THESIS

ABOVEGROUND WOODY BIOMASS ESTIMATION OF GREEN ASH TREES (*FRAXINUS PENNSYLVANICA* MARSH.) ALONG COLORADO'S NORTHERN FRONT RANGE IN RESPONSE TO THE INVASIVE EMERALD ASH BORER (*AGRILUS PLANNIPENIS* FAIRMAIRE)

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ABSTRACT

ABOVEGROUND WOODY BIOMASS ESTIMATION OF GREEN ASH TREES (*FRAXINUS PENNSYLVANICA* MARSH.) ALONG COLORADO'S NORTHERN FRONT RANGE IN RESPONSE TO THE INVASIVE EMERALD ASH BORER (*AGRILUS PLANIPENNIS* FAIRMAIRE)

The invasive emerald ash borer (*Agrilus planipennis* Fairmaire) has killed hundreds of millions of ash trees (*Fraxinus* spp.) in forests and urban areas across the United States. Green ash (*Fraxinus pennsylvanica* Marsh.) is the most widely planted street tree in the greater Denver Metro Area, comprising 15% of the urban tree population on a per-stem basis, and up to 33% of the canopy cover in some cities. EAB is currently established in Boulder, Colorado and as the infestation progresses along the Colorado Northern Front Range, municipalities will need to predict and budget for woody debris disposal from EAB-killed trees. Though existing green ash biomass predictive equations exist, most were developed for areas outside the arid West and generally represent only trees in natural forests, with full, healthy crowns. This study aimed to test whether these equations can accurately predict aboveground woody biomass of green ash trees removed as part of emerald ash borer mitigation efforts in urban areas of Colorado's Northern Front Range.

Data from 42 destructively sampled ash trees removed from 11 sites as part of emerald ash borer mitigation efforts were used to evaluate the predictive capability of 12 forest-derived and five urban green ash biomass equations. The published urban equations underpredicted total sampled biomass by as much as 38% and overpredicted by as much as 47%. Forest-derived equations underpredicted by as much as 57% and overpredicted up to 52%. A local, published equation developed in the Northern Front Range overpredicted biomass by 47%. This local urban equation was developed using only open-grown trees with full, healthy crowns while the trees sampled for this study exhibited a broad spectrum of crown conditions, better representing trees that will routinely be removed as part of emerald ash borer management strategies. Sampled trees were also used to develop new local green ash biomass equations, more appropriate for use in emerald ash borer management strategies in Colorado's Northern Front Range cities. In addition, the locally-derived average specific gravity value for green ash wood was 0.57, and the locally-derived average moisture content value was 41%. These are 7.5% higher and 24% lower respectively than widely-used published values. The locally-derived values can be used to further improve the accuracy of urban forest mensuration efforts in Colorado's Northern Front Range.

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DEDICATION

This work is dedicated to my husband, Ian Truslove, for his unfailing support, gentle encouragement, immeasurable patience, and indefatigable optimism in the face of my many doubts while I navigated a significant professional volte-face, earned three degrees, and slogged through several unpaid "internships" to get to this point. To call him a good sport would be a massive understatement. I am and will be forever grateful for him.

TABLE OF CONTENTS

ABSTRACT ... ii
ACKNOWLEDGEMENTS ... iv
DEDICATION ... vi
LIST OF TABLES ... viii
LIST OF FIGURES ... ix
1. INTRODUCTION ... 1
2. LITERATURE REVIEW ... 6
2.1 Emerald ash borer and the issue of wood disposal ... 6
2.2 Biomass equations: Their uses and challenges ... 7
2.3 The ambiguous origins of biomass equations ... 10
2.3.1 Sources of uncertainty and error in biomass equation development ... 10
2.3.2 Local, regional and species-specific equations ... 14
2.3.3 Generalized, mixed species equations ... 16
2.3.4 Other methods of indirect tree biomass measurement ... 18
2.4 The lack of urban, species-specific biomass equations ... 20
3. GREEN ASH (*FRAXINUS PENNSYLVANICA* MARSH.) BIOMASS EQUATIONS FOR URBAN TREES REMOVED IN RESPONSE TO THE EMERALD ASH BORER (*AGRILUS PLANIPENNIS* FAIRMAIRE) ... 23
3.1 Introduction ... 23
3.2 Methods ... 27
3.2.1 Study area ... 27
3.2.2 Field measurements ... 27
3.2.3 Laboratory measurements ... 29
3.3 Statistical analysis ... 31
3.3.1 Evaluation of published green ash biomass equations ... 31
3.3.2 Development of Northern Front Range green ash biomass equations ... 35
3.4 Results ... 36
3.4.1 Performance of existing green ash biomass equations ... 36
3.4.2 Locally-derived Northern Front Range green ash biomass equations ... 42
3.4.3 Locally-derived average specific gravity and moisture content of green wood ... 44
3.5 Discussion ... 46
3.5.1 Some existing biomass equations adequately predict green ash biomass ... 46
3.5.2 The green basis Northern Front Range predictive equation for green ash is recommended for emerald ash borer mitigation activities ... 49
3.5.3 DBH-only model for urban tree biomass estimation ... 50
3.5.4 Locally-derived green ash specific gravity and average moisture content differs from published values ... 51
3.6 Conclusions ... 52
REFERENCES ... 54
APPENDIX A: SCATTERPLOTS ... 75
APPENDIX B: BOX AND WHISKER PLOTS ... 78

LIST OF TABLES

Table 2-1 Summary of literature sources that provide tree removal costs related to EAB infestation 9
Table 3-1 Northern Front Range cities from which green ash trees were destructively sampled during this study. 27
Table 3-2 Summary statistics for trees destructively sampled for this study. 28
Table 3-3 Green ash biomass equations evaluated in this study 33
Table 3-4 Measured green and oven-dry biomass versus predictions from published equations 37
Table 3-5 Predictive equation developed for the Northern Front Range. 42
Table 3-6 Comparison of published equations and Northern Front Range predictive equations on a green and an oven-dry basis 45

LIST OF FIGURES

Figure 2-1 Biomass equations used to estimate green ash (*F. pennsylvanica*) and assessed by McHale et al. (2009) along with their origins...11
Figure 2-2 Biomass equations used to estimate green ash (*F. pennsylvanica*) and assessed by Olson (2017) along with their origins..12
Figure 3-1 Bland-Altman plots comparing mean observed green biomass versus published equation green predicted biomass...38
Figure 3-2 Bland-Altman plots comparing mean observed oven-dry biomass versus published equation oven-dry predicted biomass...41
Figure 3-3 Plotted regression lines for locally-derived Northern Front Range green and oven dry biomass equations..43
Figure 5-1 Scatterplots for observed green biomass and predicted biomass from green basis equations for the 42 destructively sampled trees..76
Figure 5-2 Scatterplots for observed oven-dry biomass and predicted biomass from oven-dry basis equations for the 42 destructively sampled trees...77
Figure 6-1 Box and whisker plots representing the distribution of the residuals for green basis published equations...79
Figure 6-2 Box and whisker plots representing the distribution of the residuals for green basis published equations...80

1. INTRODUCTION

Since its discovery in Detroit, MI in 2002, the emerald ash borer (EAB) (*Agrilus planipennis* Fairmaire) has caused the death of hundreds of millions of ash trees (*Fraxinus* spp.) in the U.S. and is considered to be the most destructive and costly invasive forest pest in U.S. history (Herms and McCullough, 2012). Sydnor et al. (2009) estimate that treating or removing 50% of the ash trees in urban areas in the U.S. will cost approximately $10.5 billion by 2019. This number does not include suburban areas, which are also often heavily planted with ash. Another important cost to municipalities and landowners is wood disposal. Trees that are either killed by EAB outright or are preemptively removed are often chipped into mulch or disposed of in regulated landfill sites inside federal quarantine areas. The resulting volume of mulch from routine forestry operations, let alone mulch produced during peak EAB infestation, is often more than can be utilized by a municipality, and cities often pay to have mulch hauled away at considerable expense (Tom Wells and Kathleen Alexander, pers. comm.). Trees killed by EAB have generated an unprecedented amount of wood waste in states where the insect has become established, resulting in storage and disposal issues for those cities.

At the time of writing, Colorado is the westernmost state in which EAB has been detected, having been discovered in Boulder in September of 2013. Ash has been widely planted in many of Colorado's communities due to its suitability as a street tree and its adaptability and ability to cope with Colorado's changeable climatic conditions. Green ash is the most widely planted street tree in the Denver Metro Area of the Northern Front Range, and many Colorado communities' urban forests are comprised of 15-20% ash on a per-stem basis, with percentages in individual neighborhoods of up to 70-80%. According to a recent i-Tree Eco study (i-Tree Eco v6.0, www.itreetools.org) performed by Davey

Resource Group in Fort Collins, CO, ash trees constitute 33% of the city's canopy cover (Ralph Zentz, pers. comm.), suggesting that ash contribute even more to the urban canopy than previously thought (a 2013 canopy assessment of the Denver Metro Area estimated ash populations on a per-stem basis), especially in cities that have many older, large diameter ash trees.

The cost of EAB management in the Denver Metro Area could be devastating to many cities' budgets and will overwhelm forestry operations. The City of Denver has estimated removal costs of $432 million (Wood, 2014). Additional economic losses associated with lost environmental services provided by the ash canopy in the Denver Metro Area, such as property value increases, stormwater mitigation, and air temperature reductions, could be as high as $82 million (Colorado State Forest Service, 2015; McPherson et al., 2013). Experience from other states managing EAB infestations has shown that the best way to avoid this is prior planning for the arrival of EAB by creating a comprehensive management plan that includes treatments to slow tree mortality so a controlled removal schedule can be implemented. Even with treatments, removals can quickly become unmanageable once EAB populations peak in an area, which has been estimated to occur around eight years after the initial arrival of the insect. Boulder is already experiencing this phenomenon in most areas throughout the city. Once this point is reached, wood volumes can become overwhelming as most cities do not have large sort yards able to handle the rate at which trees must be removed during peak infestations.

The Colorado Department of Agriculture's Emerald Ash Borer Response Team has stated that comprehensive management plans including a wood utilization plan should be in place before the arrival of the insect (Colorado Department of Agriculture, 2014). The first step to understanding the potential impact of EAB in a community is a complete inventory of ash trees. Most cities do not include privately owned trees in municipal inventories, but urban foresters have long used rule-of-thumb of 10:1 private to public trees. Inventories including routine measurements such as tree height and diameter at breast height (DBH, 1.37m) can be used to estimate biomass and give resource managers a better understanding of the amount of ash material produced from EAB-killed and preemptively removed trees. McHale et al. (2009) produced biomass equations for 10 commonly planted tree species in the Fort Collins area, including green ash; however, these equations used LiDAR measurements to predict tree volume, and estimates were not verified using harvested trees due to the difficulty in destructively sampling and weighing trees.

There are several real and perceived barriers to the utilization of urban wood, including logistical (transportation, lack of sort yards), financial (economics of processing urban logs for solid sawn timber products), unknown resource quantity (lack of complete inventories, and lack of knowledge of number of trees on private property), and marketing (perception of urban wood as low-value and lack of existing supply chain networks and markets). Some states have created successful urban wood utilization programs even prior to the arrival of EAB (Bratkovich, 2001), and several books and other resources that promote the utilization of wood from urban areas exist to help promote putting trees removed from urban forests to their highest value use rather than simply mulching the material or directing it to landfills (Brashaw et al., 2012; Solid Waste Association of North America, 2002).

To overcome these issues, more needs to be known about the quantity and quality of the ash resource across urban landscapes. While biomass equations exist for ash trees, they have often been developed for traditional forestry settings, and do not address the differences that exist between forest trees and urban trees (McHale et al., 2009).

Furthermore, the accuracy of biomass equations has been shown to be location specific (Pillsbury et al., 1998).

This thesis provides urban forest managers in Colorado's Northern Front Range with a way to predict the amount of ash wood produced from trees preemptively removed as part of an EAB management strategy or from trees that are removed as they become infested with EAB. This was achieved by developing an equation to accurately predict aboveground woody biomass for green ash trees growing in Northern Colorado's urban forests. It is the intention that the equation will be incorporated into the Colorado Tree Coalition's inventory and EAB cost calculator tool, CO-TreeView (https://cotreeview.com, n.d.). Municipal forest managers will have the ability to identify ash trees scheduled for removal from inventory data. The EAB tool will calculate a biomass quantity that can be used in debris disposal estimates. A specific gravity and moisture content value for this area is also of interest as these can further assist urban foresters, researchers and others interested in making accurate biomass estimations.

The objectives of this study were to determine: 1) whether locally developed, species-specific biomass equations outperform equations developed for areas outside of Colorado's Northern Front Range; 2) the best predictive equation for above-ground woody biomass of green ash trees for emerald ash borer management activities in urban areas of Colorado's Northern Front Range; and 3) whether the average wood specific gravity and moisture content of urban ash trees along Colorado's Northern Front Range differed from published values.

These findings will assist urban forest managers in Colorado's Northern Front Range in making management decisions regarding ash trees in response to the recent discovery of emerald ash borer in Colorado. Data and tools generated from this study can be used in conjunction with municipal tree inventories to predict the amount of wood waste from EAB-killed trees in Northern Front Range urban areas.

2. LITERATURE REVIEW

2.1 Emerald ash borer and the issue of wood disposal

The emerald ash borer (*Agrilus planipennis* Fairmaire, EAB) presents an unprecedented management challenge to urban foresters and other resource managers in the municipalities in which it has become established. Ash trees in the U.S. have no natural resistance to this pest, and EAB has no effective natural enemies outside of its native range. Mortality rates exceeded 99% for untreated trees 8 years after its detection at the original infestation epicenter in Michigan (Herms and McCullough, 2014). While effective treatments exist, not every ash tree is a good candidate for treatment because insecticides used to control EAB are systemic, therefore requiring that the tree's vasculature is uncompromised by previous injuries. Such pre-existing injuries (resulting from abiotic and biotic issues) are commonly found in ash trees in urban areas (Cranshaw, 2017; Jesse et al., 2011).

This invasive insect has been difficult to detect in Colorado since many of the symptoms produced by EAB-infested trees are also caused by Colorado's often harsh climactic conditions, such as drought, unseasonable snowstorms and freezes, and other insect and disease problems. Many municipalities and other organizations managing ash trees have moved away from detection activities and instead are primarily focused on management activities, including conducting ash inventories, initiating treatment, and preemptive removal of ash trees with small diameter, trees in poor health, or trees in undesirable planting locations. To date, Colorado communities have removed over 5,000 ash trees as the result of EAB management activities (Keith Wood, pers. comm.).

All too often the issue of wood disposal resulting from large numbers of trees killed by EAB is a low priority until the problem is present and the need to find solutions becomes urgent. Many resources exist to aid municipalities in planning for the logistics of wood disposal (e.g., the Ash Utilization Options Project developed by the Southeast Michigan Resource Conservation and Development Council, Southeast Michigan RC&D, 2007), but the costs associated with disposal are not well documented. Several estimates for costs resulting from EAB infestations are available in the literature, but none specifically address wood disposal (Table 2-1). The insect has now spread to over 30 states and has killed hundreds of millions of ash trees. A means of predicting the amount of ash wood waste for budgetary and utilization purposes is therefore of great need and value to urban forest managers.

