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Urban forests are an essential green infrastructure of our cities. Due to the proximity of urban trees to more than 250 million people and the grey infrastructure within United States cities, urban forests are uniquely positioned to provide a host of social, environmental and economic benefits. Careful management that maximizes benefits of the urban forest while minimizing cost is necessary for healthy, livable urban areas.

A key component to effective forest management is inventory. The United States government regularly inventories forestland trees at present but efforts have begun to extend this monitoring effort to urban forests as well. This study utilizes the first Urban Forest Inventory and Analysis (FIA) from the states of Washington, Oregon and California. Not only does this inventory help to identify the structure, composition, health and benefit of urban forests in these states, but it also provides an unprecedented opportunity to develop regional urban tree attribute models.

This work develops species-specific models for predicting tree height, height to crown base and largest crown width for five principal species represented in the inventory including Douglas-fir (*Pseudotsuga menziesii*), red alder (*Alnus rubra*), western redcedar (*Thuja plicata*), big leaf maple (*Acer macrophyllum*) and oak (*Quercus* spp.). Models can be calibrated with localized data and used for obtaining additional information on the structure of the urban forest when field measurements are unobtainable or costly. Height and canopy attributes are important components for understanding the extent of the benefits imposed by the urban forest.

Predicting Urban Tree Attributes for Major Species in Urbanized Areas of the Western Pacific States

by
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I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Lacey M. Jeroue, Author

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CONTRIBUTION OF AUTHORS

Dr. Jacob Strunk, John Mills, Paul Ries and Dr. Temesgen Hailemariam made contributions to the second chapter of this thesis. Dr. Charlotte Wickham and Dr. Temesgen Hailemariam contributed to the third chapter.

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1 General Introduction

1.1 Background

Urban forests are commonly confused with city parks and greenbelts. By the usual notion of what makes a forest a forest, it is difficult to imagine a forest in the city apart from parks and other natural tracts intermittently dispersed throughout a city. Two components are associated with the definition of forest; one is that a forest is composed of densely packed trees and shrubs and two, is that this vegetation spans over large areas. Urban forests are composed of city parks and remnant natural areas, but it is important to recognize that the urban forest also includes the single planted tree in a backyard, the few trees in a row along the roadside, nicely manicured shrubs in the front of a business center and the various waterways in ditches of residential neighborhoods. All trees, shrubs and water bodies that make up the green infrastructure throughout a city comprise the urban forest no matter how densely composed or widespread they are.

Green infrastructure is an essential component to the livability of urban environments. Urban forests provide quantifiable social, economic and ecological benefits (Nowak and Dwyer 2007) apart from timber value. More than 80 percent of the U.S. population reside in urban areas. The result is over 250 million people in the U.S. that are directly impacted by urban forests and their associated benefit on a daily basis. Due to the proximity of trees in cities to buildings, pollution sources and human traffic, they are uniquely positioned to provide beneficial environmental services but they can also present a liability to the grey infrastructure and humans they coexist with. With such a substantial component of the urban landscape being composed of green infrastructure affecting the majority of the Nation's population, effective urban forestry management that aims to maximize beneficial outcomes while minimizing costs is necessary.

A key component to effective urban forest management is inventory. The state of the current composition, structure and health of the urban forest is necessary in order to devise goals, schedule maintenance, assess progress and make management decisions. Large cities generally conduct inventories for extensive management and strategic plans. Smaller towns may conduct inventories but funding is often preventative. Inventories on public land on a long-term rotation (i.e. 10-year basis), principally for hazard tree identification are priorities. Most often, city inventories are restricted to public areas and mainly for street and park trees. Federal programs recognize the essentiality of inventorying and conduct them annually on forestlands but at this time not on our urban forests.

There is no standard inventory protocol across cities nor does an inventory extend outside a given metropolitan area. Sample designs, information collected and times of collection vary among cities. The lack of cohesion among city inventories limits comparisons of regional urban forest populations and inhibits consistent periodic data collection. Inventorying urban forests at the national level could provide a basis for effective monitoring and management of the urban forest at a much greater scale.

