0.96 and 0.99), bias (all were within ± 0.01), and RMSE, an additional comparison was done using Akaike's Information Criterion corrected for small sample size (AIC_c). This test statistic produced considerably more discrimination between the biomass models. Of the 17 models evaluated, six produced ΔAIC_c scores that met or exceeded the threshold for substantial support. To recommend a single preferred model, we then extrapolated beyond our actual data and qualitatively compared model predictions with those from the National Biomass Estimator. Our "best" model did not have the minimum AIC_c score, but rather predicted logically consistent aboveground biomass values at both the upper and lower ends of our extrapolation.

Introduction

Both carbon (C) sequestration and bioenergy production have become a growing interest for timber managers in recent years, and the accurate estimation of tree biomass is essential in the determination of the ability of forests to support these ecosystem services (Parresol 1999). Tree biomass is typically estimated from an allometric equation that predicts oven-dry biomass for individual stems based on diameter at breast height (DBH), and then summed to yield biomass per unit land surface area (Whittaker and Woodwell 1968). However, very few biomass models are available for the most commercially important Arkansas tree species such as loblolly pine (*Pinus taeda*).

Lacking options, many have applied equations from other regions, stand conditions, and (in some cases) species in order to estimate individual tree biomass. This approach has a number of challenges inherent to it, especially if substantial errors in biomass estimations accumulate when used incorrectly (i.e., applied to dissimilar species or extrapolated beyond the original DBH range for which the model was derived; Parresol 1999, Chave et al. 2005). For instance, adaptation of traditional timber volumes (e.g., board feet) is sometimes done to estimate biomass, but can be complicated and is particularly sensitive to the assumptions built into both the original models and how they are interpreted (e.g., Bragg 2011). Alternatively, a more generalized approach using regional- and national-scale tree biomass equations applicable to a larger geographic area has been pursued (Schroeder et al. 1997, Jenkins et al. 2003, 2004, Lambert et al. 2005, Case and Hall 2008). Others prefer to use "stand-scale" equations to predict biomass, which for some purposes can be as effective as more site- and species-specific equations applied to individual trees in a stand (Snowdon et al. 2000, Asner et al 2012). The consequences of using these alternatives on biomass predictions are poorly understood, however.

Thus, the preferred solution was to develop site- and species-specific biomass equations, which entailed destructive sampling trees that were then oven-dried, weighed, and fit to an appropriate equation. This research project involves the development of such a biomass equation for the US Forest Service's Crossett Experimental Forest (CEF) in Ashley County, Arkansas to provide a more direct method of biomass estimation. The objective of this paper is to evaluate a number of existing aboveground live tree biomass equations using data from small-diameter loblolly pines from the CEF and produce a single model that works best for this location. Our final model recommendation followed both conventional test statistics and an extrapolative comparison with the predictions of the National Biomass Estimator (Jenkins et al. 2003).

Materials and Methods

Study site

The CEF, established in 1934 by the US Forest Service, covers nearly 680 ha of southeastern Arkansas. The CEF is dominated by upland forests of loblolly (*Pinus taeda*) and shortleaf (*Pinus echinata*) pine, with a minor hardwood component. The low elevation (36-48 m above sea level), gently rolling terrain of the CEF has limited vertical relief (rarely more than 3 m) and is primarily covered by silt loam soils with a loblolly pine site index of 25 to 30 m at 50 years (Gill et al. 1979). Most of the pine stands on the CEF are naturally regenerated and have a significant small-diameter pine component.

Sample tree selection and measurement

Live loblolly pines were destructively sampled from natural-origin stands across the CEF. We selected primarily precommercial loblolly pines (recorded in the field to the nearest 0.1 cm), for extraction and analysis. We chose to focus our sampling efforts on small-diameter stems due to logistical issues related to collecting and weighing above- and belowground biomass of large stems. In addition, the smallest trees from this diameter range (those <10 cm DBH) are often not sampled when developing biomass equations (Snowdon et al. 2000), yet can be a significant fraction of many forest stands.