2.2 Biomass equations: Their uses and challenges

Allometric equations in forestry relate measurements of one or more tree characteristics to another. In this way, an easy-to-measure characteristic, such as diameter at breast height, can be used to estimate whole tree volume or the volume of tree components. Biomass estimates can then be extrapolated to different spatial scales (e.g., locally, regionally, nationally or continental) with volume-to-mass conversions using a species-specific wood density value (Asner et al., 2009; Chave et al., 2014; Dubayah et al., 2010; Pan et al., 2011). Equation development entails sampling the population of one or more species of interest and developing an equation representative of the entire population (Brand and Smith, 1985). Destructive sampling and weighing of whole trees is preferred since this is a direct measurement, but this method is often cost- and labor-prohibitive (Ketterings et al., 2001). Tree biomass equations were traditionally used for commercial forest management purposes, such as estimating the amount of merchantable timber in forest stands (e.g. Schlaegel, 1984), estimating the impacts of various forest management activities (e.g., Sollins and Anderson, 1971), to better understand nutrient cycling and other biological processes (e.g., Bunce, 1968), and estimating woody biomass stocks for use in bioenergy applications (e.g., Milbrandt, 2005). Biomass estimates are increasingly used for urban forest valuation and in carbon accounting to support climate change initiatives. The latter has resulted in numerous studies of forest structure and function, primarily in tropical areas (e.g. Banin et al., 2012; Chave et al., 2014; Chave et al., 2005; Chave et al., 2004; Ngomanda, 2014), but also Canada (Pasher et al., 2014), China (Fang et al., 2001), and other places. The U.S. Forest Service Forest Inventory and Analysis (FIA) Program provides comprehensive inventory data on U.S. forests. These data have been used for numerous analyses relating to forest structure and function including carbon accounting in U.S. forests (Brown, 2002; Houghton, 2005), and in worldwide carbon stock estimates (Pan et al., 2011), land cover and land use change (Homer et al., 2015; Lawler, 2014; McGarigal et al. 1995), the effects of disturbance (Asner et al., 2016, Cohen et al., 2016, Kurz et al. 2008), and developing biomass equations (Jenkins et al., 2003; Chojnacky et al., 2014).

Similarly, biomass equations have been used to study urban tree ecosystem services in the United States and elsewhere (e.g. McPherson et al. 2016, Roy 2012, Nowak et al. 2013). Applications include using allometric equations to predict various attributes of tree growth to assist with urban planning and management functions (for example, planning tree placement to avoid conflicts with structures and utilities based on estimated mature crown spread) (Peper et al. 2014, Pretzsch et al. 2015, Dahlhausen et al. 2016), and improving risk assessment related to tree failure by predicting biometric variables (Rust 2014).

Though there have been many studies related to allometry and biomass estimation, there are still many sources of uncertainty in developing accurate predictive equations. The challenges associated with the development and use of biomass equations are outlined subsequently.

Table 2-1 Summary of literature sources that provide tree removal costs related to EAB infestation.

Literature source	Management activity	Source of estimate	Estimated cost	Disposal costs[1]	Study area
Hauer and Peterson 2017	Tree and stump removal	Survey of 1723 communities in 50 US states	Tree and stump removal costs increased from 20% of total urban forestry budgets prior to EAB infestation to 38.1% after infestation	N/A	Survey of 1723 US communities
Kovacs et al. 2011	Tree removal and replacement	Kovacs 2010	$800/tree residential and non-residential; $600 parks	N/A	Twin Cities Metropolitan Area, MN
Kovacs et al. 2010	Tree removal	Purdue EAB Cost Calculator	$850 - $2400/tree homeowner[2] $150 - $1200/tree public	N/A	25-state region centered on Detroit, MI
McCullough and Mercader 2012	Tree removal and replacement	2010 cost estimates from arborists or urban foresters in six Midwestern cities	$888 ± 54/tree	Included in removal/replacement estimate	Simulated environment/ Midwestern US
McKenney et al. 2012	Community overhead costs (also includes managing the response, communication and monitoring activities)	City foresters in study area	CAD $0.40/year for the duration of an outbreak (USD $0.42)	Included in community overhead costs	641 urban areas (pop. ≥ 1000) in eastern and western Canada
McKenney and Pedlar 2012	Tree removal	City foresters and tree removal companies in study area	CAD $16 - $20/cm DBH[3] (USD $16.78 - $20.97)	N/A	Canada
Sadof 2017	Tree removal and stump grinding	City of Indianapolis, IN 2014	$14.00 - $36.00/cm DBH[4]	N/A	Indianapolis, IN
Sydnor et al. 2011	Tree removal – stump removal dep. on site: street and private yes, park no	Based on survey responses of commercial arborists	$413/tree private or street $331/tree park	N/A	Four-state area, including IL, IN, MI, WI
Sydnor et al. 2007	Tree removal (stump removal dep. on site: street and private yes, park no)	Based on survey responses of commercial arborists	$675/tree private or street $600/tree park	N/A	State of Ohio
VanNatta 2012	Tree removal	Based on MacPherson 2005, which includes removal and disposal	$10/in DBH	Included in removal estimate	University of Wisconsin, Stevens Point campus
EAB Cost calculators					
Hauer 2012 EAB Planning Simulator (EAB-PLANS)	Tree removal	User specified	User specified	Does not include functionality to specify wood waste disposal	
Sadof 2016 EAB Cost Calculator	Tree removal	User specified	User specified	Does not include functionality to specify wood waste disposal	Model assumptions validated using EAB experience from cities in Indiana

[1] A value of N/A indicates disposal costs were not specified, so it is unclear whether they are included in the cost of removal and/or replacement.
[2] Estimates for trees 2.5 cm to >61 cm DBH.
[3] Estimates for trees <20 cm to >40 cm DBH.
[4] Estimates for trees 3 to >91 cm DBH.

2.3 The ambiguous origins of biomass equations

A large body of literature exists for development and use of tree allometric and biomass equations. Most U.S.-derived information for calculating wood volume and biomass relies on literature-based volume tables and specific gravity measurements developed decades ago, primarily for forests in eastern or Midwestern states (e.g., the publication by Clark et al. (1985) for the Gulf and Atlantic coastal plains is the green ash reference used by Jenkins et al., 2003, which is in turn used by the FIA Program for green ash across the U.S.). Newer references for wood characteristics simply aggregate a wide array of published values and report them in a compendium (e.g., Alden, 1995; Miles and Smith, 2009). Likewise, biomass and volume equations may also be aggregated for a single or for multiple species (e.g., Ter-Mikaelian and Korzukhin, 1997), leaving the practitioner unsure which to use for a given purpose.

More place-based research is needed to support studies of climate change impact and worsening disturbances causing widespread tree mortality. Many newer studies are forced to rely on unsuitable equations due to the lack of more appropriate alternatives (McPherson et al., 2005). Uncertainty around the origin of equations, including the conditions under which they were developed, can lead to unintentional misuse of the equations and the opportunity for error propagation through time. Figure 2-1 and Figure 2-2 illustrate the origin of the equations used in the current study.

2.3.1 Sources of uncertainty and error in biomass equation development

The process of creating biomass and allometric equations unavoidably includes many sources of error. The main sources of error are sampling design, measurements in the field, and model development. The uncertainties associated with each are compounded throughout the biomass equation development process. Individual biomass studies often have limited sampling areas due to the challenging logistics required to sample even a

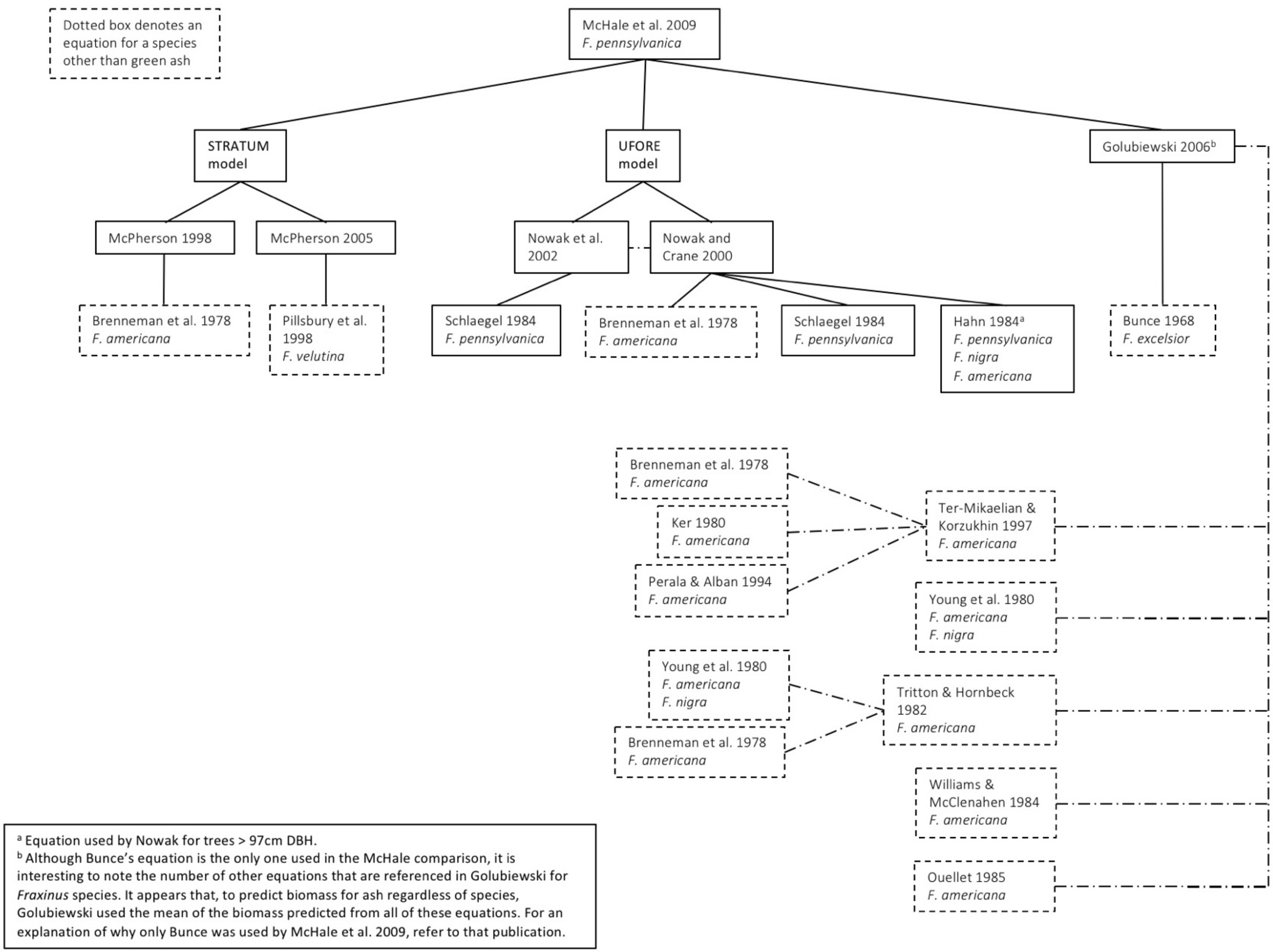
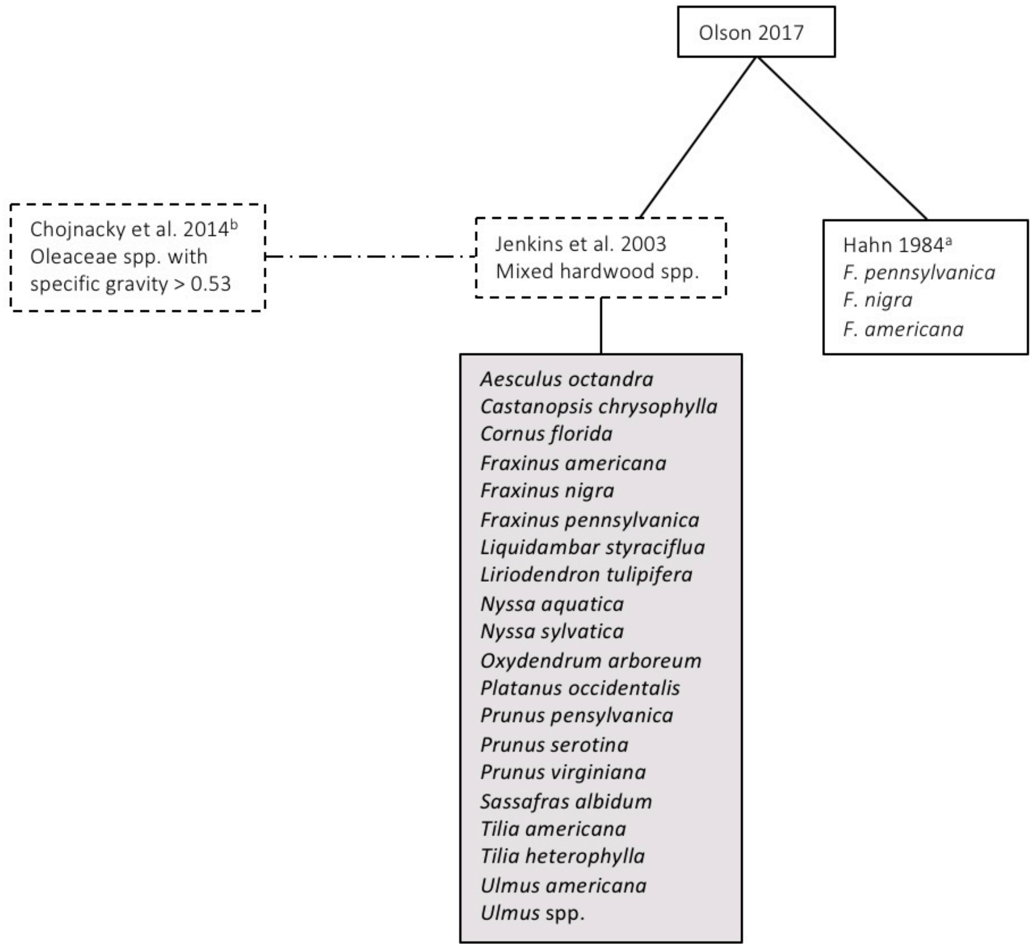


Figure 2-1 Biomass equations used to estimate green ash (*F. pennsylvanica*) and assessed by McHale et al. (2009) along with their origins.



[a] Hahn uses a component ratio method for which volume of different components is estimated from specific measurements of each component and transformed to biomass. Biomass of components are then summed to attain a whole-tree biomass estimate. We did not take the measurements necessary to make a direct comparison to the Hahn equation, so this equation was not included in our analysis.
[b] Chojnacky et al. 2014 provided an updated set of generalized biomass equations to those developed by Jenkins et al. 2003. This equation was not included in Olson's study, but we included it in our comparisons as it was meant to provide a more accurate prediction compared to the older Jenkins et al. equation.

Figure 2-2 Biomass equations used to estimate green ash (*F. pennsylvanica*) and assessed by Olson (2017) along with their origins.

small number of trees, and it is questionable whether samples used in many biomass studies are truly random (Chave et al., 2004; Clark and Kellner, 2012; Paul et al., 2016; Temesgen et al., 2015). Samples may represent individuals taken from a single stand, or a small number of stands, or from an area that is easily accessible. In some cases, trees are weighed opportunistically when they are removed for reasons other than for research purposes (Lopez-Lopez, 2017; Olson, 2017). Trees of varying sizes, ages, and conditions are rarely represented in a single sample (McPherson et al., 2016). Small and large trees are often underrepresented (Chave et al., 2014), and there are idiosyncrasies associated with each: the amount of variance increases with tree size, and small trees are often inaccurately estimated with biomass equations because tree form changes during ontogeny (MacFarlane, 2015; Troxel et al., 2013). To provide an accurate representation of "average" trees, some datasets include only trees with full healthy crowns, leaving trees with less-than-perfect crowns underrepresented (Paul et al., 2016). These factors create uncertainty in model parameters (Temesgen et al., 2015).

