Draft for Urban Forestry Protocol meeting on May 12, 2008.

A REVIEW OF THE ACCURACY OF URBAN FORESTRY BIOMASS FUNCTIONS: UTILITY FOR THE CALIFORNIA CLIMATE ACTION REGISTRY PROTOCOL

Timothy Robards[1]

Summary

A question regarding the accuracy of the biomass functions for urban forestry settings was raised during the development phase of the urban forestry protocol for the California Climate Action Registry (CCAR). Specifically, the relative accuracy of the urban forestry biomass functions for each in situ carbon pool compared to wildland forestry biomass functions was questioned. To address this query an error analysis was performed that characterized the statistical variability and appropriateness of application of the biomass functions to urban areas of the State.

The general findings were that there was no evidence that the methods presented in the protocols for estimating biomass were any less reliable on average than their wildland counterparts. Professional analysis in the application and improvement of biomass estimates is encouraged, which is consistent with the wildland application of allometric functions to tree inventory data.

Introduction

The application of biomass prediction equations is a necessary step since a complete characterization of tree form would be prohibitively expensive and actual weighing would destroy the tree and be expensive. Tree biomass is often estimated as species specific regression functions with diameter at breast height (DBH) as a minimum predictor variable. Total tree height is commonly included with DBH as this reduces the variance substantially. Height, however, is a more expensive variable to measure on each tree. Height is often measured as a subsample and regressions of DBH to height developed to provide unbiased estimates of height for trees not measured.

Crow and Schlaegel (1988) described how to evaluate and compare biomass estimators. They discussed commonly used variables, model forms, transformations and statistical measures. They point out that care must be taken to ensure that comparisons are valid by looking at units of measure, assumptions of model forms in developing statistical measures, and bias corrections after logarithmic transformations. The statistical measures they recommend examining for comparing equations include coefficient of determination (R^2), standard error (S_e), fit index (FI), coefficient of variation (CV), and the range of the data. In applying biomass equations the authors recommend applying equations derived from data similar to that to which they are being applied. An idea of the variability may be estimated by applying multiple equations to a dataset.

[1] Forest Biometrician, Fire and Resources Assessment Program, California Department of Forestry and Fire Protection, Sacramento. California Registered Professional Forester 2521, Certified Forester 2015. tim.robards@fire.ca.gov

Methods

A survey of the biomass literature was conducted to summarize the variability within biomass functions. Common statistical measures were used to facilitate the comparison; they were standard error (S_e), coefficient of variation (CV), data ranges, and fit index (FI) (Parresol 1999). Example biomass curves were presented to compare the suggested protocol functions to a range of available models in a check for reasonableness.

A critique of the potential error sources that exist when applying biomass functions was done for wildland cases. The analysis was extended then to urban forests and placed in context of total error potential. Finally, conclusions and recommendations were made to address the initial question of the applicability of the available biomass functions to urban forests relative to wildland forests.

Results

Table 1 shows the results of biomass comparisons. The variety of functional forms, the evolution of the statistical reporting over time, lack of raw data reporting, and confusion regarding transformed data make comparisons problematic. The fit statistics address individual tree regression modeling but do not account for the application of individual tree biomass models to whole inventories, whether wildland or urban.

Table 1. Biomass function comparison.