Urban Forest Inventory and Analysis

The United States Department of Agriculture (USDA) Forest Service has initiated pilot urban forest inventory and analyses in several states across the nation. Preliminary monitoring strategies for urban forest inventories at the state-level have been conducted for Indiana (Lake et al. 2006), Wisconsin (Cumming et al. 2007), New Jersey, Tennessee (Nowak et al. 2011), Colorado, California, Oregon, Washington, Alaska, and Hawaii by the USDA Forest Service. Urban trees in these states were inventoried according to the USDA Forest Service Enhanced Forest Inventory and Analysis Program (FIA) and Forest Health Monitoring Program (FHM) protocols.

FIA is the nationwide program used to collect, compile, archive, analyze and publish forest inventory data across varying spatial scales and ownership types continually throughout the nation. Forestlands were recognized for providing substantial values to U.S. citizens in 1929 when the federal FIA program began (Smith 2002). The program persists today largely with support from the 1998 Farm Bill or more formally called the Agricultural Research, Extension, and Education Reform Act.

At the federal level, the Farm Bill mandates (Smith 2002):

1. Annualized state forest inventories with data collected in each state each year;

2. 5-year reports for each state and nationally including an analysis of forest health; and
3. National standards and definitions, including a core set of variables to be measured on all sample plots and a standard set of tables to be included in 5-year reports

Urban areas have historically been classified as nonforest and therefore have not been sampled through the FIA program. Forestland is defined by the USDA Forest Service as land that is at least 0.405 hectares (one acre) in size and at least 10% stocked by trees of any size (Bechtold and Patterson 2005).

The 2012 Farm Bill passed in early 2014. Although the outcome is unknown at this time, the Sustainable Urban Forests Coalition (SURC) sought for the inclusion of revisions that could place urban forest programs on a mandatory federal agenda across the nation. The Coalition is composed of 30 National Coalition Members from supportive organizations across the nation with an equal vision for bolstering urban forestry programs.

The SUFC composed three recommendations for the 2012 Farm Bill:

1. Encourage interagency coordination to protect urban-forest health;
2. Address issues at the landscape level and promote urban forests and trees as green infrastructure; and
3. Provide research, tools and resources that support local initiatives, minimizing overall costs and maximizing impacts for every dollar invested

In the way that the Farm Bill has greatly influenced the capabilities of the FIA program for traditional forests (Smith 2002), the Farm Bill may also encourage effective management of urban forests at the national level. The outcome of the new Farm Bill as it pertains to an urban FIA is unknown at this time.

i-Tree

i-Tree is a peer reviewed software suite developed by the USDA Forest Service and cooperators that analyzes and quantifies urban forest structure, composition and benefits

(USDA Forest Service 2012a). It is public domain and has been employed by many cities in and outside of the U.S. Three published pilot urban forest inventory and analyses used i-Tree Eco to analyze urban forest benefits.

i-Tree hosts a suite of products including Eco, Streets, Hydro, Vue, Species Selector, Storm, Design and Canopy. All of which have a specific purpose. i-Tree Eco is broadly focused to describe many attributes and benefits of an entire urban forest. It uses local air pollution and meteorological data coupled with tree measurements to quantify amounts of pollution removal, carbon storage and sequestration, building energy reductions and other benefits (USDA Forest Service 2012a). i-Tree Streets alone, a more focused product requiring a complete inventory, uses over 1,800 equations to describe urban street tree structure and benefits (McPherson and Peper 2012).

Complete or sample inventories for cities (e.g., Ciecko 2012; Nowak et al. 2013) are relatively simple to handle with i-Tree. i-Tree provides users with (1) a set of protocols for designing inventories, (2) an easy-to-use interface to input data and (3) an automated analysis and inventory report. State inventories are not supported by the software interface at this time. The three published state inventories were analyzed in line with i-Tree Eco methods with the data handled outside the software. California, Oregon and Washington are undergoing the same process.