There is no standard protocol for obtaining field measurements of destructively sampled trees (Weiskittel et al., 2015). Different weighing instruments are used, each having varying accuracy. Trees may be weighed using hanging scales, ground scales, or whole trees may be placed in a truck which is driven over a truck scale. Similarly, height measurements may be taken with a plummet, clinometer, a Biltmore stick (sighting), or other methods. Sometimes methods differ within a single study (Blood et al., 2015; Pretzsch et al., 2015). There are measurement errors associated with laboratory techniques used to determine moisture content and specific gravity. In addition, moisture content and specific gravity values are commonly based on a small number of samples for practical reasons (Paul et al., 2017). This is problematic because moisture content and specific gravity values greatly influence biomass estimation, and each varies throughout the tree (Mate, et al., 2014; Paul et al., 2016, Weimann and Williamson, 2012).

There is a tradeoff between simple model forms using easy-to-measure variables and including more measurements that may improve model performance. Height is often considered an important characteristic to include in biomass predictive equations (Chave et al., 2005; Duncanson et al., 2015). However, there is more measurement error associated with height than with DBH (Chave, et al., 2004; Ducey, 2012). Error in height measurements is introduced when personnel are unfamiliar with measuring equipment (Kim, 2016) or simply because measurements are not taken correctly (Arias-Rodil et al., 2017). The error associated with taking certain measurements can outweigh the predictive accuracy achieved by including them (Temesgen et al., 2015; Weiskittel et al., 2015).

Lastly, there is a considerable amount of error introduced when developing biomass estimation models. Chave et al. (2004) found the most important source of error in biomass estimation comes from model selection. A thorough exploration of the data should be performed, and model diagnostics consulted rather than relying solely on mechanical model selection processes or model dredging (Sileshi, 2014). While these processes select the most parsimonious form of the model based on specified criteria, such as AIC, these processes rely on the correct form of the full model being included in the selection process to begin with.

The combination of these sources of uncertainty can result in grossly erroneous biomass estimations. Sileshi (2014), Temesgen et al. (2015), and Weiskittel et al. (2015) provide comprehensive summaries of error propagation in biomass equation development.

2.3.2 Local, regional and species-specific equations

Many datasets used to develop biomass equations from harvested trees represent few individuals of a single species or a limited number of species. It is widely recognized that species-specific, locally developed equations provide the most accurate biomass estimates (Basuki et al., 2009; Ngomanda et al., 2014).

Oftentimes, bias occurs when published equations are applied to areas outside of those for which they were developed. Timilsina et al. (2017) found the widely used i-Tree Eco model (i-Tree Eco v6.0, www.itreetools.org) developed by the U.S. Forest Service, and based on trees sampled in Chicago, Illinois by Nowak (1996), overpredicted leaf area of trees in Stevens Point, Wisconsin by 106%–115%. Similarly, Boukili et al. (2017) found that the i-Tree Streets model and the newer U.S. Urban Tree Database (UTD) (McPherson et al., 2016) equations overpredicted carbon sequestration estimates in Cambridge, Massachusetts when compared to empirical measurements combined with the UTD equations. McHale et al. (2009) found that the predictive capability of the published equations they evaluated was inconsistent, and that depending on the equation source and the species to which the equation was applied, published equations underpredicted biomass by up to 76% and overpredicted by as much as 205%. The authors stated that some of the equations had been applied to trees outside of the diameter range for which they were developed, demonstrating that predictive equations become unreliable when applied to trees outside of the ranges for which they were developed (McHale et al., 2009).

There is evidence that biomass equations are highly location specific and it may not be appropriate to apply the same model across areas that aren't relatively close in proximity or similar in character to those for which they were developed. Escobedo et al. (2012) found that trees sampled in two subtropical forests in Florida yielded different carbon storage estimates. Pillsbury et al. (1998) found that no one predictive equation developed for each of seven sites across the range of a single species *(Lithocarpus densiflorus*) in the western U.S. accurately predicted biomass at the other sites. These examples demonstrate the need to use caution even when applying intraspecific equations to relatively small geographic areas.

2.3.3 Generalized, mixed species equations

Destructively sampling trees and developing species-specific, local equations is time consuming, labor intensive, and in many cases infeasible, especially if the trees to be measured must represent the average tree form (i.e., healthy trees with full crowns). General equations have been proposed by researchers attempting to balance accuracy of biomass estimates with the need to obtain suitable estimates within operational constraints. Now that more datasets are publicly available, researchers have avoided the issue of small sample sizes by fitting new equations to multiple datasets. In this way, many individual trees representing one species are used to expand the size range and area represented by the equations.

Jenkins et al. (2003) developed a series of 10 national-scale regression equations intended to provide consistent biomass predictions for all tree species found in the U.S. Jenkins et al. (2003) used a "modified meta-analysis" method after Pastor et al. (1984), which uses predictions (referred to as "pseudodata" by Pastor and others) from all discoverable published equations to refit new regression equations. Jenkins et al. (2003) grouped species according to taxonomic relatedness and similarities in specific gravity, then fit equations for each of these groups. Based on these groupings, green ash was placed in a general "mixed hardwood" category representing 289 data points from trees of 13 genera and over 20 species. This grouping contained plants ranging in form from small, multi-stemmed ornamental trees to large-maturing shade trees. Specific gravity values within this grouping ranged from 0.32 to 0.64. Pseudodata generated from 40 published equations were used to create new regression coefficients relating biomass to diameter at breast height. To extend the accuracy of the Jenkins et al. (2003) equations, Chojnacky et al.

(2014) provided a set of updated generalized biomass equations using refined taxonomical groupings that attempted to place individuals within family groupings. The authors further subdivided family groupings with wide ranges in specific gravity.

Generalized, mixed-species equations were not necessarily intended to replace species-specific biomass equations for smaller-scale biomass estimation; however, MacFarlane (2015) found generalized multi-species models based on an individual components method applied at the stand level produced estimates that were as good as, or better than, species-specific models due to intraspecific variability in tree form at a local level, especially when a small number of trees are included in a sample. Paul et al. (2016) found generalized multi-species biomass equations created for Australian forests representing a wide range of ecotypes predicted stand-level biomass with an accuracy of 99%.

In contrast, subsequent studies found that wide-scale generalized biomass equations produced biased estimates when applied at a finer scale. Zhou and Hemstrom (2009) used the Jenkins et al. (2003) equations to provide regional estimates of major softwood species in Oregon. This resulted in overpredictions of aboveground biomass by 17%. According to Zhou and Hemstrom (2009), local and regional equations are more appropriate when the goal is to obtain accurate biomass predictions at smaller scales in forests dominated by a few species. The authors recommended against using generalized wide-scale biomass equations without understanding the implications of doing so.

The national-scale models may produce biased biomass estimates even at the scale for which they were intended. A recent study by Domke et al. (2012) found that the Jenkins et al. (2003) national-scale biomass equations overpredicted biomass, and thus carbon, on a national scale when compared to the newer components ratio method (CRM; Heath et al., 2009; Woodall et al., 2011) employed by the U.S. Forest Service FIA program. The authors compared biomass estimates between the two methods for 20 of the most common tree species in the U.S. and found that the CRM provided estimates of national-scale biomass that were 16% lower than those produced using the Jenkins et al. (2003) approach. Ironically, the authors attribute this reduction in estimated biomass to adding tree height into equations as a measurement variable. Jenkins et al. (2003) decided to exclude all equations that used height as variable in favor of DBH-only equations so they would be more accessible for practitioners.

Other studies have found that wide-scale generalized equations can perform accurately. Fayolle et al. (2013) found pan-tropical moist forest generalized multi-species equations developed by Chave et al. (2005) produced accurate predictions when applied to regions in central Africa, illustrating the range to which generalized equations may be extended. Fayolle et al. (2013) point out the importance of this finding given the magnitude of forestland requiring biomass estimation in central Africa and the absence of local equations. Thus, generalized equations have a place where local equation development is not feasible due to limitations of resource availability, scale, or timeframe in which estimations must be done. However, these equations should be used with caution when accurate estimations of biomass are critical since it would be necessary to carry out national-scale mensuration campaigns to truly know the extent of bias associated with wide-scale mixed-species equations (Jenkins et al., 2003).

2.3.4 Other methods of indirect tree biomass measurement

Allometric scaling theory

To create the most accurate predictive biomass equations, trees must be destructively sampled; that is, they must be cut down, meticulously measured, and weighed. The labor and cost involved in this endeavor commonly leads researchers to pursue non-destructive sampling methods acknowledged as less accurate, but more practicable (Ketterings et al. 2001, Pearson et al. 2007, McHale et al. 2009, Ngomanda et al. 2014). Equations based on various allometric scaling theories, first described by Huxley and Tessier (1936), have led to several attempts to create an idealistic representation of tree form, invariant across species, environment, age or location, thus eliminating the need to destructively sample trees (Pilli et al., 2006). These include Metabolic Scaling Theory (MST), and the Geometric Similarity and Stress Similarity models. Each theory attempts to explain archetypical growth based on physical constraints, such as the tree's ability to effectively transport water throughout, or mechanically support the entire organism (Enquist, et al., 2009; West, 1999).

Attempts by subsequent studies to substantiate these models have shown that tree form does not follow universal scaling rules when architecture is affected by environmental conditions (Feldpausch et al., 2011; Lines et al., 2012; Lopez-Serrano et al., 2005; Motallebi and Kangur, 2016), competition (Forrester et al., 2017; Poorter et al., 2003), disturbance (Moncrieff et al., 2011; Tredennick et al., 2013), or in cases where a tree's canopy is altered by management activities such as pruning (Peper et al., 2001; Rust, 2014). By definition, allometry relies upon stable scaling relationships; therefore, scaling laws do not adequately describe trees whose forms are altered by adverse growing conditions, pruning, insect damage, or mechanical damage.

Remote sensing of biomass

Remote sensing techniques are increasingly used to create biomass estimates. Terrestrial laser scanning has been used to produce biomass estimates of individual trees in lieu of costly destructive sampling techniques (McHale et al., 2009; Lefsky and McHale, 2008; Stovall et al., 2017). Larger scale estimation is accomplished via airborne LiDAR scanning or satellite imagery (Lefsky et al., 2005; Muukkonen, 2007; Ploton et al., 2012). Direct measurements of individual trees obtained in the field using measuring poles and diameter tapes are still more accurate than remote sensing methods (Dassot et al., 2010; Dittmann et al., 2017; Weaver et al., 2015; West, 2009) because errors in sampling, measurement, and model selection are combined with errors associated with the remote sensing equipment used (Clark and Kellner, 2012). For instance, Vastaranta et al. (2009) found laser-based measurements of height and DBH varied widely depending on the equipment used. However, the authors determined that errors for some methods were within "acceptable limits" given traditional measurement instruments (such as calipers in the case of DBH) had similar error rates.

Remote sensing is prone to the same sources of error as biomass indirectly estimated with allometric techniques because direct measurements needed to calibrate these methods are also error-prone. Further, there are additional sources of error inherent to remote sensing equipment. While remote sensing may not produce estimates as accurate as other indirect allometric techniques or destructive sampling, the technology is evolving quickly, and these methods have the advantage of being able to achieve biomass estimates over large areas that are otherwise impractical, and in a short amount of time without the need for removing and weighing trees (Stovall et al., 2017).

2.4 The lack of urban, species-specific biomass equations

The problem of scale and unrepresentative datasets is compounded in the case of urban-based biomass equations. This is a comparatively new area of interest with relatively few extant urban-specific studies. This paucity underscores the need for urban-based equations, since there are many well-documented differences between open-grown trees and those grown in natural forests (McPherson and Peper, 2012; McPherson et al., 2016; Zhou et al. 2015).

Urban trees are often open-grown and intensively managed. Management regimes with different pruning, supplemental irrigation and fertilization, and tree placement approaches result in trees with architecture varying widely from one location to another and differing from the "average" form of a forest conspecific (McHale et al., 2009; McHale and Lefsky, 2008; McPherson et al., 2016, Peper et al., 2014; Quigley, 2004). Though there is an amount of genetic control exerted over tree form, tree growth habit, and thus biomass allocation, are plastic and are strongly influenced by growing conditions (MacFarlane, 2015; Pretzsch and Dieler, 2012). Urban trees are often not native to the area—and thus climate—in which they are planted. This, along with a host of various anthropogenic stressors found in urban environments such as compacted soils, planting sites that offer limited rooting space, impervious surfaces leading to increased temperatures and reduced soil water, pollutants and contaminants, and insufficient irrigation, all influence tree growth, often in the form of a decrease (Jim, 1998; Quigley, 2004). Each of these factors can produce differences in growth within and across sites (Blood et al., 2016; McPherson and Peper, 2012).

As noted in section 2.2.1 (Figure 2-1 and Figure 2-2), it is often difficult to determine the provenance of published equations. Equations used for urban areas are typically based on those developed for natural forests in areas with different growing conditions from the locations in which the equations are applied. When an equation is used in an urban study it is often reused by subsequent urban studies, and the original source of the now "urban" equation becomes unclear. Authors self-cite, further obfuscating the origin of an equation (e.g., Nowak et al., 2013). Equations used for green ash are often equations developed for other species of ash (Brenneman, 1978; Bunce, 1968; Pillsbury et al., 1998), or are generalized equations applied to a large group of related or unrelated species (Jenkins et al., 2003; Chojnacky et al., 2014). Unintended misuse of forest-derived equations occurs when forest equations are applied to urban areas without understanding their provenance.

If an equation is cited in an "urban" study, this equation is often reused in studies in other urban areas, resulting in error propagation over time.

To account for differences between urban trees and those growing in forested areas, published correction factors have been proposed and are intended to be used in conjunction with forest-derived equations for open grown trees. One such correction factor from a study by Nowak (1994) found forest-derived equations overpredicted urban tree biomass by 20%. Nowak (1994) proposed that biomass estimates from forest-derived equations be multiplied by 0.80 in all urban areas to reflect this difference. This correction has often been used without regard to the potential differences in tree biomass based on factors such as regional climactic, site, and management differences mentioned previously (e.g., McPherson, 1998; Nowak and Crane, 2001; Nowak et al., 2008; Strohbach and Haase, 2012; Yang et al., 2005; Zhao et al., 2010). A different correction suggested by Zhou et al. (2011) states that biomass estimations for open-grown trees be multiplied by a correction factor of 1.2. This 20% upward correction in biomass directly contradicts Nowak's suggested use of a 20% decrease. While the trees in both cases are pruned and grown in open conditions, the difference highlights that such corrections cannot be applied generally or without scrutiny and reinforces the need for a greater understanding of factors contributing to variations in urban tree growth across locations.

In an attempt to address these matters, the U.S. Forest Service Pacific Southwest Research Station recently introduced their Urban Tree Database and Allometric Equations (McPherson et al., 2016). Though this resource provides numerous equations for the most widely grown tree species in the 17 cities covered by the study, the authors stress the need to continue improving the accuracy of urban biomass equations by obtaining data for more regions across the country.