Source	Species	Biomass Type	Predictor(s)	SE (kg)	Mean (kg)	CV (%)	Fit Index	No. of Trees	DBH (cm)
Schlaegel, B.E. 1982. Boxelder (Acer negundo L.) biomass component regression analysis for the Mississippi Delta. Forest Science 28(2):355-358.	Acer negundo	Total above ground without leaves	DBH Tree height	11.8	62.7	18.8	0.985	49	3.6 - 36.8
Adams, J.C. 1988. Variability of understory sweetgum biomass relationships. Southern Journal of Applied Forestry 12:5-7.	Liquidambar styraciflua	Total above ground	DBH Tree height	NA	26.7	NA	0.90 (r-sq)	65	5.1 - 25.4
Jenkins, J.C., D.C. Chojnacky, L.S. Heath, and R.A. Birdsey. 2003. National-scale biomass estimators for United States tree species. Forest Science 49(1):12-35.	All species groups (nationwide assessment)	Total above ground	DBH	NA, from psuedo data	NA, from psuedo data	NA, from psuedo data	NA, from psuedo data	61 to 485 data points	2.5 - 78 in hardwoods, 2.5 - 250 in softwoods
Brown, S., A.J.R. Gillespie, and A.E. Lugo. 1989. Biomass estimation methods for tropical forests with applications to forest inventory data. Forest Science 35(4):881-902.	Various tropical species	Total above ground	DBH Tree height	Approx. 3	NA	NA	0.61 to 0.99 (r-sq)	32 to 168	5 - 130
Ter-Mikaelian, M.T., and M.D. Korzukhin. 1997. Biomass equations for sixty-five North American tree species. Forest Ecology and Management 97:1-24.	Various, compendium of North American biomass equations	Total above ground	DBH	0.04 to 35.9	NA	NA	0.812 to 0.998 (r-sq)	4 to 734	1 - 76

The lack of specific biomass predictive equations may be handled by using stem volume functions, wood density values that are species-specific, and carbon pool ratios to expand to total tree biomass (Smith et al. 2006; Smith et al. 2004). Volume equations specific to California urban trees were developed by Pillsbury et al. (1998) for fifteen species. Nine cities were sampled, which were stratified by climatic zone (coast, southern, central valley). Each city was blocked to ensure representative sample coverage. Species were selected based on a number of criteria including large size at maturity, frequency of occurrence and lack of existing volume equations. The non-destructively measured wood volume included bole and branches but not roots and foliage. The percent aggregate difference or accuracy over the entire sample was in the 0 to 3% range, which is a highly accurate fit. The authors recognize that using the functions outside the range of the data, outside the geographical range for which they were modeled or on odd trees such as those that have been recently topped require diligence on the part of the urban forester.

I examined a draft of McHale (2008) that developed volume equations for urban tree species in Fort Collins, Colorado and compared results with Pillsbury et al. (Pillsbury et al. 1998). A graphical comparison did not indicate substantial deviations in predictions although the local equations were superior for the local data as one would expect.

A meta analysis that pooled all available biomass functions for hardwood and softwood species across the United States was done by Jenkins et al. (2003). They systematically sampled data points from total aboveground biomass functions that were a function of DBH only. From these sampled data points they constructed new functions that were pooled by species groups. They found that 80% of the estimates from their functions were within about 30% of the mean estimates, which is an indication of goodness of fit and not a measure of accuracy from independent data.

Figure 1 shows a comparison of biomass functions for sugar maple (*Acer saccharum*). The estimates of carbon dioxide for individual trees vary by up to 60%. The biomass function from the protocol is near the bottom of the curves. See Ter-Mikaelian (1997) for the specific curves used except Jenkins (2003). Figure 2 is a comparison of using the Pillsbury (1998) urban tree volume functions to derive biomass to two other direct biomass estimates. The results show total above ground biomass and are from a function on a Yale University course web site (www.yale.edu/fes519b/biomass.html) and from Jenkins et al. (2003). In this case, again, the protocol estimates appear conservative.