The ability to quantify urban forest benefits is extremely valuable for managers and policy makers. Inventory and analysis provides managers with a means to strategize decisions in a way that maximizes beneficial components. Policy makers respond to monetary values for decisions and funding allocations. Perhaps i-Tree's most useful component is the ability to quantify and place monetary values on urban forest benefits.

1.2 Urban forest benefits

Urban forests perform ecosystem functions that translate into social, environmental and economic services. Urban trees store and sequester carbon (Nowak 1993; Akbari 2002; Nowak and Crane 2002; Myeong et al. 2005), remove air pollution (Brack 2002; Nowak et al. 2006; Escobedo and Nowak 2009; Morani et al. 2011), reduce building energy use (McPherson

1994a; Simpson and McPherson 1998; Akbari 2002; Sawka 2013), reduce the urban "heat island" effect (Shashua-Bar and Hoffman 2000), increase property values (Sander et al. 2010; Saphores and Li 2012) and intercept rainfall thereby attenuating stormwater runoff (Xiao et al. 1998; Gill et al. 2007). Urban forests have additionally been suggested to improve commerce in business districts (Wolf 2003; 2005) and influence rental rates (Laverne and Winson-Geideman 2003). Views of natural areas from windows may improve attention spans for students (Tennessen and Cimprich 1995; Faber et al. 2002) and increases recovery rates for patients in hospitals (Ulrich 1984).

Ecosystem functions are natural processes working continuously at various temporal and spatial scales. As a result of these functions, humans are granted with ecosystem services which can either be directly or indirectly beneficial (Farber et al. 2006). Forest structure, composition and health will determine the degree of acting ecosystem services. But there is more. The proximity of the forest to society also influences the magnitude of their service. Since trees in urban areas are aggregated into society, they can be uniquely positioned to provide a wide range of beneficial services. In Chicago the average monetary value benefit of a single tree is $402 after investment and maintenance costs (McPherson 1994b). Nowak et al. (2002a) estimated the total compensatory value of urban trees in the U. S. to be $2.4 trillion. The ability to quantify the benefits in monetary terms delivers the message to managers, landowners and policy to effectively manage the urban forest in a way that maximized benefits and minimizes costs.

Carbon Storage and Sequestration

Carbon storage and sequestration by forests are valuable global and long-term scale services (Farber et al. 2006). Carbon dioxide is thought to be a dominant greenhouse gas contributing to global climate change. Trees uptake carbon dioxide from the atmosphere through photosynthesis and assimilate the carbon into their biomass, effectively storing carbon and sequestering it over time. Urban forests in the U.S. store 25.1 tC/ha on average compared to 53.5 tC/ha in forestlands (Nowak and Crane 2002). Though less than in forestlands, urban forests play an important role in decreasing atmospheric carbon dioxide.

Management practices could lead to a net loss of carbon storage from urban forests. Fossil-fuel use for tree maintenance could eventually lead to a net emission of carbon without secondary measures to reduce emissions (Nowak et al. 2002b). In Seattle, Washington, urban expansion at the expense of forests was estimated to be at a rate of 1±0.6% per year reducing carbon stocks on average by 1.2 MgC/ha annually (Hutyra et al. 2011). i-Tree uses the mean social cost of carbon dioxide gas emissions estimated at $22.80/tC by Fankhauser (1994). Planting long-lived, fast growing, low-maintenance trees species in urban areas mitigates the effect of carbon emission from maintenance activities and urban expansion (Nowak et al. 2002b).

Pollution Removal

Trees provide a valuable ecosystem service by removing a host of pollutants. Due to the proximity atmospheric pollution sources typically found in urban environments, urban trees are in an opportune position to reduce pollution.

Leaves are sites of gas exchange. The ecosystem service of removing harmful pollution can be attributed to the forest canopy. Carbon monoxide (CO), nitrogen dioxide (NO_2), ozone (O_3), particulate matter less than 10μm (PM_{10}) and sulfur dioxide (SO_2) pollutants are removed primarily through uptake by stomata on tree leaves or by the plant surface (Nowak et al. 2006). In the U.S., urban forests improve air quality by removing 711,000 metric tons of pollution annually (Nowak et al., 2006).

