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Biogeosciences Discussions

Interactive comment on "Predicting biomass of hyperdiverse and structurally complex Central Amazon forests – a virtual approach using extensive field data" *by* D. Magnabosco Marra et al.

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GENERAL COMMENTS: Given the intense current interest in the role of forests in mitigating the adverse effects of greenhouse gas emissions, the topic of the paper is extremely timely and relevant. Regardless of whether the application is tropical, temperate, or boreal forest applications, allometric individual tree biomass models are crucial for estimating plot-level biomass which is then scaled up to estimate landscape-level biomass or combined with remotely sensed data either to map biomass or to enhance landscape-level estimation. The national forest inventories (NFI) of many

northern hemisphere countries have a long history of constructing and applying allometric models for individual species or small groups of species; for southern hemisphere countries, this work is just beginning. However, as the authors correctly note, the combination of the greater number of species, greater site variation, and perhaps limited access, makes construction of individual species models prohibitive for many tropical applications. The authors further correctly note that construction of a small number of multi-species models is likely the only alternative. Thus, the focus of the study is assessment of the degree to which multi-species tropical allometric models produce accurate landscape-level estimates should be of considerable interest to a wide variety of tropical forest researchers.

For these kinds of applications, multiple sources of uncertainty affect both the accuracy of landscape-level biomass estimates and the precision of those estimates. These sources may be readily grouped into four categories. For the first category, model prediction uncertainty, there are two primary sources of uncertainty: the residual uncertainty around the model predictions and the uncertainty in the model parameter estimates. Residual uncertainty is a function of the quality of the fit of the model to the data and is often assessed using R2 or root mean square error. R2 would be expected to be greater for individual species and smaller when combining data for multiple species, as the authors propose. Model parameter uncertainty is a function of both residual uncertainty and sample size. Thus, the disadvantage of constructing a multi-species model is greater residual variable, whereas the advantage is a larger sample size and, therefore, less model parameter uncertainty. A second category of sources of uncertainty distinguishes between the data used to construct the model and the data used as input to the model when applying it. For NFI applications, the models are often constructed using very accurate tree-level data, often acquired via destructive sampling as noted by the authors, whereas the models are applied to routine plot-level data which may be subject to considerably diameter and height measurement error. A third category of sources of uncertainty relate to conversion factors: uncertainty in wood densities for converting individual tree volume to biomass, and if carbon is to be estimated, carbon content proportions for converting biomass to carbon. A fourth category of sources of uncertainty pertains to the manner in which population variability is accommodated. In particular, how was the landscape sampled and which statistical estimators were used? Simple random and systematic sampling designs and estimators are common, but depending on sample size and landscape variability, often produce large variance and small precision estimates. Auxiliary information, often in the form of remotely sensed data, can be used to post-stratify the landscape to produce greater precision with no increase in sample size. Similarly, the same auxiliary information can be used with model-assisted regression estimators to increase precision even more than with post-stratified estimators (McRoberts et al., 2013). A relevant issue is that if the effects of landscape variability are reduced via post-stratified or regression estimators, then the relative effects of model prediction uncertainty increase.

The authors focus exclusively on the effects of using a multi-species model on the accuracy of model predictions and landscape estimates. Although this is an entirely appropriate objective, their conclusions would have been strengthened if they had assessed lack of accuracy in the context of uncertainty. In particular, if the magnitudes of deviations in model predictions are substantially greater than the uncertainty of the predictions, then those deviations have serious consequences; however, if the deviations are substantially smaller than the uncertainty, then the deviations can be attributed to random variation and possibly ignored. Further, models are generally not stand-alone products but rather are intermediate products enroute to an inference in the form of a confidence interval for the landscape-level population parameter. The important point is that the effects of model lack of fit are best assessed in the context of the model application (i.e., landscape level estimation), not at the intermediate level of model prediction accuracy, although of course the two are closely related. The authors conduct landscape-level assessments, albeit with an ad hoc procedure, but they neither specify the assumed sampling design and statistical estimator (Gregoire et al., 2016) nor the precision (variance) of the landscape-level estimates. Again, the analyses would have been strengthened if the magnitudes of the effects of the multi-species model would

have been assessed relative to the uncertainty of the landscape-level population estimates.