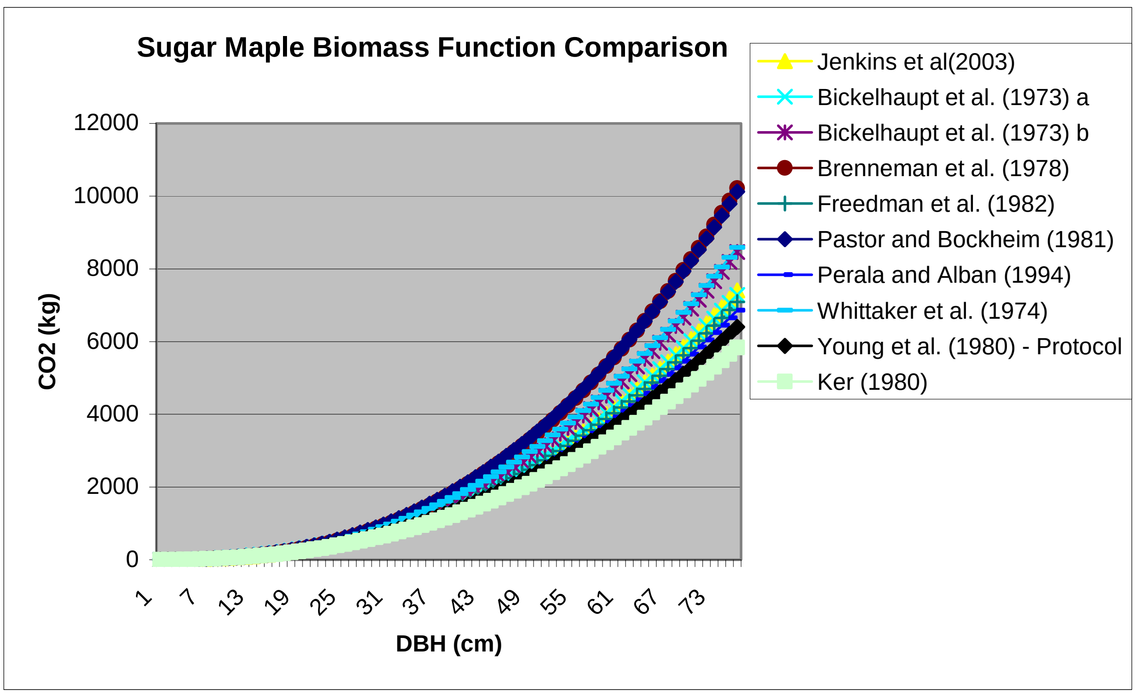

Figure 1. Comparison of above-ground biomass functions for sugar maple with 20% reduction applied for being urban trees. See Ter-Mikaelian (1997) for most references.