3. GREEN ASH (*FRAXINUS PENNSYLVANICA* MARSH.) BIOMASS EQUATIONS FOR URBAN TREES REMOVED IN RESPONSE TO THE EMERALD ASH BORER (*AGRILUS PLANIPENNIS* FAIRMAIRE)

3.1 Introduction

Since the arrival of the emerald ash borer (*Agrilus planipennis* Fairmaire) in the United States in 2002 (Haack et al., 2002; Cappaert et al., 2005; Poland and McCullough, 2006), urban forest managers have been faced with an unprecedented challenge. Emerald ash borer (EAB), labeled as the most destructive forest pest in United States history (Herms and McCullough, 2014), has caused the death of hundreds of millions of ash trees (*Fraxinus* spp.) in the 34 U.S. states in which it has been detected. Since eradication of EAB is infeasible due to the difficulty of detection (Herms and McCullough, 2014; Knight et al., 2014; McCullough et al., 2009), most emerald ash borer management programs aim to slow the spread of the insect to give urban forest managers time to respond (Fahrner et al., 2017; McCullough and Mercader, 2012).

Costs for treating and removing trees is expected to reach USD $10.5 billion by the year 2019 (Sydnor et al., 2009). However, the cost estimates for EAB management activities presented by Sydnor et al. (2009), Kovacs et al. (2010; 2011), Hauer and Petersen (2017), Sadof et al. (2017) and others do not include wood disposal costs, or combine disposal costs with those for other management activities. Costs can be expensive at the local scale; for example, between March, 2015 and April, 2016, wood disposal costs for the City of Boulder's Forestry Division related to EAB and a winter kill event primarily affecting Siberian elm (*Ulmus pumila*) trees were approximately USD $35,000 (Kathleen Alexander, pers. comm.).

Urban wood disposal is an ongoing problem in U.S. cities. In 2014, yard trimmings and wood accounted for 7.9% and 8.1% respectively of the 136 million tons of total landfilled municipal solid waste (EPA, 2016). Nash (2009, unpublished thesis) estimated that 128,292 tons of urban forest residues were generated in the Tri-City Area of the Northern Front Range annually, an area including the cities of Fort Collins, Loveland and Greeley. Of this, the study found that approximately 40 percent of the material was disposed of in landfills while the remaining fraction was taken to wood recycling facilities to be turned into mulch, compost, or firewood.

The Colorado State Forest Service developed a statewide inventory tool, CO-Tree View (https://cotreeview.com, n.d.), to assist Colorado municipalities in creating accurate ash tree inventories as the first step in creating an EAB management plan. The software includes an EAB cost calculator which currently allows urban forest managers to estimate planned treatment, removal, and replacement costs for ash trees. It does not include a way to predict costs of ash wood disposal. There is a need for an accurate method to predict and budget for wood disposal costs as part of a comprehensive emerald ash borer management plan (Colorado Emerald Ash Borer Response Team, 2015).

Part of the difficulty in making such predictions is that biomass equations are regionally specific. Environmental factors and site conditions affect tree growth, leading to intraspecific differences in allometric relationships, thereby decreasing prediction accuracy when equations are applied to areas for which they were not developed (Duncanson et al., 2015; Hulshof et al., 2015, Urban et al., 2010). For instance, Forrester, et al. (2017) and Hulshof et al. (2015) found that trees growing in cold, arid environments and whose climates experienced high seasonal variability were shorter than those growing in areas experiencing less extreme environmental conditions. These conditions are similar to those found along Colorado's Northern Front Range.

In using existing forest and urban equations to predict biomass of urban green ash trees in Fort Collins, Colorado, McHale et al. (2009) found that biomass predictions from these equations ranged from a 27% overprediction to a 96% underprediction of total aboveground woody biomass woody biomass when compared to detailed tree measurements taken with ground-based LiDAR. Furthermore, Blood et al. (2016) found that models were location-specific, and that models developed for one location may not provide accurate predictions when applied to another location in the same climactic zone or region. McPherson and Peper (2012) found that green ash growing in Cheyenne, Wyoming were consistently smaller than same-aged trees in nearby Fort Collins, Colorado, likely due to Cheyenne's harsher climate and poorer soil conditions.

Current green ash aboveground woody biomass (AGB) predictive equations have largely been developed for areas in the eastern and Midwestern states, or Canada (e.g. Bunce, 1968; Peper et al., 2014; Schlaegel, 1984). Furthermore, most have been developed for trees growing in natural forests, not urban areas. Due to the unique and varied growing conditions of urban trees versus those growing in natural forests, and the climactic differences between Colorado's Front Range versus the Midwest and eastern United States, it is uncertain whether these equations provide adequate predictions of biomass for green ash growing in Colorado's urban areas.

The study conducted in Fort Collins, Colorado by McHale et al. (2009) provided volume equations for ten urban street tree species, including green ash. Measurements of individual trees were obtained using ground-scanning LiDAR as part of a carbon storage analysis of urban trees in Fort Collins, Colorado. These equations were not validated using destructively sampled trees. Although removing and directly weighing trees remains the most accurate measure of tree biomass (McHale et al., 2009; Nelson et al., 1999; Nogueira et al., 2008), researchers commonly use non-destructive sampling methods to estimate biomass due to prohibitive cost and labor requirements.

Furthermore, specific gravity is another important attribute influencing mechanical and physical properties of wood, such as the quality of wood used for solid sawn products, paper and pulp, and wood energy applications (Shmulsky and Jones, 2011; Zobel and van Buijtenen, 1989). Specific gravity values may be converted to density values, which can then be used in volume-to-mass calculations whereby a known volume is multiplied by a known density to produce a mass. These calculations are widely used for estimating biomass for individual trees as well as on varying spatial scales from single stands to entire landscapes. Specific gravity values for urban trees are largely absent from the literature (McHale et al., 2009). Values from sources such as Alden (1995) and Miles and Smith (2009) have long been the standard for green ash and other tree species in the United States, but as is the case with the aforementioned biomass equations, these measurements were primarily taken from natural forests in areas whose climates differ greatly from Colorado's. Specific gravity is influenced by climate, growing conditions, and management regimes (Whitmore 1973; Wiemann and Williamson 1989; Wiemann and Williamson 2007), and differs between forest-grown and open-grown trees (Zhou et al., 2011); therefore, published values may not accurately represent wood specific gravity of green ash trees growing in Colorado's Northern Front Range cities.

The objectives of this study were to determine: 1) whether locally developed, species-specific biomass equations outperform equations developed for areas outside of Colorado's Northern Front Range; 2) the best predictive equation for above-ground woody biomass of green ash trees for emerald ash borer management activities in urban areas of Colorado's Northern Front Range; and 3) whether the average wood specific gravity and moisture content of urban ash trees along Colorado's Northern Front Range differed from published values. To accomplish the first objective, predictive accuracy of existing published equations, including an equation developed for Fort Collins, Colorado, was evaluated using pairwise multiple comparisons with repeated measures. To accomplish the second objective, locally-derived equations for Colorado's Northern Front Range were developed and compared to existing biomass equations that have been used for urban green ash biomass prediction. Published specific gravity and moisture content values were compared to locally-derived values for Colorado's Northern Front Range to accomplish the third objective. Identifying biomass equations and specific gravity and average moisture values suitable for green ash along Colorado's Northern Front Range will allow resource managers engaged in EAB wood disposal efforts and urban forest mensuration initiatives to more accurately estimate green ash biomass.

3.2 Methods

3.2.1 Study area

For this study, 42 green ash trees were destructively sampled at 11 sites in publicly-managed parks, rights-of-way, and municipal open spaces in five cities along Colorado's Northern Front Range Urban Corridor (Chronic and Chronic, 1974): Fort Collins, Loveland, Longmont, Boulder and Broomfield. Location attributes can be found in Table 3-1.

Table 3-1 Northern Front Range cities from which green ash trees were destructively sampled during this study.

City	Collection Site(s)	City Latitude, Longitude	No. of trees	Site Description
Fort Collins	North Meldrum Street	40.59219, -105.08246	3	Irrigated public right-of-way
Loveland	Westside Park	40.395, -105.08314	1	Public park, irrigated turf
	Centennial Park		1	Public park, irrigated turf
	Winona Outdoor Pool		1	Public park, irrigated turf
Longmont	Izaak Walton Park	40.16175, -105.11895	7	Public park, irrigated turf
	Boulder County Fairgrounds		7	Fairgrounds, irrigated turf
	AHI Property Open Space		8	Non-irrigated property boundary
Boulder	University of Colorado, Boulder Campus	40.00758, -105.26594	4	Irrigated turf
Broomfield	Community Center	39.92041, -105.06875	4	Irrigated parking lot island
	City and County Building		5	Irrigated parking lot island
	The Bay Aquatic Park		1	Irrigated parking lot island

3.2.2 Field measurements

Trees were measured, removed, and weighed after leaf-drop during the early spring of 2016, and the fall of 2016 through the winter of 2017. Foliage biomass was not included given the goal of the study was to determine aboveground woody biomass (AGB) on both a green and oven-dry basis. The destructively sampled trees had been designated for removal prior to the study as part of planned efforts to reduce the number of ash trees at risk from EAB. Removal locations were in cities willing to provide trees, staff, and equipment required for destructive sampling.

Measurements included diameter at breast height (DBH) measured in cm at 1.3 m from the base of the tree, total tree height (m), and height to the first live branch (m). Percent canopy thinning was recorded using the ash canopy thinning scale created for emerald ash borer-infested ash trees in Michigan by Smitley et al. (2008). Additional data collected included whether or not the tree was infested with EAB as evidenced by the presence of larval feeding galleries or larvae, whether the tree was dead, and whether the tree was multi-stemmed (defined as having two or more leaders starting below diameter at breast height). Summary statistics for the trees sampled for this study are presented in Table 3-2.

Table 3-2 Summary statistics for trees destructively sampled for this study. Numbers in parentheses represent the standard deviation of each measurement.

	DBH (cm)	Branching Ht. (m)	Tree Ht. (m)	% Crown Dieback	Total Green Wt. (kg)
Range	7.6 - 66.0	0.63 - 6.40	2.79 - 20.12	0 - 100	7.26 - 3276.30
Mean	33.9 (8.5)	2.28 (1.11)	10.0 (4.03)	22.41 (31.53)	1051.25 (1028.27)
s^2	352.08	1.26	16.68	1029.68	1083132.21

Twigs and branches less than 10.16 cm (4 in) in diameter were processed in a chipper. Chips were blown directly into Flexible Intermediate Bulk Containers (FIBCs) attached to the spout of a drum-style wood chipper. Each FBIC was weighed on a low-profile floor scale (Uline model H-754, 2267.96 kg (5000 lb) x 0.453592 kg (1 lb)). The FBICs were of known weight, and the weight of the container was subtracted from each FBIC of chips weighed to obtain biomass of twigs and branches < 10.16 cm. A representative sample of chips per tree were collected from the FBICs at different points during the chipping process for later laboratory processing to determine moisture content (MC). Each sample bag was given a unique identifier associating it with a specific tree. Larger woody material was broken down into two size classes, and each was weighed separately: branches 10.16 cm (4 in) in diameter up to 25.4 cm (10 in) in diameter, and logs 25.4 cm or greater in diameter. Branches and logs were weighed whole when feasible; if they were too large to rest on the scale they were sectioned, and the weight of the sections summed for a total branch or log biomass.

Wood cross sections were removed from the stump end of the main stem and top of one > 25.4 cm log of each tree to later be used in determining MC in the lab. Paul et al. (2017) demonstrated that, if it is not feasible for reasons of practicality to collect moisture samples from many locations throughout the tree, then collecting representative samples of the bole and crown to use in MC estimation best approximates whole-tree moisture. Moisture loss was mitigated by wrapping tree cross sections in plastic as soon as they were cut. Once the cross sections were relocated to the laboratory at the end of each field day, the bags were placed in large plastic tubs with tight-fitting lids to further prevent moisture loss until the samples could be processed.

3.2.3 Laboratory measurements

Whenever possible, sample processing in the laboratory was completed the day following sample collection to minimize changes in MC from the time the tree was felled to the time green wood measurements were taken.

Wood moisture content and specific gravity

Each cross section was de-barked and sawn into portions. All cuts were made through the pith of the cross section to capture differences in specific gravity from the cambium to the pith (Wiemann and Williamson, 1989; Woodcock and Shier, 2002; Williamson and Wiemann, 2010). Each was labeled with a unique identifier indicating whether the portion was from a cross section from the top or the bottom of the main stem, and the tree from which it was cut. Each cross-section portion was then weighed to obtain its green weight (g). After each portion was weighed, it was placed into a tub of water for at least 48 hours to ensure the cell walls exceeded fiber saturation point (FSP). FSP is defined as the point at which free water has been removed from cell lumina, but the cell walls are saturated. Above FSP point, the dimension of the wood does not change as a function of moisture content (Glass and Zelinka, 2010).

As outlined in American Society for Testing and Materials Standard D2395 Method B, Mode II, once each cross-section portion reached FSP, its green volume was measured using water displacement. The weight in grams of the water displaced when the specimen was fully submerged was used to represent the specimen's volume in cm^3. Specific gravity was measured on a green basis (basic specific gravity) using the equation:

$$SG_{Basic} = M_{OD} / (Vol_{Green} * \rho_{water})$$

where:

M_{OD} is the oven-dry weight of wood in g

Vol_{Green} is the green volume of wood in cm^3

ρ_{water} is the density of an equal volume of water in g/cm^3

After obtaining volume measurements, each cross-section portion was placed in an oven maintained at 105° C. Weight was checked periodically until it remained unchanged for at least three consecutive hours, at which time the portion was considered to have reached oven-dry status. Drying time ranged from 2 days for small samples to 4 days for large samples. Cross-section portions were then reweighed, and their weight recorded in grams. The moisture content as a percentage of the green weight of the cross-section pieces was calculated using the formula:

$$MC\% = 100 * (W_G - W_{OD}) / W_{OD}$$

where:

MC% is the moisture content of the wood expressed as a percentage

W_G is the green weight of the chips or cross section pieces (g)

W_{OD} is the oven-dry weight of the chips or cross section pieces (g)

Moisture content of chips

The green weight of a sample of chips taken from the FBICs representing twigs and small branch wood < 10.16 cm diameter for each tree were weighed (g). The chips were then placed in an oven at 105° C, and their weight was checked periodically until it remained unchanged for at least three consecutive hours, at which time the chip specimens were considered to have reached oven-dry status. Drying time took approximately 48 hours. The chips were then re-weighed and their weight recorded in grams. Moisture content of the chips was measured using the same method outlined previously for cross sections. The percent moisture content for the chips and two cross sections collected from each tree were used to obtain an estimate of the moisture content of the whole tree.

3.3 Statistical analysis

All statistical analyses were done using R Studio statistical software version 1.0.153 (R Studio Team, 2015). A significance level of $\alpha = 0.05$ was used for all statistical tests.

3.3.1 Evaluation of published green ash biomass equations

The Fort Collins, Colorado equation developed by McHale et al. (2009) and the equations identified as having been used in other urban biomass studies by McHale et al. (2009) were evaluated in this study (hereafter, the McHale equation). Some of the equations evaluated by McHale et al. (2009) had several forms (e.g. volume, oven-dry weight, green weight), and since it was not always clear which form of the equation was used, all forms of each literature equation evaluated by McHale et al. were included (hereafter, the

Brenneman equations, Bunce equations, Pillsbury equations, and Schlaegel equations). Another green ash biomass equation developed by Olson (2017) using destructively-sampled urban green ash in the Twin Cities Metro Area, Minnesota was evaluated (hereafter, the Olson equation), in addition to an equation developed by Jenkins et al. (2003) (hereafter, the Jenkins equation) since it was one of the underlying published equations assessed in that study.

An equation developed by Hahn (1984) evaluated in the Twin Cities study was not included in the comparisons of published green ash models for three reasons: 1) comparing models for which data collection methods were different introduces error into the comparisons (Sileshi, 2014); 2) it is unlikely that urban forest managers would routinely take the measurements specified by Hahn as part of their tree inventory process (cull percentage, volume of a 1-foot stump, etc.); and 3) if total tree mass is the measurement of interest, as was the case in the present study, a total mass equation may perform better than a components-based equation (McFarlane, 2015).