Techniques for propagating the effects of sources of uncertainty through to the uncertainty of the landscape-level population estimates are not well-understood, not necessarily trivial, and not often used. Three primary approaches are common: sampling theory (Ståhl et al. 2014, Chen et al., 2015), Taylor series approximations (Berger et al., 2014; Thurner et al., 2014), and Monte Carlo simulations (Breidenbach et al. 2014; McRoberts et al., 2014, McRoberts & Westfall, in press). The accumulating evidence suggests that for temperate and sub-tropical forests, when simple random sampling designs and estimators are used, the effects of diameter and height measurement error may be negligible. In addition, when 100 or more observations are available for construction of allometric models and $R2>0.95$, then the effects of model parameter uncertainty and residual variability may also be negligible. However, when post-stratified estimators are used, the combined effects are non-negligible. The 700+ observations used by the authors to construct models would seem to be sufficient to assume non-negligible effects of parameter uncertainty. However, the authors do not report R2 values, but rather only “high R2 adj.” (p. 15552, line 4). Further, they do not report the assumed sampling design or associated statistical estimators, so the degree to which the effects of landscape variability contribute to uncertainty are unknown.

TECHNICAL COMMENTS: p. 15539, line 28: Destructive sampling is not always necessary (Westfall & Scott, 2010).

p. 15539, lines 10, 11, and throughout the paper: Avoid use of subjective terms such as “good”, “poor”, “better”, etc whose criteria are not defined.

p. 15541, line 10, and throughout the paper: In statistics, unbiasedness or biasedness is a property of a statistical estimator (a formula), not estimates, not predictions, not models, and not samples. Formally, an assessment of unbiasedness or biasedness entails a comparison between the true value of a parameter and the expected value over all possible samples that could have been obtained using the sampling design. Thus, a bias assessment requires knowledge of the true value and at least a very large number of samples. Unless a very large number of samples (sets of observations, not individual observations) are used, predictions should not be characterized as “biased.” Rather, something related to “predictions that deviate from their observations” could be used.

p. 15541, line 23, elsewhere: The term “coefficient” is only appropriate if the model is linear; check any good dictionary. A generic term that includes both linear and nonlinear models is “parameter.”

p. 15442, line 1: The term “multivariate” refers to multiple response or dependent variables. When the model is linear and multiple predictor or independent variables are used, then the term “multiple regression model” is often used.

p.15443, line 17: Is there any assurance that these simulated plots represent actual plots on the landscape?

p. 15443, line 26: The term “bias” is incorrect here. A preferable term would be “mean deviation.”

p.15545, line 8: Although issues of cost and access are acknowledged, observations for trees on the same plot should not be considered independent when constructing models because they are all affected by the same site, competition, and other factors, i.e, these observations are surely correlated.

p. 15547, line 12: How is the categorical variable “successional group” used as a predictor variable? Predictor variables are usually assumed to be continuous?

p. 15548, line 21: Change “equation” to “model” as in the rest of the paper. Despite widespread erroneous usage in the applied literature, the two terms are not synonymous.

p.5549, line 21: The measure expressed in Eq. (3) is highly questionable when there

is heteroscedasticity.

p. 15550, line 13: Are 100 replications sufficient? The general understanding is that replications should continue until the statistic of interest stabilizes. Note that Efron and Tibshirani (1994) who wrote the bible on bootstrapping recommend at least 200 replications.

p. 15551, line 19: Because the actual parameter estimates have been included, in Eq. (5), place a caret (ˆ) over “logAGB” to indicate that it is a prediction.

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