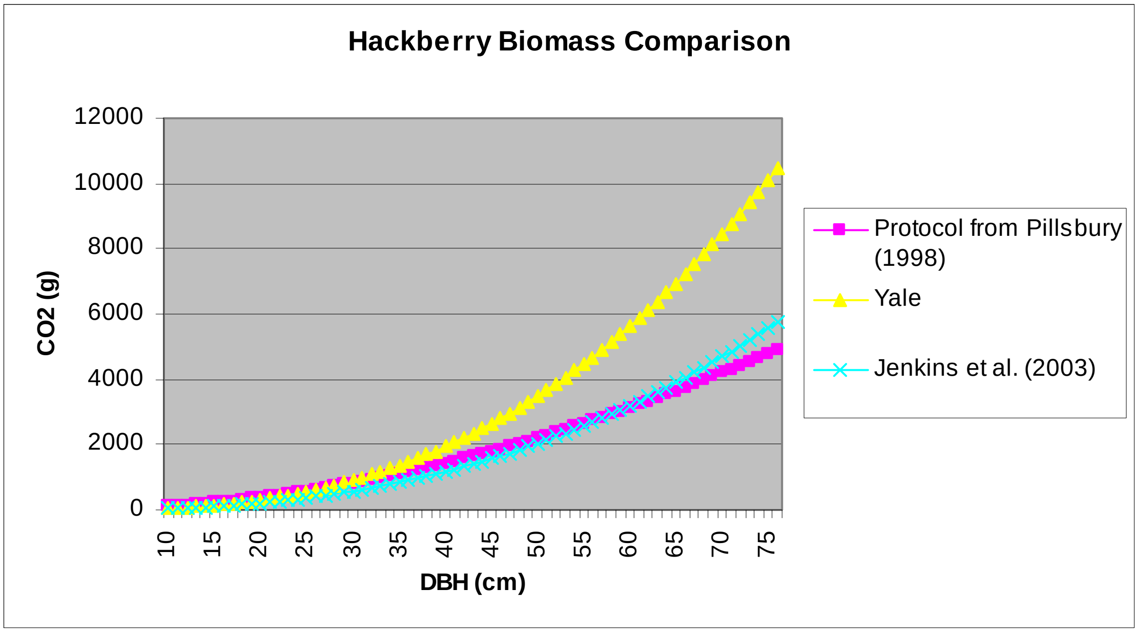

Figure 2. Comparison of above-ground biomass functions for hackberry with 20% reduction applied for being urban trees (where appropriate).

The following discussion follows section 2 of Parresol (1999) and addresses the sampling error of forest biomass inventory estimates. There are two main components, the first of which is the random selection of sample units. This is influenced by

- Sampling design
- Sample size
- Type of estimator used
- Inherent variation.

The second component is the error of the biomass regression and is affected by

- Sampling design used to select trees used in regression
- Sample size of trees used in regression
- Estimation procedure
- Inherent variation of trees about regression function.

Statistical techniques have been developed by Cunia (i.e. 1988) to meaningfully combine these error sources for specific situations so that the contributions of each error component may be estimated. The biomass estimation component of the total error will be project specific. As is often the case in forest inventory or growth analysis, functions are nested with each function being a deterministic estimate. Error propagation can be complex to quantify in such cases (Cunia 1988; Parresol 1999).

Discussion

Trees in a wildland setting may be either from planted stock or from natural regeneration. The vigor and mortality rate for a tree will depend on its physiological and competitive situation. Each species occupies a niche where it has a competitive advantage over other species. Drought stress, inundation periods, canopy position or light availability are some examples of factors that describe a species niche. However, a tree that is planted and grown in the open with no competitors and plentiful resources does not behave as it would in the wild. A tree found only in dry conditions in the wild may do well in a watered lawn; in other words the ecologically limiting factors in the wild do not necessarily follow to the urban landscape. Trees in urban settings have other challenges such as over-watering, under-watering, damage, disease, etc, and certainly they succumb to these stresses and senescence. Assuming no human caused aberrations such as severe pruning, while vigorous and growing these urban trees will likely exhibit less tree to tree variability in size, as a function of age, than wildland trees. In fact, wildland growth models sometimes use open grown trees as a standard by which to quantify competition (Krajicek et al. 1961).

Statistically significant differences in estimated biomass between locations were generally found by researchers (i.e. Adams 1988; Jenkins et al. 2003; Phillips 1981; Ter-Mikaelian and Korzukhin 1997). This was more evident for crown components than for boles. Open grown trees in urban settings may be more likely to have multiple main stems than in a managed forest since these are selected against when growing trees for sawlogs. Applying consistent rules for measuring multi-stemmed trees will minimize this issue (Francis 1984).

A key point is that regardless of the origin of biomass estimators, an analysis of their applicability must be conducted (i.e. Crow and Schlaegel 1988; Gholz et al. 1979; Wang and Kimmins 2002). This analysis may be qualitative or quantitative depending on the level of accuracy desired. The potential for error is large for both wildland and urban applications. The more trees in an inventory the higher the precision should be; bias however cannot be corrected for by sample size. Carbon projects that include a quantitative evaluation of the accuracy of biomass estimates should be noted by project verifiers so that appraisals of project value or risk may incorporate this information. The protocols state that inherent or scientific uncertainty is not to be specifically addressed in a project, but reporting uncertainty is to be addressed. The reduction of uncertainty below the accepted level in the default process is what I am referring to; this applies to both wildland and urban protocol applications.