Lastly, because Olson evaluated the performance of the national scale biomass equation developed by Jenkins et al. (2003), the updated national scale biomass equation developed by Chojnacky et al. (2014) (hereafter, the Chojnacky equation), was also evaluated. Chojnacky et al. (2014) used finer-scale groupings than in the Jenkins et al. (2003) equations to improve estimates. A list of the equations evaluated in this study can be found in Table 3-3.

One-factor repeated measures using linear mixed-effects models (Pinheiro and Bates 2000) allow for comparison of the mean predicted weight (biomass) of each equation for each tree. In this way, published equation predictions of biomass were compared to measured green and measured oven-dry biomass. This methodology is common in the

Table 3-3 Green ash biomass equations evaluated in this study. All are for total aboveground woody biomass minus foliage.

Equation source	Species[1]	Equation	Quantity measured (Y)	Moisture basis[2]	a	b	c	*n*	DBH range (cm)
McHale et al., 2009	Green ash	tvol = a(DBH)^b	Volume (kg/m^3)	N/A	0.0005885	2.206	---	15	14.8-122.6
Brenneman, 1978	White ash	Y = a x^b	Biomass (lbs)	Oven-dry	4.1914	2.4309	---	15	5.1-50.8
			Biomass (lbs)	Green	2.3626	2.4798	---		
Bunce, 1968	European ash	$\log_e y = a + b (\log_e (DBH))$						15	
Meathop			Biomass (kg)	Oven-dry	-5.308133	2.488218	---		9.0-104.0
Roudsea			Biomass (kg)	Oven-dry	-5.386958	2.546645	---		9.5-57.5
Pillsbury, 1998	Modesto ash	V = a(DBH^b)	Volume (lbs/ft^3)	N/A	0.022227	2.633462	1.427822	50	14.5-84.8
		V = a(DBH^b)(Ht^c)	Volume (lbs/ft^3)		0.001287	1.762964			
Schlaegel, 1984	Green ash	ln(Y) = b0 + b1 ln(D^2*H)	Volume (lbs/ft^3)	N/A	-5.371	0.92436	---	70	2.3-77.7
			Biomass (lbs)	Green	-1.104	0.88814	---		
			Biomass (lbs)	Oven-dry	-1.759	0.91023	---		
		ln(Y) = b0 + b1 ln(D^2)	Volume (lbs/ft^3)	N/A	-2.644	1.17048	---		
			Biomass (lbs)	Green	1.518	1.12431	---		
			Biomass (lbs)	Oven-dry	0.935	1.1515	---		
Olson, 2017 (Jenkins refit)	Green ash	Bm = exp(b0 + b1 log(DBH))	Biomass (lbs)	Green	1.8865	2.2166	---	38	7.6-83.8
		Bm = exp(b0 + b1 log(DBH) + b2 log(ht))	Biomass (lbs)	Green	0.4693	1.8394	0.6316		
Jenkins et al., 2003	Mixed hardwood spp.	Bm = exp(b0 + b1 ln DBH)	Biomass (kg)	Oven-dry	-2.48	2.4835	---	148	2.54-27.69
Chojnacky et al., 2014	Oleaceae spp., specific gravity < 0.55	ln(biomass) = b0 + b1 ln(DBH)	Biomass (kg)	Oven-dry	-2.0314	2.3524	---	Unk.	3-42

[1]Species for which the published equation was developed.
[2]Moisture basis as indicated by author.

medical field for assessing agreement between instruments or methods (van Stralen et al., 2008). The lmer() function in R from the lme4 package (Bates et al., 2014) was used for Repeated measures analyses. Individual trees were treated as the "by-subject" random effect in order to account for individual tree variability, and measured biomass of each tree served as the fixed factor. Published equations served as the blocking variable (each tree's biomass was estimated using each of the 17 predictive equations). If there was no significant difference ($p > 0.05$) between a published equation's mean predicted biomass (PB) versus the mean measured biomass (MB), this indicated the two methods agreed (mean PB of the published equation was not significantly different from mean MB of the sample trees). RMSE and mean absolute deviation (MAD) were used to evaluate the predictive accuracy of these equations. MAD is calculated as:

$$\text{MAD} = \sum_{i=1}^{n} |\, measured\ biomass - predicted\ biomass \,| \,/\, n.$$

Volume equations were included in both green biomass and oven-dry biomass analyses since either green or oven-dry wood density values can be used for volume-to-mass conversions. Published density values for *F. pennsylvanica* wood from published sources as specified by the author of each published equation were used for volume-to-biomass conversions. In the case of the Pillsbury equations, no published source for density was given, so a density value from Miles and Smith (2009) was used.

Bland-Altman plots provide a graphical technique to clearly visualize the degree of agreement between methods (Bland and Altman, 1986), and were constructed to further evaluate consonance between MB and PB produced by published equations. The center dashed line on the plot represents the mean predicted biomass of the published equation. Top and bottom dashed lines represent ±2 standard deviations (SD). Dotted lines are the 95% confidence intervals for mean response and SD lines. Mean response lines that are near zero with points scattered relatively evenly about the mean and within two standard deviations indicates agreement between the mean observed green biomass values and the mean predicted published equation green biomass values.

3.3.2 Development of Northern Front Range green ash biomass equations

Northern Front Range biomass predictive models for green ash were developed on a green-wood basis and an oven-dry wood basis. The response variable of interest in this study was total tree biomass (kg) on either a green- or an oven-dry basis. Due to a small number of unique values relative to the sample size for each of these variables (in this case n<5,) the independent variables "infested" (n=4), "dead" (n=2), and "multi-stemmed" (n=1) were excluded from further analysis to avoid bias in regression coefficients, thus lowering model fit (Ogundimu et al., 2016; Royston and Saurbrei, 2008). The remaining independent variables were diameter at breast height ("DBH"), total tree height ("height"), height to the first live branch ("branching height"), and percent crown dieback ("dieback"). Biomass and DBH were transformed using the natural logarithm to correct for unequal variance. All possible models containing the remaining predictor variables DBH, height, branching height and dieback were evaluated, and a model based on lowest AICc for a small sample size (Akaike, 1973) was chosen for further evaluation. Diagnostic plots of the final model were assessed to ensure regression assumptions were satisfied.

Correction factor for a log transformation

It has been widely noted that back-transforming data from the log scale to the arithmetic scale introduces a downward bias to predicted values (Baskerville, 1972; Beauchamp and Olson, 1973, Clifford et al., 2013, Moscaro et al., 2013, Sprugel 1983); therefore, a correction factor was calculated for both the green and oven-dry predictive equations to account for this bias. The correction factor was calculated after Baskerville (1972), and has the form:

$CF = e^{(MSE/2)}$

where:

MSE is the mean square error of the regression.

3.4 Results

3.4.1 Performance of existing green ash biomass equations

Evaluation of published equations on a green wood basis

Measured biomass (MB) of the 42 destructively sampled trees was compared to predicted biomass (PB) of the green basis and volume (converted to green biomass using published wood density values) equations. Three green biomass and one volume equation produced PB values that were not significantly different from MB for the sample trees: both the Olson DBH and DBH-height equations, the Schlaegel DBH volume equation, and the Schlaegel DBH green biomass equation (Table 3-4). The Olson DBH-height (4% overprediction of MB) and the Schlaegel DBH green biomass equations (4% underprediction of MB) produced estimates of PB that were nearly identical; however, the Olson DBH-height equation had an RMSE seven times that of the Schlaegel green biomass DBH equation (RMSE = 448.7 and 64.3, respectively). This indicates the Schlaegel equation better predicts green ash tree biomass on a per-tree basis with fewer extreme over- or underpredictions. The Olson DBH-only equation was only marginally significant (t_{448} = -3.050, p = 0.0582). It overpredicted mean biomass by 26%, and therefore less accurately predicted mean MB than the Olson DBH-height (+4%), Schlaegel green biomass DBH (-4%), and Schlaegel volume DBH (+10%) equations (Table 3-4).

The local urban equation developed by McHale et al. (2009) for Fort Collins overpredicted biomass on a green wood basis by 47%. The greatest overprediction of

Table 3-4 Observed green and oven-dry biomass versus predictions from green and oven-dry published equations

Equation source	Difference from MB (kg)[a]	Standard deviation of the errors (kg)	Minimum and maximum relative prediction errors (kg)[b]	MAD (kg)[c]	RMSE (kg)	t	Holm-adjusted p-value[d]
Volume and green biomass published equations (*n = 42, SE of the differences = 88.76 and df = 451 for all tests)*							
Brenneman green	539.2	873.5	0.78-3.82	565.6	158.4	-6.074	<.0001
McHale	491.2	728.3	0.81-5.66	513.0	135.6	-5.534	<.0001
Olson-Jenkins refit DBH + height	45.0	446.4	0.59-4.09	262.2	448.7	-0.507	1.000
Olson-Jenkins refit DBH	270.7	561.3	0.69-4.75	342.0	623.2	-3.050	.0582
Pillsbury DBH + height	-360.0	526.0	0.25-1.24	392.9	98.4	4.056	.0018
Pillsbury DBH	-287.9	441.0	0.35-1.77	351.5	81.3	3.243	.0318
Schlaegel volume DBH + height	-499.01	561.7	0.22-1.28	566.8	115.9	5.622	<.0001
Schlaegel volume DBH	103.67	492.4	0.51-2.88	264.0	77.6	-1.170	1.000
Schlaegel green DBH + height	-555.2	604.0	0.23-1.57	555.4	126.7	6.255	<.0001
Schlaegel green DBH	-43.8	414.5	0.52-3.41	253.8	64.3	0.493	1.000
Volume and oven-dry published equations (*n = 42, SE of the differences = 63.13 and df = 533 for all tests)*							
Brenneman oven-dry	287.3	525.5	0.71-2.99	328.7	92.4	-4.551	.0003
Bunce – Meathop	111.7	380.3	0.59-2.49	211.2	396.3	-1.770	1.000
Bunce – Roudsea	320.7	576.3	0.72-3.14	358.1	659.5	-5.080	<.0001
Chojnacky	26.5	303.6	0.55-2.29	171.9	304.7	-0.419	1.000
Jenkins	79.1	356.4	0.56-2.39	196.2	365.1	-1.253	1.000
McHale	290.5	448.5	0.76-4.05	320.8	82.5	-4.602	.0003
Pillsbury DBH + height	-284.2	393.2	0.22-1.18	305.2	74.9	4.502	.0004
Pillsbury DBH	-235.4	303.6	0.33-1.53	266.5	59.3	3.730	.0085
Schlaegel volume DBH + height	-416.4	445.3	0.22-0.92	423.6	94.1	6.595	<.0001
Schlaegel volume DBH	-51.6	276.8	0.48-2.06	168.8	281.6	0.820	1.000
Schlaegel oven-dry DBH + height	-431.4	457.0	0.22-0.96	431.4	97.1	6.834	<.0001
Schlaegel oven-dry DBH	-89.5	270.8	0.47-2.14	169.6	285.2	1.417	1.000

[a]A positive value indicates the mean predicted biomass is more than the mean observed biomass, and a negative value indicates the mean predicted biomass is less than the mean observed biomass.

[b]Minimum and maximum relative prediction errors are a ratio of min(published equation predicted values:observed values) and max(published equation predicted values:observed values). This illustrates how much each published equation over- or underpredicted observed green or oven-dry biomass.

[c]Mean absolute deviation (MAD) is calculated as $\sum^{n}_{i=1}$ | measured biomass – predicted biomass | /n.

[d]P-values adjusted using the Holm method for multiple comparisons to control FWER may produce p-values = 1.

biomass was produced by the Brenneman green biomass equation (+52%). In their analysis of equations used to predict biomass of green ash trees, McHale et al. (2009) found that the Brenneman equation was the only equation that predicted within the 95% confidence interval compared to their observed biomass values. The results of the multiple comparison analysis found that the predictions produced by the McHale equation were not significantly different from the predictions produced by the Brenneman green biomass equation (difference in mean predicted green biomass = 48kg, $t_{41} = -1.90$, $p = 0.0623$). The Pillsbury DBH volume equation, the Pillsbury DBH-height volume equation, the Schlaegel DBH-height volume equation, and Schlaegel DBH-height green biomass equations underpredicted mean observed green biomass. McHale et al. (2009) reported the same result when the Pillsbury and Schlaegel equations were used for PB of green ash trees in Fort Collins, Colorado. The Schlaegel DBH-height volume equation produced the largest underprediction, predicting 53% less than the mean MB on a green wood basis.
Figure 3-1 provides Bland-Altman plots illustrating prediction trends for the published green basis biomass equations.

Evaluation of published equations on an oven-dry basis

Of the seven oven-dry biomass equations and five volume equations (converted to oven-dry biomass using published wood density values), five produced a PB value that was not significantly different from oven-dry MB of sample trees: the Bunce Meathop equation, the Chojnacky generalized equation for trees in the family Oleaceae with specific gravity <0.55, the Jenkins general hardwood equation, Schlaegel's DBH volume equation, and Schlaegel's DBH oven-dry biomass equation (Table 3-4). Schlaegel's DBH volume equation underpredicted MB by 7% and had the lowest MAD and RMSE values compared to the other published oven-dry biomass and volume equations (Table 3-4); however, prediction accuracy of the Bunce Meathop (15% overprediction), Schlaegel oven-dry biomass (12%

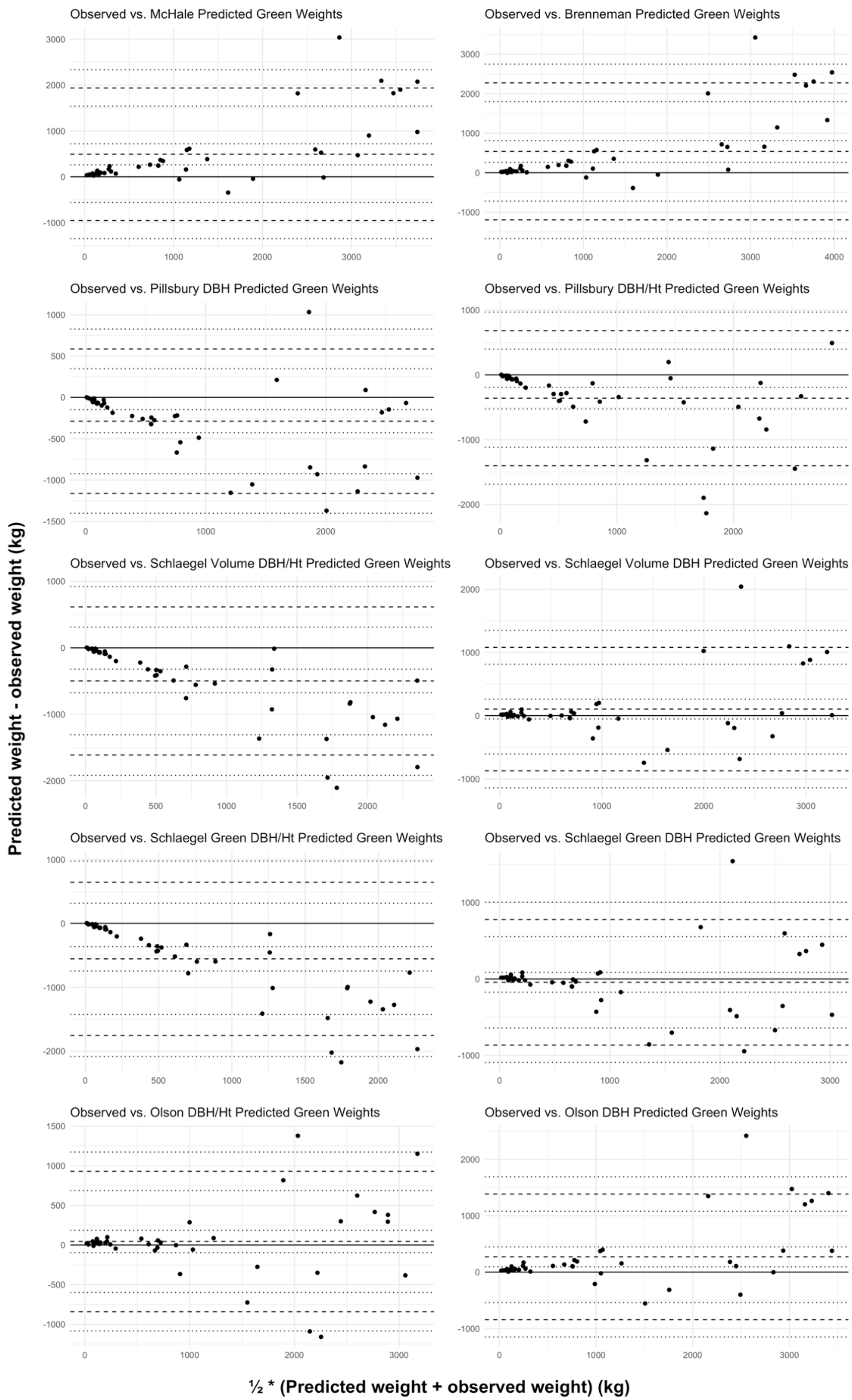


Figure 3-1 Bland-Altman plots comparing mean observed green biomass versus published equation green predicted biomass.

underprediction), Chojnacky (4% overprediction) and Jenkins (11% overprediction) generalized biomass equations was nearly identical to the Schlaegel DBH volume equation.