Smaller sample trees were pulled directly from the soil using a small tractor with a hydraulic boom extension lift. Bigger pines that could not be lifted from the ground were partially excavated using a backhoe attachment for the tractor, then pulled. Once out of the ground, pines were separated into aboveground (foliage + branch and stemwood), and belowground (taproot) components—for this study, only the aboveground components were modeled. The green weight of tree components was determined immediately following extraction using a laboratory balance. All components were then dried in an air-forced oven at 90^o C to a constant weight (kg), and the stem, branch, and foliage components then summed to produce aboveground, oven-dry biomass (B_D).

Biomass equation design and statistical comparisons

Twenty-five biomass equation forms for American and European tree species were selected for a preliminary evaluation. These designs are not an exhaustive list of possible models, but include the most commonly applied examples found in current biomass literature (e.g., Ter-Mikaelian and Koruzkhin 1997, Jenkins et al. 2003, Posey et al. 2005, Zianis et al. 2005, Doruska and Patterson 2006). Most of these allometric equations used DBH or some combination of DBH and total tree height (HT) as independent variables. Any model that required height applied the following equation for loblolly pine (Bragg 2008):

$$HT = 1.37 + \frac{55.9834}{1+97.0874DBH^{-1.1703}} \tag{1}$$

To evaluate differences in biomass projections, all of these initial models were fit to our local data using ordinary least squares regression and evaluated using a fit index called pseudo-R^2. As calculated by Statistica (version 8.0), pseudo-R^2 is a nonlinear analog to conventional R^2 used in linear regression (i.e., sum of squares residual (SSR) divided by the total sum of squares (SST)) (StatSoft 1995). Of the initial 25 models tested, those that best fit our CEF loblolly pine data (i.e., those with pseudo-R^2 > 0.80) were further evaluated using additional goodness-of-fit measures including root mean square error (RMSE):

$$RMSE = \sqrt{\sum_{i=1}^{n}\left(\widehat{HT_i} - HT_i\right)/(n-p)} \tag{2}$$

and bias, determined from:

$$bias = \sum_{i=1}^{n}\left(\widehat{HT_i} - HT_i\right)/n \tag{3}$$

where HT_i is the height of the *i*th pine, $\widehat{HT_i}$ is the predicted height of that same tree, *n* is the total number of observations, and *p* is the number of function parameters. To further discriminate between the allometric equations, we used an additional statistic—corrected Akaike Information Criterion (AIC_c):

$$AIC_c = 2p + n[ln(\hat{\sigma}^2)] + \frac{2p(p+1)}{n-p-1} \tag{4}$$

where $\hat{\sigma}^2 = \sum \hat{\varepsilon}_i^2/n$ and $\hat{\varepsilon}_i^2$ are the estimated residuals from the fitted model. AIC_c allows for the comparison of multiple models with differing numbers of parameters and contains a second-order correction for small sample sizes (Burnham and Anderson 2002). The actual AIC_c test statistic used to compare multiple models is the difference between the lowest AIC_c score and the AIC_c for each other model (ΔAIC_c). Models with ΔAIC_c scores of ≤ 2.0 are held to have considerable support as being the correct design(s) to use (Burnham and Anderson 2004).

Extrapolation and final recommendation

Given the results of our initial evaluations, we expected that we would have multiple models that more-or-less equally fit the data. For a final evaluation, we decided to compare the "best" (final) subset of equations by extrapolating their predictions for smaller- (< 0.9 cm) and larger- (> 15.0 cm) DBH trees in order to observe their behavior beyond the range of data used to derive them. The equation that produced the most biologically consistent predictions over this extrapolation would be considered our preferred design. For small diameter stems, this consistency required that trees have positive biomass, even when DBH = 0 cm—by definition any tree, even those too short to record diameter at breast height (1.37 m tall), has biomass, so zero (or negative) biomass values are illogical (even if statistically possible).