Improved air quality in turn, improves human health. This can be extremely useful in geographically confined cities like Santiago Chile where air pollution is unable to escape and threatens human health (Escobedo et al. 2008). Morani et al. (2011) incorporated pollution concentrations into a planting priority index to determine the best locations to plant trees in New York City. On the other side, these same pollutants in urban areas can have concentrations that are damaging to tree health (Percy and Ferretti 2004). Mortalities or damaged trees arising from high pollutant uptake could become liabilities and have costly impacts.

Building Heating and Cooling Energy Reduction

Trees alter building energy use by modifying temperature and microclimates in urban areas (Simpson 2002; Donovan and Butry 2009; Pandit and Laband, 2010). Through water transpiration, altering wind speed and direction, shading surfaces, and by modifying surface heat storage and exchanges, trees influence climate on a range of scales (Nowak and Dwyer 2007). In urban areas, these processes can beneficial by reducing energy costs and thereby reducing carbon emissions as well.

Shade plays a significant role in altering microclimates. During the summer, shade produced from urban trees decreases adjacent buildings' energy use. Summertime electricity use in Sacramento, California was reduced by 185 kWh with tree cover on the west and south west sides of residential homes (Donovan and Butry 2009). Residential plantings in Toronto, Canada are estimated to contribute 167 kWh per tree in savings and between 435 and 483 kWh per tree after a twenty-five year period (Sawka et al. 2013). Baton Rouge LA, Sacramento CA and Salt Lake City UT may reduce power plant carbon emissions by 16,000, 41,000 and 9,000 tons respectively by planting an average of four, 50 m2 crowned shade trees per residential home (Akbari 2002). Dense shade may mean a $21.22 to $32.20 savings per month in the summer for households in Alabama (Pandit and Laband 2010). Shade has powerful implications for modifying energy consumption.

Tree canopies and shade creation can have negative effects as well. If shade is produced in the wintertime, household energy use could be exacerbated (Pandit and Laband 2010). Simpson and McPherson (1998) estimated a penalty of $5.25 per tree due to exacerbated energy use; however, annual savings were still $10.00 per tree for the average home due to shade. Tree location also plays a factor building energy use. Plantings on the north side of homes in Sacramento, CA increased energy use by 55kWh or by 1.5% even in the summer months (Donovan and Butry 2009). Savings from trees depend on species, pre-existing canopy and placement with respect to direction and distance from buildings (Sawka et al. 2013).

The other major factor effecting microclimate is wind (Nowak and Dwyer 2007). In the wintertime, trees are beneficial by blocking wind and effectively buffering building cooling. Wind speeds in residential areas with 70% tree density were reduced by 65% in winter and 75% in summer compared to 22% across both seasons in areas with no trees in Heisler's

(1990) study. Depending of tree directing and distance from the building, the effect of trees influence on wind can be both beneficial as well as a hindrance.

Urban microclimate modification caused by trees has implications for management plans focused on urban energy use and carbon emission mitigation. Canopy is the key to shade creation and wind modification creating microclimatic conditions, which if managed properly, can lead to beneficial energy savings.

Stormwater Mitigation

Through rainfall interception, urban tree canopies attenuate runoff and mitigate fluxes of pollution saturated stormwater entering water bodies. In summer, 36% of rainfall is intercepted by canopies dominated by large broadleaves deciduous trees and 18% is intercepted in urban canopies dominated by evergreens (Xiao et al. 1998). Attenuating runoff and altering urban hydrology with urban trees also has implications for flood mitigation, stormwater treatment cost reductions, and other water quality issues (Nowak and Dwyer 2007). With increased precipitation expected in the future in the face of climate change, there will be increase surface runoff and the role of green infrastructure will become even more useful (Gill et al. 2007).