The Bunce Roudsea equation produced the largest overprediction of oven-dry MB (43%). The McHale urban volume and Brenneman oven-dry equations both overpredicted oven-dry MB by 38% for local green ash trees. The Pillsbury urban DBH-height volume equation and the Pillsbury urban DBH-only volume equation underpredicted MB by 38% and 32%, respectively. The Schlaegel DBH-height volume and oven-dry DBH-height equations underpredicted oven-dry MB by the largest amount (55% and 57%, respectively), and their predictive capability was nearly indistinguishable as indicated by mean difference in PB compared to MB, MAD, and RMSE (Table 3-4). Bland-Altman plots illustrating the prediction trends for each of the published oven-dry equations are presented in Figure 3-2.

Additional methods of comparison for published equations

APPENDIX A contains scatterplots illustrating the range of predictions obtained from each published equation compared to observed values for each of the 42 destructively sampled trees. Nowak (1994) proposed that a correction factor of 0.80 (20% reduction) be applied to biomass estimates when using forest-derived equations to estimate urban tree biomass based on a sample of 30 urban trees representing nine species in Oak Park, Illinois, U.S.A. Conversely, Zhou et al. (2011) recommend a correction factor of 1.2 be applied to biomass estimates when using forest-derived equations to estimate open-grown tree biomass based on a study in the Great Plains region of the U.S. Panel B of APPENDIX A, Figure 3-4 and Figure 3-5 demonstrate forest-derived equations produced both over- and underpredictions of urban tree biomass indicating such broad corrections may be unsupported. The box and whisker plots of the distribution of the errors between PB and MB in APPENDIX B further illustrate this fact. In addition, the box and whisker plots

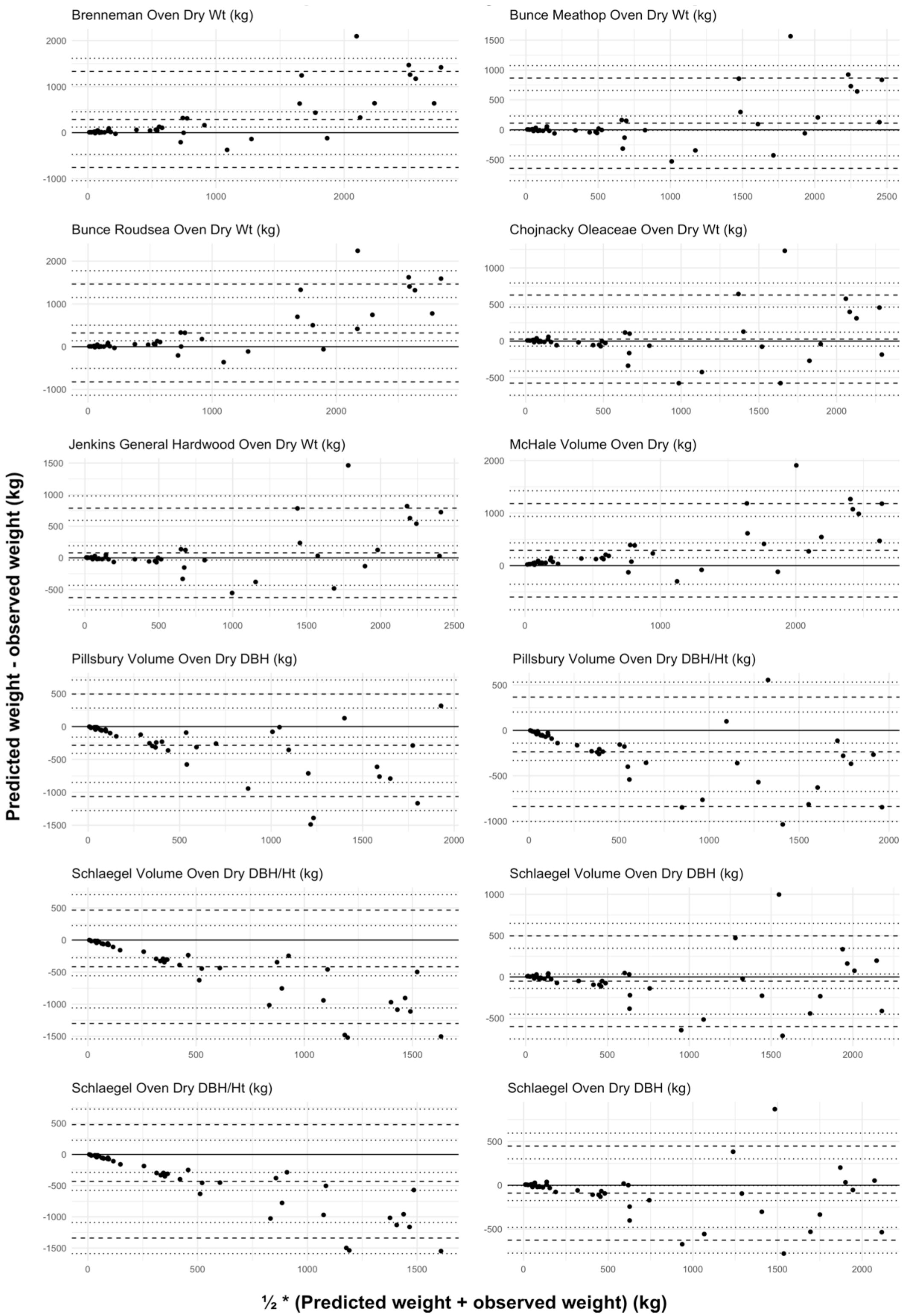


Figure 3-2 Bland-Altman plots comparing mean observed oven-dry biomass versus published equation oven-dry predicted biomass.

more clearly illustrate bias in the predictions produced by each equation, as well as overall accuracy of published equation predictions.

3.4.2 Locally-derived Northern Front Range green ash biomass equations

Green wood biomass equation

Model selection based on lowest AICc using ln(green biomass) as the response variable resulted in a model containing the predictors ln(DBH), branching height, and dieback (AICc= 12.57). The predictor ln(DBH) explained the greatest proportion of the variability in ln(green biomass) ($F1,25 = 646.92$, $p < 0.0001$). Additional steps were taken to explore a model containing only ln(DBH). Examination of a plot of residuals versus fitted values showed curvature in the residuals that indicated a higher order term was needed in the model. When compared to the model containing ln(DBH), branching height, and dieback ($R2 = 0.9766$, RMSE = 0.2440), the reduced second order polynomial model with ln(DBH) ($R^2 = 0.9744$, RMSE = 0.2516) resulted in a model with very similar fit to the full model. Therefore, using the quadratic form of the model containing predictors $\ln(DBH) + \ln(DBH)^2$ is recommended. The form of the final predictive oven-dry biomass equation, partial regression coefficients, RMSE, MAE, and R^2 values are displayed in Table 3-5. A graph showing the fitted regression line and the associated 95% confidence and prediction intervals is shown in Figure 3-3, panel A.

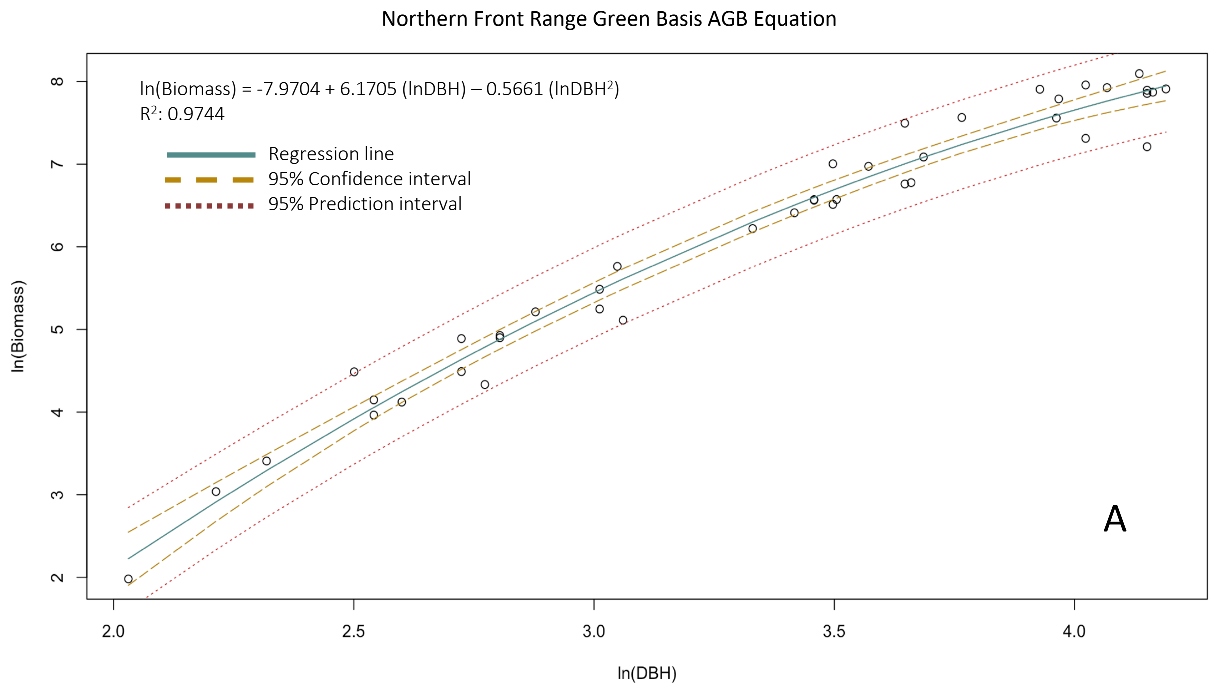
Table 3-5 Predictive equation developed for the Northern Front Range

Model[a]	Estimated coefficients[b] a	b	c	RMSE	MAD	R^2
Green basis model	-7.9704 [-10.41, 5.54]	6.1705 [4.64, 7.70]	-0.5661 [-0.80, -0.33]	0.2516	0.1913	0.9744
Oven-dry basis model	-7.3965 [-9.77, -5.02]	5.6248 [4.13, 7.12]	-0.4867 [-0.72, -0.26]	0.2491	0.1819	0.9631

[a]The form of the model is $\ln(\text{biomass}) = a + b(DBH) + c\,(DBH)^2 + \mathcal{E}$. The correction factor (CF) for both models is 1.03. Exponentiated predicted values should be multiplied by the correction factor to account for back- transformation from the log-predicted value.
[b]Numbers in brackets are the 95% CI for the estimated coefficients.

Oven-dry wood biomass equation

Model selection based on lowest AICc using ln(oven-dry biomass) as the response variable and the predictors ln(DBH), branching height, and dieback resulted in a model



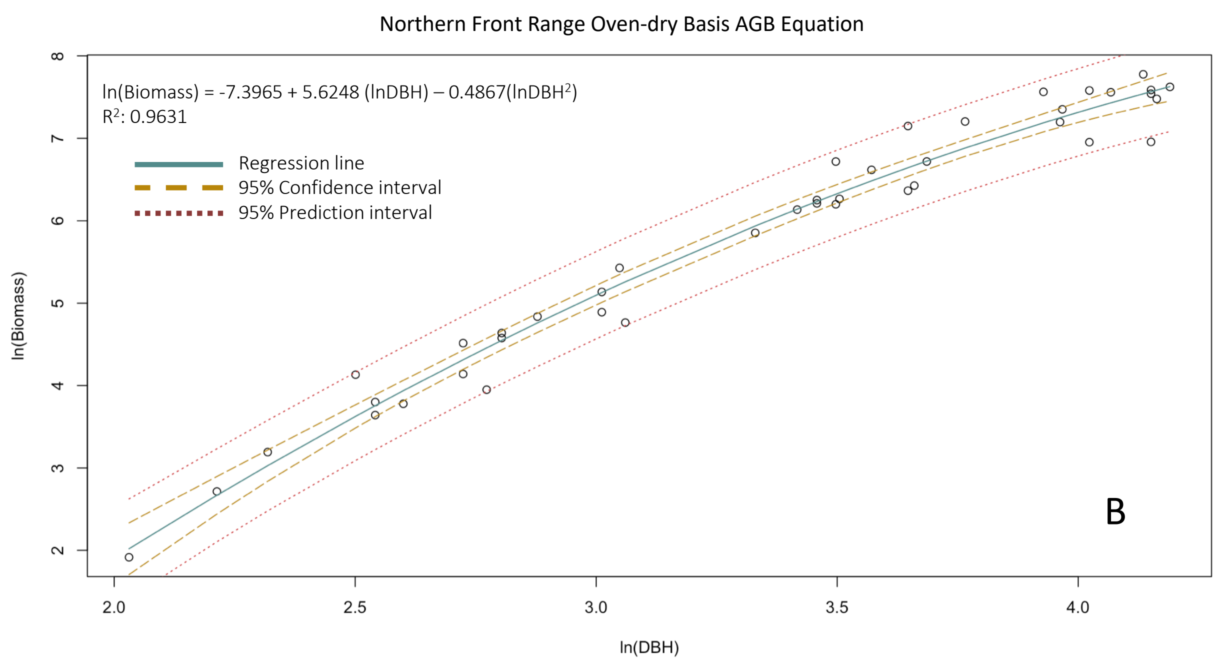


Figure 3-3 Plotted regression lines for locally-derived Northern Front Range green and oven dry biomass equations, showing actual tree biomass (points), fitted regression line (solid), 95% confidence interval (dashed lines), and 95% prediction intervals (dotted lines) of trees measured for this study on both a green (panel A) and an oven-dry (panel B) basis.

containing predictors ln(DBH) and dieback (AICc = 18.05). The greatest proportion of the variability in this model was explained by regressing ln(oven-dry biomass) on ln(DBH) ($F_{2,26}$ = 504.8, p = 0.0001). The model containing both ln(DBH) and dieback was compared to a second-order polynomial model with the independent variable ln(DBH). When compared to the model containing dieback and ln(DBH) (R^2 = 0.9749, RMSE = 0.2491), the second order polynomial ln(DBH) model (R^2 = 0.9631, RMSE = 0.3021) performed relatively well. Therefore, the recommendation is to use the quadratic model regressing ln(dry biomass) on ln(DBH). The form of the final predictive oven-dry biomass equation, partial regression coefficients, RMSE, MAE, and R^2 values are displayed in Table 3-5. A graph showing the fitted regression line and the associated 95% confidence and prediction intervals is shown in Figure 3-3, panel B. Residual diagnostic and quantile-quantile plots of the final models on a green and oven-dry basis indicate the assumptions of equal variance and normality were satisfied.