Interpretation of the extrapolation results for larger trees is more challenging, since we had no guidance for which benchmark for comparison to choose. We decided that a conservative, well-documented, and data-based option would be to compare our predictions with those of the National Biomass Estimator (NBE) developed by Jenkins et al. (2003). The NBE estimates aboveground oven-dry tree biomass (B_D, in kilograms):

$$B_D = e^{-2.5356+2.4359(\ln(DBH))} \tag{5}$$

The NBE was developed from a collection of "pseudodata" generated from 43 different equations from 14 different species of *Pinus* found across North America, including 4 equations for *Pinus taeda*. This national equation is commonly used by agencies and land managers to estimate tree and forest biomass, including the official greenhouse gas inventories of the United States (US EPA 2008).

Results and Discussion

Of the 62 live loblolly pines that we destructively sampled on the CEF, DBH ranged from 0.9 to 15.0 cm, with an average DBH of 4.6 cm and a standard deviation of 3.6 cm. After processing, the measured B_D for these trees ranged from 0.23 kg to a maximum of 60.87 kg, averaging 7.19 kg (standard deviation = 12.77). The NBE generally fit these data well, with few prominent departures apparent (Figure 1). The most noticeable difference appears to be in the smallest of the trees (those less than 3 cm DBH), for which the NBE underestimates B_D.

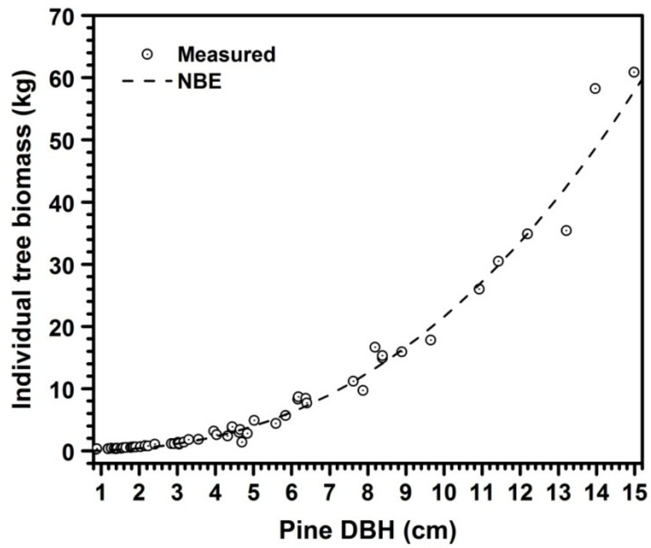

Figure 1. Observed and NBE-predicted B_D for loblolly pine as a function of DBH.

Model fitting

Of the more than two dozen initial models tested, 17 fit our locally-derived biomass data well (Tables 1 and 2). For these 17 allometric equations, there was very little difference between the conventional goodness-of-fit measures. Pseudo-R^2 values of 15 of the 17 equations exceeded 0.96, and 11 of the 17 exceeded 0.98, suggesting a very high proportion of the variation in the data was explained by any of these models. Almost no bias was apparent in any of these equations, either—across the range of data, only two of the 17 equations had biases that exceeded 0.004, although most had a very slight tendency to underestimate biomass, as suggested by the negative bias values. No dramatic differences appeared between most of the RMSE, either (Table 1).

The ΔAIC_c test statistic proved to be more helpful in determining the most appropriate subset of models. According to the conventional interpretation of this test statistic (Burnham and Anderson 2002, 2004), only 6 of the 17 equations had ΔAIC_c scores that met or

Table 1. Pool of 17 candidate allometric equations (pseudo-R^2 > 0.80) for estimating aboveground oven-dry pine biomass (B_D), where β are model parameters, *DBH* is expressed in centimeters, and *HT* is the total tree height (in meters).