1.3 Study Objectives

The purpose of this study is to investigate strategies to predict height, height to crown base and largest crown diameter for trees in urbanized areas of California, Oregon and Washington. Forestland tree attributes have been well modeled in the western pacific states but this study seeks to show that separate equations developed from the same species in urban areas are more suitable for the urban forest type. The modeling strategies developed in this study can be employed with separate urban forest inventory data and subsample for a calibrated prediction or the coefficients can be used to predict tree attributes more generally in the urbanized western pacific states. This study fills a gap in urban tree attribute modeling and demonstrates the usefulness of an Urban Forest Inventory and Analysis (UFIA) at the national level.

1.4 Literature Review

Modeling Urban Tree Attributes

Urban tree modeling is in its beginning stages (McPherson and Peper 2012). Height, leaf area, biomass and crown width urban tree attribute models have been investigated however; there are few publications on this work (Nowak 1990; Nowak 1996; Pilsbury et al. 1998; Peper et al. 2001a; 2001b; Martin et al. 2012; Troxel et al. 2013). Dimensional relationship studies of municipal tree species that do exist are commonly developed without validation and are from observations subjectively selected (Peper et al. 2001a; 2001b). Major forest inventory and analysis tools such as i-Tree, use equations developed from forestland tree species because regional models for urban specific trees simply do not exist in most cases.

When biomass equations for example, are not available, forestland tree models are used (Nowak 1993). The only biomass equations developed specifically for urban trees are those by Pilsbury et al. (1998) for 15 common California trees (McHale et al. 2009). Those models were developed by measuring multiple tree segments and calculating geometric volumes for each.

Biomass equations developed from forestland trees overestimate open-grown urban trees by 1.25 (Nowak 1994). Carbon storage in urban areas was estimated from forestland biomass equations that were multiplied by a factor of 0.8 (Nowak and Crane 2002) or by 0.9 (Nowak et al. 2002b) as in i-Tree to account for the differences. Specific gravity, used for biomass equations, may be different in urban areas compared to forestlands for a given species as well due to more rapid growth rates from nutrient and water application (McHale et al. 2009). In many cases, even forestland biomass equations are not available for certain species. In this case, genera averages are used as a replacement and if those are non-existent, then hardwood or softwood equations are used (Nowak 1993). McHale et al. (2009) investigated the variability in error of urban tree allometry associated with using models developed for trees in typical forestlands by comparing biomass predictions. They suggest biomass estimates in urban environments may be more accurate with the development of allometric equations specific to urban trees.

Impermeable surfaces, fertilizer application, watering regimes, pollutions fluxes and pruning are all indicative of urban environments. Crown width is influenced by soil, light, moisture and crown loss due to storms or pruning (Martin et al. 2012). Urban forest conditions and the subsequent difference in tree allometric relationships from those in typical forestlands constitutes the need for using models developed specifically for urban tree species. Predictive equations are essential to growth modeling and can provide a means to evaluate management plans and the effects of climate change for urban forests (Peper et al. 2001a; 2001b).

Modeling Height

Tree height is an essential component to describing the structure of the urban forest. Height is needed to estimate carbon storage, carbon sequestration and building energy reductions, and it is a required input variable for i-Tree Eco. However, collecting tree height is time consuming and costly (Wang and Hann 1988; Dolph 1989, Hanus et al. 1999; Temesgen and Gadow 2004). In urban areas it can be dangerous and unobtainable as well. Hazardous conditions such as highways or properties without owner-granted access may not allow for tree height collection or any other direct measurment. Therefore, equations that predict height from a given set of variables obtained remotely would be useful. When modeling tree growth, equations to predict tree height are necessary (Garman et al. 1995; Temesgen and Gadow 2004; Sharma and Parton 2007).

Diameter at breast height is relatively quick and easy to measure making it inexpensive and a conventional forest measurement (Sharma and Parton 2007). Because dbh is so strongly correlated with tree height and is a conventional, low-cost measurement, models for predicting height include at minimum, dbh as a predicting variable for forestlands (Larsen and Hann 1987; Hanus et al. 1999).