Compared to published green and oven-dry basis equations, the local equation produced the most accurate predictions of green ash biomass for the Northern Front Range sample trees. Differences between mean MB and PB, percent over- or underprediction, and SD of residuals for the four green-basis equations and five oven-dry basis equations that predicted values that were not significantly different from observed values along with the local green-basis and oven-dry equations are presented in Table 3-6.

3.4.3 Locally-derived average specific gravity and moisture content of green wood

Specific gravity was measured on a green (basic) basis. Specific gravity values for the trees sampled for this study range from 0.43 to 0.74 with a mean of 0.57 (SD 0.11). The average value for specific gravity for trees in this study is higher than that of the published value of 0.53 (Markwardt, 1937; Miles and Smith, 2009), is in the upper range of the values used by Jenkins et al. (2003) for mixed hardwood species, and is higher than the value of

Table 3-6 Comparison of published equations and Northern Front Range predictive equations on a green and an oven-dry basis

Equation source	Difference from MB (kg)	Standard deviation of the errors (kg)	Average over- or underprediction	MAD (kg)	RMSE (kg)
		Green basis equations			
Northern Front Range green DBH	8.7	359.2	+0.8%	217.4	359.3
Schlaegel green DBH	-43.8	414.5	-4%	253.8	64.3
Olson-Jenkins refit DBH + height	45.0	446.4	+4%	262.2	448.7
Schlaegel volume DBH	103.7	492.4	+10%	264.0	77.6
Olson-Jenkins refit DBH	270.7	561.3	+26%	342.0	623.2
		Oven-dry basis equations			
Northern Front Range oven-dry DBH	4.6	244.3	+0.2%	138.8	244.37
Chojnacky	26.5	303.6	+4%	171.9	304.7
Schlaegel volume DBH	-51.6	276.8	-7%	168.8	281.6
Jenkins	79.1	356.4	+11%	196.2	365.1
Schlaegel oven-dry DBH	-89.5	270.8	-12%	169.6	285.2
Bunce – Meathop	111.7	380.3	+15%	211.2	396.3

0.55 used by Chojnacky et al. (2014) for the Oleaceae family grouping that contains green ash. Moisture content values of green wood ranged from 7% to 55% with an average value of 41% (SD 7.5%), which is lower than the average moisture content of 57% published in Miles and Smith (2009).

3.5 Discussion

3.5.1 Some existing biomass equations adequately predict green ash biomass

A range of over- or underpredictions were associated with the existing green ash equations evaluated in this study when applied to trees removed as part of EAB management strategies. The published equations developed by Olson (2017) for urban areas in the Twin Cities, MN that use DBH and height as predictors of green biomass, and the DBH-only green biomass and volume equations developed for trees in the Mississippi Delta region by Schlaegel (1984), performed well when predicting green ash biomass on a green basis for the trees sampled for this study. Conversely, the volume equation developed by McHale et al. (2009) for Fort Collins, Colorado overpredicted biomass on both a green and an oven-dry basis. McHale's equation was developed using only healthy trees with full crowns. Trees sampled for the present study were removed as part of emerald ash borer response plans. This often meant that the trees removed were small and/or in poor condition due to any number of factors, including excessive dieback, damage related to weather events or mechanical injury, or damage caused by insects or diseases. These trees were also pruned to varying degrees, so may contain less biomass relative to DBH than the trees in the McHale et al. (2009) study.

The Schlaegel equations represent trees growing in forested areas where crowding increases competition, leading to taller trees with narrower crowns. Furthermore, these trees would experience reduced edge effects, such as exposure to wind, which leads to higher trunk biomass and less branchiness in the crown. Therefore, they are less likely to represent healthy, open-grown trees with full crowns. However, this may explain why these models adequately predicted biomass of the trees sampled for this study as many had reduced crowns.

The Olson (2017) DBH and DBH-height equations, which performed well when predicting green biomass of the sample trees, were refits of the general hardwood equation developed by Jenkins et al. (2003). Interestingly, Olson's measurements were based on green biomass of urban green ash trees, whereas the Jenkins et al. (2003) equation explicitly states that model parameters are based on oven-dry biomass, and all equations used by Jenkins et al. (2003) were forest-derived.

Brenneman's biomass equations were developed for white ash (*F. americana*). White ash wood has a slightly higher specific gravity than green ash wood (0.55 and 0.53, respectively), which may account for the overprediction in both green and oven-dry biomass. On average, white ash is a larger tree compared to green ash and may reach mature heights of over 30.48 meters (100 feet) (NPIN, 2013; Schlaegel, 1984; USDA, NRCS, 2018). Given the Brenneman equations use only DBH as a predictor, height may be a factor in the systematic overprediction of biomass produced by these equations if the trees were significantly taller on average than green ash which reaches heights of 15.24 to 21.34 meters (50 to 70 feet) at maturity.

The urban equations developed by Pillsbury (1998) for Modesto ash (*F. velutina*), but often used for green ash, consistently underpredicted biomass on both a green and oven-dry basis. The results presented here correspond with the McHale et al. (2009) study, which also found the Pillsbury equations underpredicted biomass of trees in Fort Collins, Colorado. Previous studies estimating carbon sequestration using this equation likely underpredicted biomass in Fort Collins (McPherson et al., 2005; McPherson, 2007). The two Pillsbury volume equations were developed for Modesto ash *(F. velutina* 'Modesto') in urban areas of California, U.S.A. Modesto ash is a smaller tree on average than green ash, rarely reaching mature heights over 12.19 meters (40 feet) in cultivation (NPIN, 2013). The equation that included height did not improve predictions, indicating differences are likely due to factors other than the biomass-height-diameter relationship.

Miles and Smith (2009) use an average of all specific gravity values for *Fraxinus* species for *F. velutina* (0.51) because there is not a published value for this species. Specific gravity values given by Miles and Smith (2009) for *Fraxinus* species range from 0.45 for *F. nigra* (black ash) to 0.55 for *F. americana* (white ash). If the actual specific gravity value for *F. velutina* is closer to the lowest value, it may partially explain why all forms of this equation underpredicted biomass for the green ash trees sampled for this study.

The Jenkins et al. (2003) hardwood equation uses a grouping of "mixed hardwoods" containing 13 genera and 19 species. Wood specific gravities in this group range from 0.32 (*Tilia* spp.) to 0.64 (*Cornus florida*). Species in this grouping differ significantly in form and range from small ornamental trees (e.g. *Cornus florida*) to large-maturing shade trees (e.g. *Fraxinus* spp.). In spite of its lack of specificity compared to other equations developed explicitly for green ash, it performed well when predicting biomass on an oven-dry basis. This was also true of the equation developed by Chojnacky et al. (2014), which is also a generalized equation, though it is slightly more specific in that it is meant for trees in the Oleaceae family with specific gravity < 0.55, which includes green ash. MacFarlane (2015) notes that generalized mixed-species models may outperform species-specific models when trees of anomalous forms are included in the sample set. He suggests that this is because generalized mixed-species models are developed using individuals that vary widely in form and thus better represent the morphological variation of atypical trees.

3.5.2 The green basis Northern Front Range predictive equation for green ash is recommended for emerald ash borer mitigation activities

The Northern Front Range biomass equations presented here provided the most accurate estimates of urban green ash trees removed as part of EAB mitigation strategies (Table 3-6). Most of the urban forest residues currently disposed of are done so immediately or soon after the tree is removed. For this reason, measuring wood waste on a green basis may be more appropriate for municipal urban wood disposal budgeting purposes. Since EAB larvae feed in the phloem of the tree, thus cutting off the movement of water and decreasing a tree's moisture content, there may be some concern regarding the green model's accuracy when used to estimate costs associated with the disposal of EAB infested trees. However, many publicly-managed trees will be removed before they are in steep decline as the structural integrity of trees infested with EAB quickly deteriorates, making them a threat to public safety. In addition, several of the trees removed for this study were planted in unirrigated open space or in parking lots with limited irrigation, therefore representing typical growing conditions of trees likely to be removed by municipal forest managers. The local oven-dry wood predictive equation presented here can be used to estimate biomass of standing dead trees.

It was decided that the trees collected for this study should be representative of the population of trees that will routinely be removed due to regular maintenance activities; therefore, trees were not selected based on their ability to represent the average green ash tree growth form. They were instead included in the sample because they were previously identified for removal as part of cities' scheduled maintenance activities, and thus better represent trees that would typically be removed. Likewise, the variety of sites from which trees were removed (irrigated park sites, road-side planting strips, parking lots) adequately represent public areas in which trees are routinely planted in urban areas, and for which maintenance responsibility falls to municipalities and other resource managers.

An oven-dry equation is presented here as oven-dry status is the standard for most research purposes. From the oven-dry state, moisture content can be adjusted as needed to accommodate a variety of uses. For instance, standing dead trees or downed trees left outdoors can be adjusted using a known equilibrium moisture content for the region, which for Denver, Colorado varies monthly from 9.4 -11.0% (Simpson, 1998).

3.5.3 DBH-only model for urban tree biomass estimation

When developing biomass equations, Bunce (1968), Zhou (2007), and others have advocated for choosing fewer predictor variables that are easy to measure and are good predictors of biomass in order to balance accuracy of estimation with labor cost associated with taking tree measurements and likelihood the equation will be used. Harrell (2015) notes one of the most common reasons predictive models do not get used is because input variables (measurements) required to use the model are not part of normal data collection.

While height is often included in tree biomass equations, some studies have indicated errors associated with height are generally larger than those associated with DBH which can reduce its usefulness as a predictor (Chave et al., 2004; Ducey, 2012; Weiskittel et al., 2015), or simply does not add to model accuracy, especially on a local scale (Paul et al., 2016; Yoon et al., 2013). With the exception of the Olson DBH-height equation, the equations that included both DBH and height measurements produced less accurate predictions than those that included only DBH. Furthermore, Peper et al. (2001) found that pruning practices for urban street trees, whether for management or aesthetics, varied widely across locations and had more of an effect on allometric relationships than did soil or climactic conditions. The difficulty in characterizing varying management regimes in urban areas makes height an unreliable variable on which to base allometric relationships as it is inherently unstable due to management interventions.

The goal of this study was to produce a model that would be widely used by urban forest managers. Given DBH is a measurement routinely collected as part of normal tree census data whereas dieback and branching height are variables rarely collected by practitioners except for reasons related to research, the DBH-only equation is recommended.

3.5.4 Locally-derived green ash specific gravity and average moisture content differs from published values

Average specific gravity for destructively sampled trees (0.57) was 7.5% higher than the widely used published value of 0.53 (Markwardt, 1937; Miles and Smith, 2009). The large range in specific gravity values found for trees in this study (0.43 to 0.74) likely reflects differences in growth rates due to considerable differences in site conditions and management regimes. The trees sampled were growing in parking lots, unirrigated open space, irrigated parks and rights-of-way. It was unclear whether some parking lot and right-of-way trees were irrigated.

Zhou et al. (2011) used forest-derived specific gravity values to convert volume to biomass for open-grown trees in an agricultural shelterbelt, including green ash. Zhou et al. (2011) found that using forest-derived specific gravity for volume to biomass equations for open-grown green ash trees in the same region led to an underprediction of trunk volume by 8.0%. Like the shelterbelt trees in the Zhou et al. (2011) study, urban trees are typically open-grown, and have larger canopies that are subjected to greater wind loads. This results in greater strain in the stem and a higher incidence of reaction wood, which in turn is associated with an increase in specific gravity (Burton and Smith, 1972).

In addition, Zobel and van Buijtenen (1989) note that, while there is some disagreement on the subject, it is generally thought that growth rate is positively correlated with higher growth ring specific gravity in ring-porous hardwoods, a group that includes ash species (also Markwardt and Wilson, 1935). Trees growing in urban locations that are actively managed receive supplemental water and nutrients and so may exhibit faster growth rates, another factor leading to an increase in specific gravity (Zhou et al., 2011).

Specific gravity values for urban-grown trees are absent from the literature. The average specific gravity value for the trees sampled for this study can be used in volume-to-mass conversions for urban tree biomass estimation. The U.S.D.A. Forest Service Forest Inventory and Analysis (FIA) Program relies on volumetric estimations of standing trees. Currently, specific gravity and density values presented by Miles and Smith (2009) are the standard by which estimates are made for many tree species in both natural forests and urban forests in the United States, including those produced by the FIA Program. This study presents the opportunity to use a specific gravity value that was locally developed in future urban biomass volume estimates for Colorado's Northern Front Range.

3.6 Conclusions

Local biomass prediction models presented here will better predict green ash biomass of trees removed in urban areas of the Northern Colorado Front Range due to emerald ash borer mitigation activities. The comparison presented here of existing predictive models for green ash used in past urban biomass prediction studies illustrates that caution should be used when applying biomass equations outside of the locations and conditions for which the equations were developed, and broad corrections should not be applied to predictions produced by those equations without first understanding how the equations perform given local conditions.

A locally-derived specific gravity value that averaged 0.57 for urban green ash wood was 7.5% higher than forest-derived values. This local specific gravity value can be used to improve biomass estimates in urban areas of Colorado's Northern Front Range. In addition, specific gravity influences wood utilization and is of interest to the forest products industry because many other wood properties are affected by specific gravity. As such, when EAB becomes more widespread in Colorado and ash trees are killed, there will be a need to find uses for the wood and this value may prove important. Lastly, a locally-derived average moisture content value was 41% and is thought to more accurately reflects conditions in arid temperate climates, such as Colorado's Northern Front Range.

Overall, the findings presented here add to an important and growing body of work that seeks to provide a greater understanding of the differences between urban-grown versus forest-grown trees, as well as the challenges associated with using forest-derived metrics for urban tree biomass estimation.

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APPENDIX A: SCATTERPLOTS

Scatterplots of observed biomass for each of the 42 destructively sampled trees and predicted weights from green and oven-dry basis published equations. Panel A is a fitted trend line for observed biomass. Panel B contains fitted trend lines for predicted biomass from the forest-derived equations. Panel C contains fitted trend lines for predicted biomass from the urban equations. Panel D contains fitted trend lines for predictions from all published equations. Note that forest-derived equations both over- and underpredict biomass of the 42 sample trees indicating broad-based corrections such as those proposed by Nowak (1994) and Zhou (2011) may not be supported.