Model code	Equation form	Source
A	$B_D = \beta_0 + \beta_1(DBH^2) + \beta_2(DBH^2) - \beta_3$	Zianis et al. (2005)
B	$B_D = \beta_0 + \beta_1(DBH^2) \times HT + \beta_2(DBH^2) \times HT$	Doruska and Patterson (2006)
C	$B_D = \beta_0 + exp[\beta_1 + \beta_2 \ln(DBH) + \beta_3 \ln(HT)]$	Posey et al. (2005)
D	$B_D = \beta_0 + exp[\beta_1 + \beta_2 \ln(DBH)]$	Jenkins et al. (2003)
E	$B_D = \beta_0 + exp[\beta_1 + \beta_2 (DBH)/(DBH + \beta_3)]$	Zianis et al. (2005)
F	$B_D = \beta_0 + \beta_1(DBH + 1)^{\beta_2 + \beta_3 \log(DBH)} \times HT^{\beta_4}$	Zianis et al. (2005)
G	$B_D = \beta_0 + \beta_1(DBH^2 \times HT)^{\beta_2}$	Zianis et al. (2005)
H	$B_D = \beta_0 + \beta_1(DBH^2) + \beta_2(DBH^2) \times HT$	Zianis et al. (2005)
I	$B_D = \beta_0 + \beta_1(DBH) + \beta_2 \times (DBH^2)$	Zianis et al. (2005)
J	$B_D = \beta_0 + \beta_1 + \exp(DBH \times \beta_2)$	Zianis et al. (2005)
K	$B_D = \beta_0 + \beta_1(DBH^2) + \beta_2[(DBH^2) - \beta_3]$	Zianis et al. (2005)
L	$B_D = \beta_0 + \beta_1 \log(DBH) + \beta_2 \times (HT)$	Zianis et al. (2005)
M	$B_D = \beta_0 + \beta_1(HT) + B_2 \times (DBH^2)$	Zianis et al. (2005)
N	$B_D = \beta_0 + \beta_1(DBH)^{\beta_2} \times (HT)^{\beta_3}$	Zianis et al. (2005)
O	$B_D = \beta_0 + \beta_1 \ln(DBH) + \beta_2 \ln(HT)$	Zianis et al. (2005)
P	$B_D = \beta_0 + \beta_1(DBH^{\beta_2})$	Zianis et al. (2005)
Q	$B_D = \beta_0 + \beta_1(DBH^2)$	Zianis et al. (2005)

exceeded the threshold for substantial support (ΔAIC_c < 2; Table 2). Indeed, a visual comparison of this final subset (Figure 2) shows that for the range of field-sampled data, it is virtually impossible to distinguish between any of these equations (Models D, E, F, G, J, and P).

Evaluating the best fitted model subset

Figure 2 shows the strong congruence between the B_D data and model predictions. In fact, the closeness of the different predictions makes their behavior hard to interpret at this scale. To alleviate this problem, we further separated our analysis into three DBH groupings: 0.9-2.0 cm, 2.0-8.0 cm, and 8.0-15.0 cm. At the smallest range, it becomes clear that none of the models actually fit the data particularly well (Figure 3a). Three models (E, J, and the NBE) consistently underestimated biomass across this range, while four (D, F, G, and P) overestimated biomass. Because of its design, the NBE will always produce zero biomass when DBH = 0. The other two models (E and J) that underestimated biomass actually predicted negative B_D for trees between 1.0 and 1.5 cm DBH. Later discussion will show why these underestimated results are undesirable, particularly for stands with a large amount of small-diameter trees.