Separate equations to predict height of three maple species in Rochester and Syracuse, New York were fit to linear and a quadratic functions of dbh by Nowak (1990). He concluded the species warranted separate equations and used the information to grow out trees to determine suitable planting locations. Warm-climate street trees in California were used to fit a height-diameter function by Peper et al. (2001a; 2001b). They recommended a logarithmic function with dbh as the predictor variable. Urban tree height and dbh were found to be strongly correlated.

Functions used to model biological data should be flexible and produce a reasonable relationship even when the data do not fully define the curve (Curtis 1969; Yang et al. 1978). Polynomial equations were commonly used to model height and diameter (Curtis 1969) but in recent years asymptotic equations are almost exclusively employed for forestland modeling. Non-asymptotic equations such as polynomial functions are inadequate for extreme sizes of dbh (Garman et al. 1995) and do not allow for flexibility. Asymptotic equations have the benefit of not allowing for unrealistic predictions when extrapolating beyond the original data used to develop them (Huang et al. 1992). In addition to being flexible, a good function passes through the origin, is monotonic with a slope approaching zero as the predictor variable increases, and is fairly simple to fit. Curves which take on a sigmoidal or concave form are asymptotic equations.

A variety of asymptotic functions have been fitted to predict tree height in forestlands. Huang et al. (1992) compares 20 different functions to tree species of Ontario. The most common and most recommended equation used in height-diameter modeling is that developed by Richards et al. (1959) called Chapman-Richards (e.g., Garman et al. 1995; Zhang 1997; Temesgen and Gadow 2004; Temesgen et al. 2006; Newton and Amponsah 2007; Sharma and Parton 2007). Though the function is well suited, it often approaches the asymptote too quickly when only a weak correlation exists between the dependent and independent variable.

Temesgen et al. (2006) fitted models by Richards (1959), Yang et al. (1978), Ratkowsky (1990) and Hanus et al. (1999) for southwest Oregon tree species. Wang and Hann (1988) fit data from tree species in Oregon's Willamette valley to a model recommended by Larson and Hann (1987). This same model was also fitted by Dolph (1989) to model red fir in northern California and southern Oregon. Zhang (1996) fit six functions including the Yang and Ratkowsky functions with data from the inland Northwest.

The addition of other predictor variables to base models is a common practice shown to improve predictive performance of height-diameter models in forestlands. Stand level predictor variables incorporate site quality and competition that can influence tree height. Basal area in larger trees, stand level basal area, crown competition factors and site index were added by Temesgen et al. (2006; 2008). Sharma and Parton (2007) included basal area, trees per hectare, dominant stand height and site index as additional predictor variables with improved model performance. Increased predictive performance with the addition of basal area and trees per hectare was achieved by Newton and Amponsah (2007) as well. Larson and Hann (1987) used basal area and site index while Hanus et al. (1999) recommended adding the average diameter and height of the 40 largest diameter trees to the base model. Wang and Hann (1988) found that the inclusion of site index improved parameter estimates but advise that the additional time required may not constitute the nominal benefit of the expanded model.

Mixed effect modeling, models which use a random and fixed effects, has improved model performance. Mixed effect models were preferred over fixed effect models by Robinson and Wykoff (2004) in predicting height. Temesgen et al. (2008) assessed the predictive performance of the Chapman-Richards and Hanus equations across fixed and mixed non-linear models, with the inclusion of stand and tree level variables to conclude greatest performance in models which included a random stand variable as well as fixed stand and tree level variables. Sharma and Parton (2007) found extended models which included a random effect to be better predictors of tree height.