Adaptive management by means of incremental improvements in the accuracy of biomass equations may occur in both wildland and urban forestry contexts. Research and monitoring activities may include non-destructive above-ground tree measurements possibly combined with destructive canopy subsampling or destructive whole-tree sampling. Below-ground sampling is more difficult and expensive but could possibly be coordinated with construction projects to minimize impacts and costs. The challenges to urban forestry to incrementally improve the accuracy of biomass equations are essentially the same as for wildland forestry. These are well articulated in the final paragraph of Jenkins et al. (2003) and include using consistent sets of measurement and reporting protocols, publishing of raw data, and sampling a wide range of tree sizes especially large trees. When using volume equations to convert to biomass estimates, Pillsbury et al. (1998, p. 26-27) provide suggestions for improved volume estimates. Parresol (1999) provides an excellent summary of statistical measures, regression approaches, carbon pool harmonization techniques, and efficient sampling procedures for developing biomass functions.

A commercial wildland forestry operation validates volume and biomass estimates by the measured and weight scaling that occurs based on loaded trucks, whether logs or chips. The accounting for wood fiber from a municipality by means of truck-load counts of chips and logs could also be used as a means of validation if accurate records exist. The participation of local governments in greenhouse gas accounting either in a voluntary or regulatory format may make this validation procedure more realistic in the near future.

References

Adams, J.C. 1988. Variability of understory sweetgum biomass relationships. Southern Journal of Applied Forestry 12:5-7.

Crow, T.R., and B.E. Schlaegel. 1988. A guide to using regression equations for estimating tree biomass. Northern Journal of Applied Forestry 5:15-22.

Cunia, T. 1988. On the error of biomass regressions and the corresponding inventory estimates. P. 93-109 *in* Proceedings of the 9th Annual Southern Forest Biomass Workshop, Daniels, R.A., W.F. Watson, and I.W. Savelle (eds.). Mississippi State, Mississippi State University.

Francis, J.K. 1984. Biomass accumulation by single- and multiple-stemmed young sycamore. Forest Science 30(2):372-374.

Gholz, H.L., C.C. Grier, A.G. Campbell, and A.T. Brown. 1979. Equations for estimating biomass and leaf area of plants in the Pacific Northwest. Forest Research Lab, Oregon State University, Corvallis. Research Paper 41:37.

Jenkins, J.C., D.C. Chojnacky, L.S. Heath, and R.A. Birdsey. 2003. National-scale biomass estimators for United States tree species. Forest Science 49(1):12-35.

Krajicek, J.E., K.A. Brinkman, and S.F. Gingrich. 1961. Crown competition - a measure of density. Forest Science 7(1):35-42.

McHale, M.R. 2008. Urban forest biomass estimates: Is it important to use allometric relationships developed specifically for urban trees? Urban Ecosystems In Press.

Parresol, B.R. 1999. Assessing tree and stand biomass: a review with examples and critical comparisons. Forest Science 45(4):573-593.

Phillips, D.R. 1981. Predicted total tree biomass of understory hardwoods. USDA Forest Service Research Paper SE-223:22.

Pillsbury, N.H., J.L. Reimer, and R.P. Thompson. 1998. Tree volume equations for fifteen urban species in California. Urban Forest Ecosystems Institute, California Polytechnic State University, Technical Report No. 7, San Luis Obispo. 57.

Smith, J.E., L.S. Heath, K.E. Skog, and R.A. Birdsey. 2006. Methods for calculating forest ecosystem and harvested carbon with standard estimates for forest types of the United States. USDA Forest Service General Technical Report GTR NE-343:222.

Smith, J.E., L.S. Heath, and P.B. Woodbury. 2004. How to estimate forest carbon for large areas from inventory data. Journal of Forestry 102(5):25-31.

Ter-Mikaelian, M.T., and M.D. Korzukhin. 1997. Biomass equations for sixty-five North American tree species. Forest Ecology and Management 97:1-24.

Wang, J.R., and J.P. Kimmins. 2002. Biomass estimation errors associated with the use of published regression equations of paper birch and trembling aspen. Northern Journal of Applied Forestry 19(3):128-136.