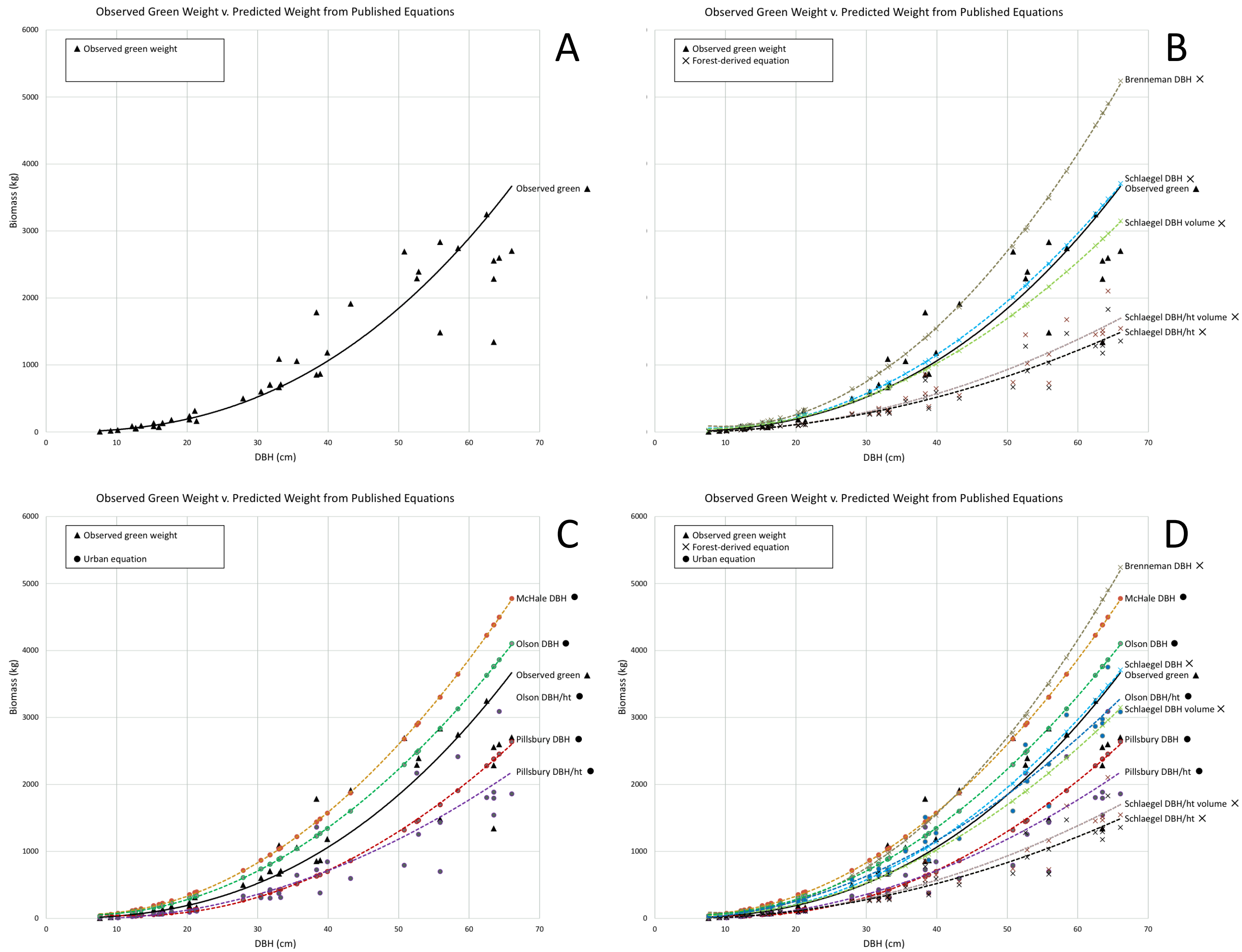

Figure 3-4 Scatterplots for observed green biomass and predicted biomass from green basis equations for the 42 destructively sampled trees.

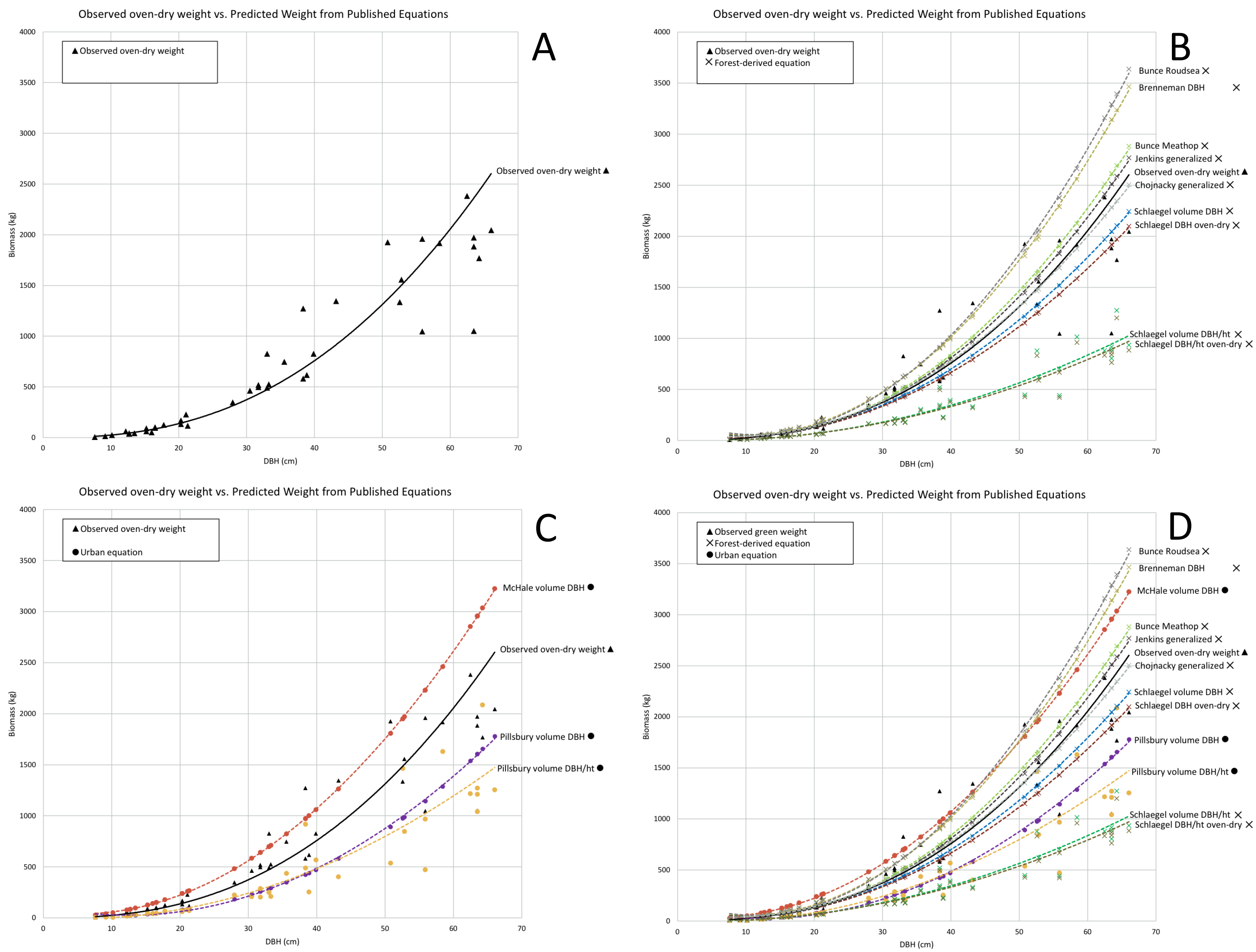

Figure 3-5 Scatterplots for observed oven-dry biomass and predicted biomass from oven-dry basis equations for the 42 destructively sampled trees.

APPENDIX B: BOX AND WHISKER PLOTS

Box and whisker plots representing the distribution of the residuals for predicted biomass. Boxes represent the interquartile range. The center line of each box represents the median value. Dots represent outliers, which are defined as points that are 1.5 times the interquartile range. The p-values were adjusted using the Holm method to account for multiple comparisons. Boxes and whiskers with less spread (variability), i.e., closer to zero with the median centered on zero, indicate predictions more closely matched observed values (accuracy). More evenly distributed whiskers and outliers indicate literature equation precision, i.e., lower bias.

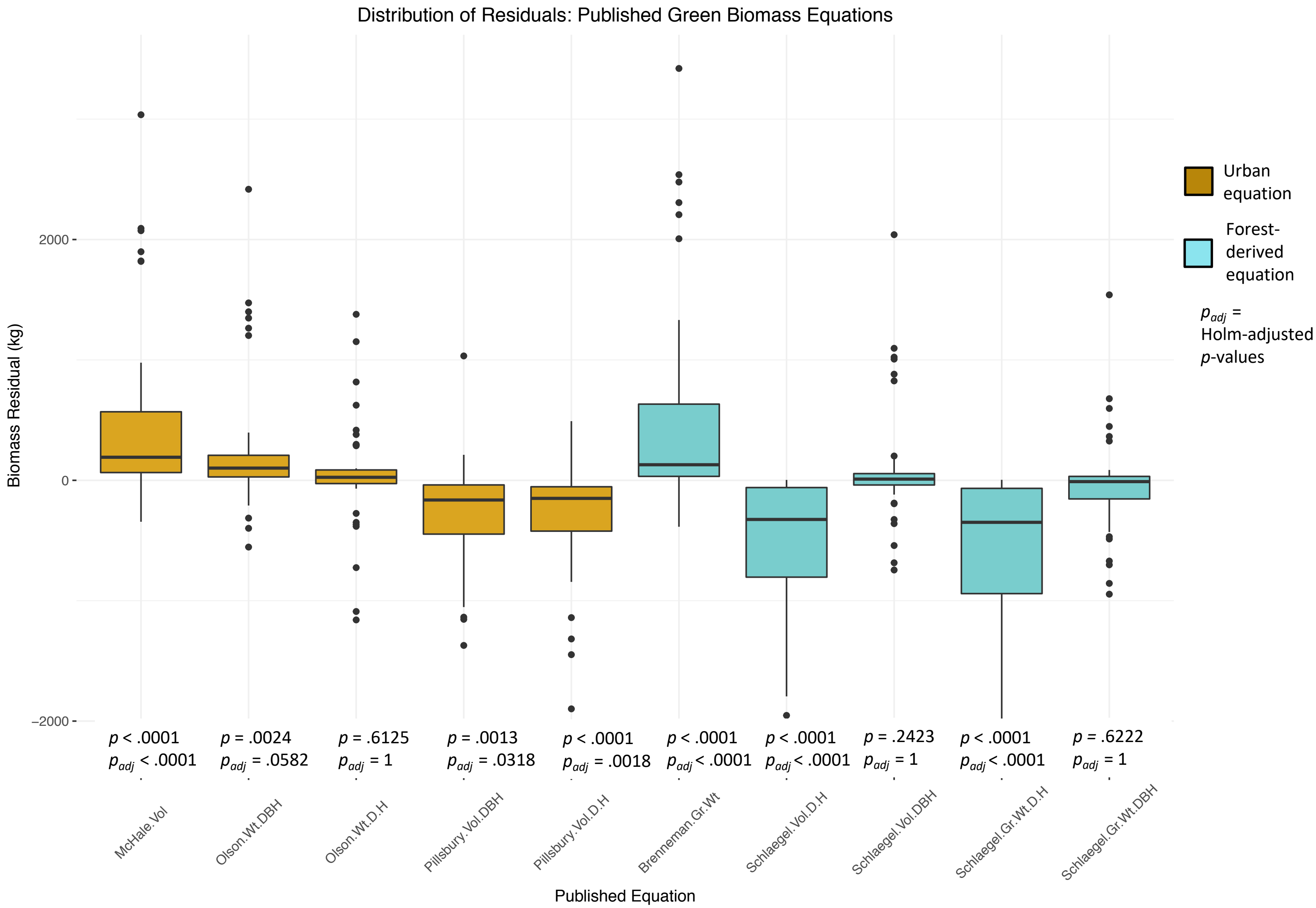

Figure 3-6 Box and whisker plots representing the distribution of the residuals for green basis published equations.

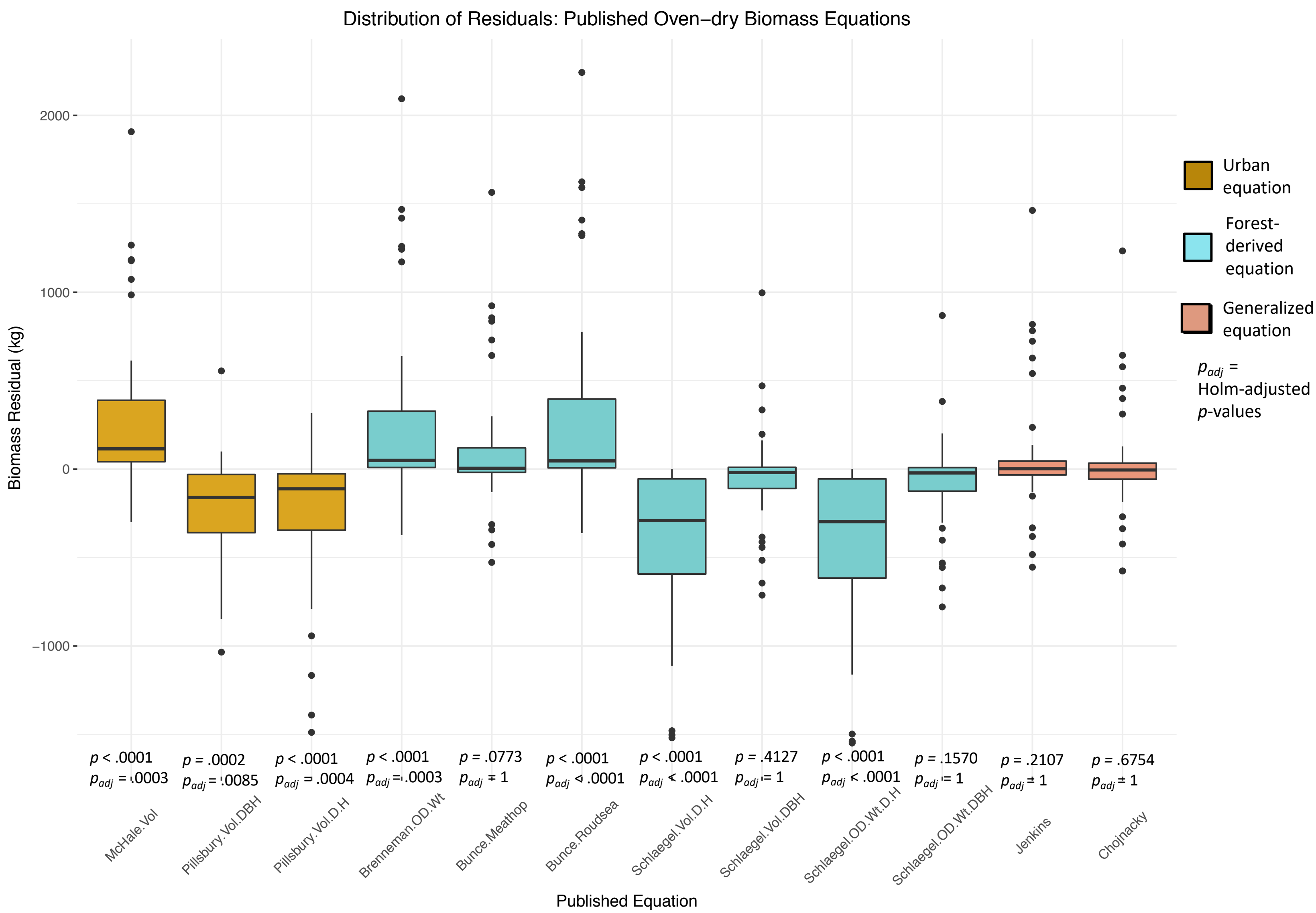

Figure 3-7 Box and whisker plots representing the distribution of the residuals for green basis published equations.