At the lowest diameter range (< 2 cm) of our sampled data, models became increasingly dissimilar (Figure 3a; Table 3). At 0.9 cm (the smallest sampled

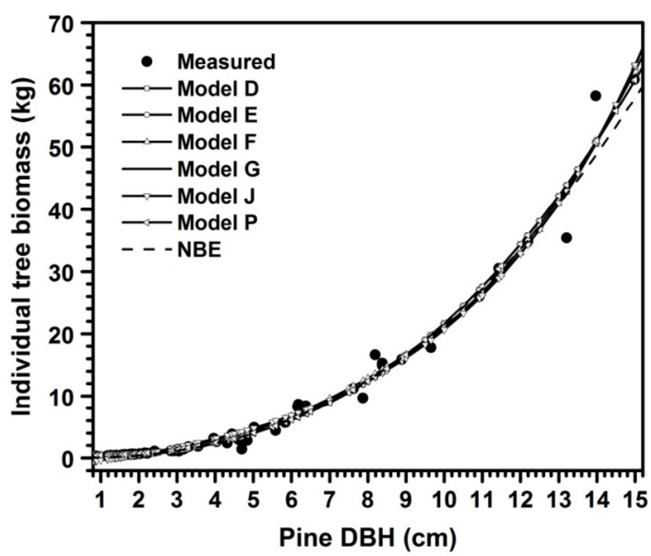

Figure 2. Predicted aboveground live-tree, oven-dry biomass (kg) as a function of DBH for loblolly pine (0 and 15 cm) using biomass equations with ΔAIC_c < 2.

Table 2. Goodness-of-fit measures for the 17 aboveground biomass models fitted to 62 small-diameter loblolly pines sampled on the CEF. The 6 models with $\Delta AIC_c \leq 2.0$ are highlighted in bold-face.

Model Code	β_0	β_1	β_2	β_3	β_4	Pseudo-R^2	RMSE	Bias	AIC_c	ΔAIC_c
A	-1.203	-0.065	0.315	-0.161	--	0.9683	2.330	-0.00014	109.45	39.85
B	0.923	0.005	0.017	--	--	0.9800	1.837	-0.00015	78.73	9.14
C	0.695	-0.861	10.800	-9.649	--	0.9827	1.723	-0.00103	72.06	2.46
D	**0.413**	**-2.875**	**2.576**	**--**	**--**	**0.9824**	**1.720**	**-0.00606**	**70.62**	**1.02**
E	**-1.782**	**0.175**	**13.288**	**35.037**	**--**	**0.9832**	**1.699**	**0.00007**	**70.26**	**0.66**
F	**0.505**	**0.000**	**37.164**	**-2.221**	**-31.622**	**0.9840**	**1.668**	**-0.00479**	**69.33**	**0.27**
G	**0.361**	**0.047**	**0.902**	**--**	**--**	**0.9824**	**1.723**	**-0.00002**	**70.83**	**1.23**
H	0.125	0.125	0.076	0.016	--	0.9827	1.724	-0.00007	72.08	2.48
I	1.968	-1.374	0.344	--	--	0.9798	1.844	0.00021	79.20	9.60
J	**-4.609**	**3.498**	**0.198**	**--**	**--**	**0.9827**	**1.706**	**-0.00003**	**69.60**	**0.00**
K	-1.203	-0.065	0.315	-0.161	--	0.9683	2.330	-0.00014	109.45	39.85
L	-6.264	-6.264	-34.945	8.350	--	0.9354	3.328	-0.00013	153.68	84.08
M	4.051	-1.818	0.345	--	--	0.9802	1.826	-0.00006	77.99	8.39
N	0.695	0.423	10.800	-9.649	--	0.9827	1.723	-0.00057	72.06	2.46
O	-61.772	-57.672	-101.599	--	--	0.8040	5.749	-0.00048	220.21	150.61
P	**0.413**	**0.056**	**2.576**	**--**	**--**	**0.9824**	**1.720**	**-0.00004**	**70.62**	**1.02**
Q	-1.152	0.250	--	--	--	0.9683	2.291	0.00002	104.95	35.35

stem), the B_D we actually measured was 0.27 kg, while predictions ranged from -0.43 kg (model E) to 0.50 kg (model F)—departures that exceed 60%. At larger diameters (2.0 to 15.0 cm DBH), all models did a better job of fitting the sampled data (Figures 3b,c).