Modeling Largest Crown Width

Few height and crown models exist for urban trees. Peper et al. (2001a) were able to predict crown diameter as a function of dbh using a logarithmic regression function for 16 species. Sample sizes ranged from 27 to 33 roadsides trees from Santa Monica, California. Root mean square errors (RMSE) ranged from 0.12 and 0.22 meters and adjusted coefficients of determination between 0.57 and 0.95. Peper et al. (2001b) predicted crown diameter as a function of dbh using the same logarithmic regression function for 12 common street tree species in Modesto, California with similar results as in Santa Monica, California. Peper's models are used in i-Tree Streets (McPherson and Peper 2012). Martin et al. (2012) fit linear regression equations to predict crown width of three open-grown oak species common to the south with dbh and a quadratic term for dbh to obtain adjusted coefficient of determination values between 0.91 and 0.96. RMSE values are not presented. Polynomial equations were fit for common urban tree species in New Haven, CT in northeastern U.S.A., to establish allometric relationships between age, dbh, crown diameter and crown volume by Troxel et al. (2013).

Methods for predicting urban crown width are the same for forestland trees. Equations at minimum are linear with dbh as the single independent variable. Commonly a quadratic term for dbh is also added along with additional independent variable will aid in better predictive performance.

Hann (1997) developed largest-crown-width (LCW) models with the inclusion of maximum-crown-width (MCW) as a predictor variable multiplied by crown ratio with an exponent as a linear function of crown length and diameter to height ratio for 15 major tree species in western Oregon. In the literature, MCW is used when describing crown width models which were fit with observations from open-grown trees. Open-grown trees are assumed to not be in competition for resources and therefor represent the maximum size a crown can achieve for a given species. LCW models are fit with data from stand-grown trees.

Bechtold (2004) used the Forest Health and Monitoring (FHM) data set to develop regional LCW models for stand-grown trees in the Western states (CA, CO, ID, NV, OR, UT, WA, WY). They evaluated stem diameter (D), live-crown ratio (CR), stand-level basal area (BA), latitude (LAT), longitude (LON), elevation (E) and Hopkins bioclimatic index (HI) as predictor variables in LCW models for western tree species and chose the best biologically justifiable model to be that which included the parameters for D, D^2, CR, BA and HI. Of the 53 species fitted 26%, 74% and 36% had significant parameters for quadratic diameter, crown ratio and basal area respectively. Weakly significant parameters for BA and unstable negative and positive parameters were attributed to collinearity with D and CR and therefore questionable as additional predictors (Bechtold 2004). No clear pattern arose from the use of latitude, longitude or elevation and to not risk over-parameterizing, and avoid interactions between the terms, Bechtold (2004) used Hopkin's bioclimatic index as an alternative to capture variation in environmental conditions.

Gill et al. (2000) considered dbh, height, height-to-crown base, crown class, basal area and trees per hectare as predictor variables for crown radius models of common California species. Stem basal area and exposed crown area, a crude measurement of light availability, explain much of the variation in stem growth rate (Wychoff and Clark 2005). Wychoff and Clark (2005) suggest that forest models will be improved by incorporating a variable for crown light exposure as knowledge advances in how trees of varying species, sizes and ages respond to light exposure.

Individual tree LCW models are used to estimate canopy cover and determine crown profiles. However, Marshall et al. (2003) found that crown profile models which incorporate a predicted LCW variable nearly double in residual. Issues with canopy cover arise as simply summing the crown areas can lead to cover values greater than 100 percent. Gill et al. (2000) suggest calibrating canopy cover models with the asymptotic 'natural growth model' from Parton and Innes (1972) to avoid this. Canopy cover is a measure of stand density commonly used to indicate wildlife habitat in forestlands and an indicator of forest condition in urban areas. Canopy cover is a performance benchmark in most urban forest management plans.