Indeed, it is virtually impossible to distinguish between the predictions, with the exception of the more conservative NBE, which forecast somewhat lower B_D for loblolly pines greater than 13.0 cm DBH (Figure 3c). Since the NBE was developed using many North American pine species, including some with lower wood specific gravity than loblolly, it is not surprising that this biomass model will underpredict B_D.

Given the inherent variation in the data, it is hard to choose any one of the final model subset over any other. The relative impacts of under- or overestimates in the smallest of the diameter range (Figure 3a) are substantial, but unless the trees being evaluated are all very small in size, the absolute differences (± 0.2-0.3 kg) suggest that errors in this range will have considerably less influence on any stand-level predictions. The data indicate that the only two models to avoid if simulations are strictly limited to the range of data we sampled are E and J, because both predict illogical results in the smallest diameters. It is important to note that models E and J had two of the lowest ΔAIC_c scores, further reinforcing the idea that AIC_c, though a useful metric for reducing the number of possible models, should not be the ultimate determining factor for final model selection.

The relatively poor job any of these models did fitting to the data at this small end of the diameter range is a consequence of the least squares regression we applied, which minimizes the departures between actual and predicted values. Since the absolute departures in this diameter range are small (mostly < 0.3 kg) compared to those at larger diameters (multiple kg), the larger trees have a much greater influence on curve fitting. In most operational contexts, loblolly pines less than 2 cm in diameter are rarely tallied (beyond simple presence/absence), so unless a stand-level biomass estimate with only very small diameter stems is being made (and there is a very large number of these), this propensity will probably not be noticed.

It is also remarkable to see that the NBE, which was not developed specifically for loblolly pine, nevertheless did a good job of predicting B_D across our sample range. The NBE model rarely differed by more than 15% from any of the other model predictions.

Model extrapolation and final recommendation

Our actual data are silent in what they can tell us

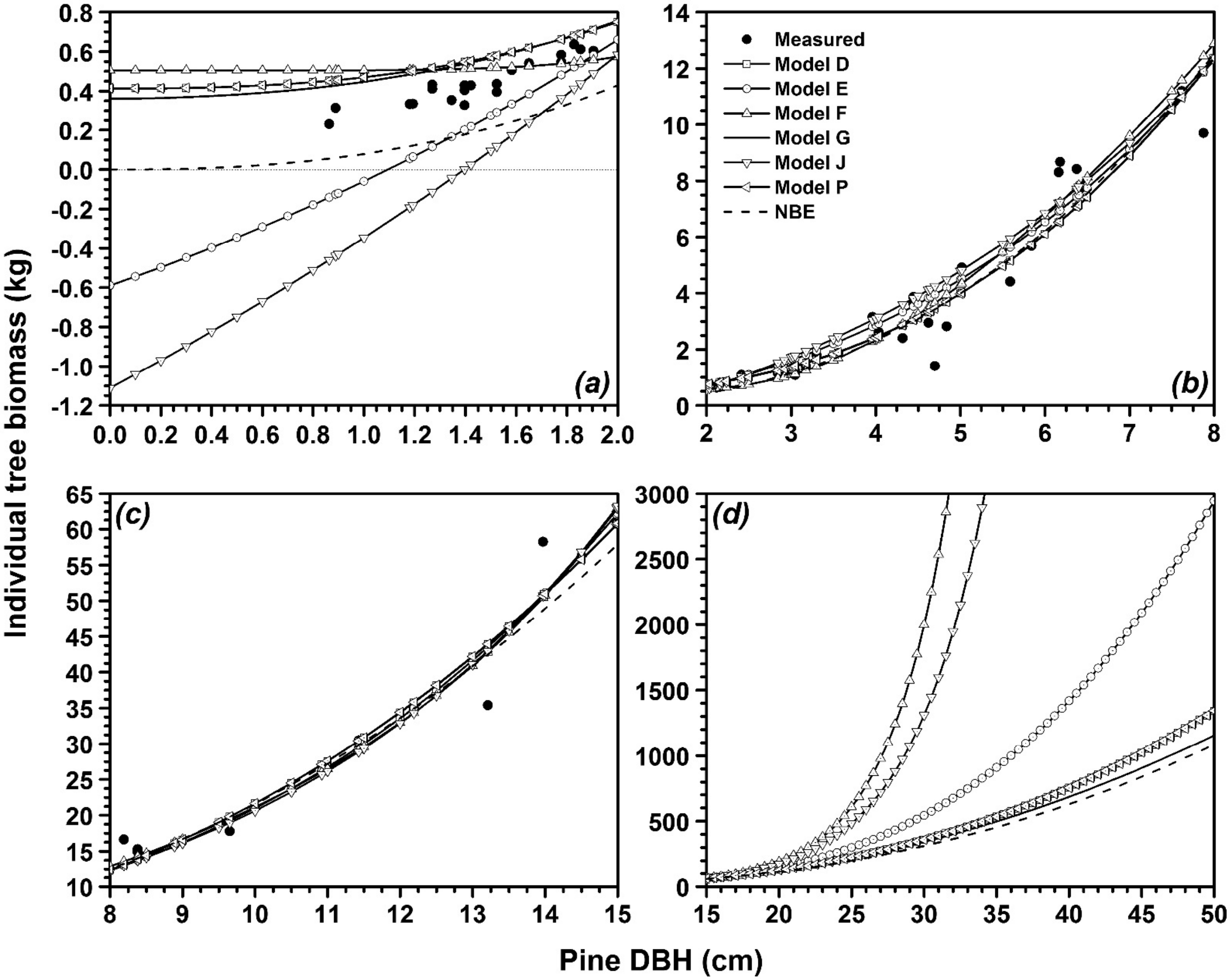

Figure 3. Predicted B_D as a function of DBH for loblolly pine from the CEF for the diameter ranges of *(a)* 0.0 to 2.0 cm; *(b)* 2.0 to 8.0 cm; *(c)* 8.0 to 15.0 cm; and *(d)* extrapolated from 15.0 to 50.0 cm.

about trees greater than 15.0 cm DBH. Statistically, it is technically inappropriate to extrapolate regression equations beyond the range of the data from which they were derived (Neter et al. 1989). However, such extrapolations are often done, and can bestow logistical advantages, particularly when used to conserve limited financial and staffing resources. Since our goal was to recommend a single pine biomass model for the CEF, and the traditional statistical tests did not seem to adequately discriminate between the six best fitting models, we viewed behavior of extrapolated models as an additional test of quality. In terms of application, this meant that we were interested in identifying the most biologically reasonable and constrained behavior of our final subset of models when extrapolated both below and above our sampled diameter range.

We have previously discussed very small diameter tree biomass outcomes using these best fit models. The negative predictions of two models even before we extrapolated towards zero DBH already removed two equations from further consideration. The NBE, as designed, will trend to zero biomass when DBH = 0.0 cm, which is a superficially logical (but incorrect) outcome—after all, pines shorter than DBH technically have DBH = 0.0 cm, but since they occupy space and have mass, they have positive (non-zero) biomass. Even though our sample lacked trees between 0.0 and 0.9 cm DBH, it is clear from the trend in Figure 3a that the likely range of biomass for very small pine trees approaching 0.0 cm DBH is between 0.1 and 0.3 kg.

Table 3. Predicted aboveground pine biomass for 6 final evaluated models (those with ΔAIC_c scores < 2) and the National Biomass Estimator (NBE) predicted result. Portions of the DBH range extrapolated beyond the field collected biomass data are shown in italics.

Model Code	DBH (in cm) range: *Extrapolated*	Field sample				*Extrapolated*		
	0.0	0.9	5.0	10.0	15.0	*20.0*	*35.0*	*50.0*
D	*0.41*	0.46	3.97	21.65	60.76	*127*	*536*	*1,342*
E	*-0.49*	-0.12	4.48	20.99	62.20	*147*	*910*	*2,944*
F	*0.50*	0.50	4.78	28.97	84.53	*231*	*5690*	*169,036*
G	*0.36*	0.43	3.97	21.47	60.27	*125*	*502*	*1,165*
J	*-1.11*	-0.43	4.79	20.64	63.21	*178*	*352*	*68,496*
P	*0.41*	0.46	3.98	21.67	60.82	*127*	*536*	*1,343*
NBE	*0.00*	0.06	3.99	21.56	57.87	*117*	*456*	*1,086*

None of the remaining models actually predict within that range, although Model G is close (between 0.35 and 0.4 kg). Model F does a better job than the others for a portion (1.4-1.9 cm DBH) of the sampled diameter range, but then quickly shifts toward the higher end of the small-diameter extrapolation (Figure 3a).

Extrapolation for large diameter stems provided a far more telling (and operationally impactful) story. Extending our six best models up to moderately large loblolly pines quickly showed the perils of careless extrapolation of regression models (Table 3, Figure 3d). Assuming the NBE's biomass predictions of B_D = 117, 456, and 1,085 kg for 20, 35, and 50 cm DBH loblolly pines are reasonable, most of the models quickly depart from this conservative trajectory and produce much higher biomass estimates. The shape of the curve of Model F, which did reasonably well at small diameters and had the second lowest ΔAIC_c value (Table 2), changes dramatically just beyond the sampled range, and increasingly departs from the rest of the models. For the 50 cm DBH pine example, Model F would predict a tree with a B_D just over 169,000 kg, or more than 100 times the NBE estimate for a tree of that size (Figure 3d). Models E and J performed poorly at both small and large diameter extrapolations (Figures 3a and 3d, Table 3). Models D and P performed reasonably at both small and large extrapolations, but were not quite as good in either extreme as Model G, which showed reasonable biological behavior at both ends of the spectrum (even though it had the lowest ΔAIC_c scores of the final subset).

Model fit quality for large diameter stems has a much bigger impact on simulation results, and is of far greater interest for timber managers. Since biomass equations can prove unreliable beyond the range of data used to fit them (Crow and Schlaegel 1988), it is critical that we consider their behavior when extrapolated—it is likely that users will apply any biomass model to trees not covered by the sample range. Based on this assumption, we recommend the use of Model G to determine aboveground oven-dry biomass on the CEF, as it fit the actual data well, and behaved sensibly when extrapolated.

Conclusions

Live tree biomass estimates are essential for carbon accounting, bioenergy feasibility studies, and productivity analyses. Existing research (e.g., Payadeh 1981, Ruark et al. 1987, Crow and Schlaegel 1988, Parresol 1999, Chave et al. 2004, 2005, Zianis et al. 2005, Bragg 2011, Melson et al. 2011) has shown that model choice and application can have a substantial impact on the estimates of biomass accumulation. Broad-scale estimates of merchantable tree biomass may differ considerably from estimates made with more regionally representative models, and the potential success of a bioenergy project might hinge on these differences (Zhou and Hemstrom 2009). Therefore, careful consideration and evaluation of models should be implemented prior to their application.

Model accuracy will likely vary among regions and species, as a result of genetics, site conditions, and growth rates. Rather than applying models developed for other locations or using other species, we destructively sampled a number of loblolly pines and tested a number of equations for their ability to fit aboveground biomass. Even though multiple models reasonably fit the actual (field sampled) data, we were able to use extrapolation in addition to conventional goodness-of-fit tests to recommend a single equation that appears capable of predicting biomass for loblolly pine across the range of diameters found on the CEF.

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