Modeling Height to Crown Base

Height to live crown base (HCB) designates the height of the tree stem where the base of the live crown begins. The height at which this occurs has been defined in several ways. Soares and Tome (2001) define the base of the crown to be at the lowest live branches occupying at least three quadrants of the stem base. FIA defines a similar line at the beginning of the 'obvious live crown' where most live branches occur and are continuous for the remainder of the stem (U.S. Department of Agriculture Forest Service 2007). Other measures visually compact the tree crown, moving lower branches into gaps and calling the crown base at the bottom of an ocularly compacted crown (Zumrawi and Hann 1989; Hanus et al. 2000). Furthermore, crown ratio (CR), the length of the crown divided by the entire stem length (H), is also dependent on an uncompacted or compacted crown. CR is related to HCB as:

$$HCB = H - (CR \times H)$$

In urban areas, modeling attempts for HCB have not been published but information for forestland HCB modeling is abundant. HCB and the related CR have been modeled across multiple regions in North America and for a variety of species (Rijal et al. 2012). McAlpine and Hobbs (1994) fit a linear model to predict HCB but this seems to be outdated as nonlinear model forms dominate the literature.

Nonlinear HCB model comparison commonly occur in the literature and the logistic form is most often preferred (e.g., Ritchie and Hann 1987; Zumrawi and Hann 1999; Hanus et al. 2000; Rijal et al. 2012). The logistic equation has the benefit of being constrained in a way that allows reliable predictions that more closely resemble the biological relationships with the predictor variables, has better fit statistics compared to other nonlinear forms and is easy to interpret compared to modes with squared expressions (Ritchie and Hann 1987). The logistic equation can be constrain so that CR cannot exceed 1 or be below zero, or to not allow HCB to be greater than the tree height. Soares and Tome (2001) suggested the 'Richards" function, a form of the logistic with constrained parameters which was later employed and recommended by Rijal et al. (2012).

At minimum, the logistic equation includes height and dbh as explanatory variables but additional covariates are often included to improve model performance. Explanatory variables can be thought of as three types; those which describe the tree size, competition or environmental conditions (Temesgen et al. 2005). Among those commonly used in forestlands are tree height (H), diameter to height ratio (DHR), crown competition factor (ccf), ccf for large trees (ccfl), basal area (BA), BA for larger trees (BAL), site index (SI) and climatic site index (CSI). Rijal et al. (2012) found H, DHR, CCF, BAL and CSI to be the most suitable with tree size covariates explaining between 40 and 77% variation in HCB models while Zumrawi and Hann (1999) found SI to be an insignificant contributor to explaining model variability. Size variables may be better at explaining some variability in CR than competitions variables because size variables intrinsically reflect measures of competition (Temesgen et al. 2005).

Crown dimensions can be important components for forest growth and yield modeling in forestlands because crown size, in terms of foliage area or weight, determines growth capacity (Ritchie and Hann 1987). Additionally, HCB is a critical component influencing initiation and propagation of a crown fire making HCB and important consideration for fire management (McAlpine and Hobbs 1994). In urban areas, the single most important forest asset in providing social, environmental and economic benefits is the crown (Nowak, 1996). Since HCB is not a common measurement for forest inventory (McAlpine and Hobbs 1994; Soares and Tome 2001; USDA Forest Service 2012b), HCB or CR models are useful.

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2 Predicting height for major urban tree species in urbanized areas of the western pacific states.

2.1 Abstract

Although regional height-diameter equations are developed for common tree species in the west, conditions resulting from the urban environment pose differences in urban tree allometry from typical forestlands. Selected concave and sigmoidal height-diameter equations were fitted to data from five principal tree species in urbanized areas of Washington, Oregon and California. Data came from a pilot urban forest inventory based on protocols set by the USDA Forest Service, Enhanced National Forest Inventory Analysis program. Stand and tree characteristics (plot basal area, trees per hectare and crown light exposure) were investigated as additional predictor variables for improving height predictions for Douglas-fir (*Pseudotsuga menziesii*), red alder (*Alnus rubra*), western redcedar (*Thuja plicata*), big leaf maple (*Acer macrophyllum*) and oak (*Quercus* spp.). A random land use variable was included in top performing base and extended equations for assessment of further improved predictive performance rendered through mixed effect models.

Predictive performance of base, extended and mixed effect models is evaluated through residual plots, and root mean square error and bias fit statistics. Four base equations are compared. Crown light exposure and stand level basal area improve fit statistics from base models for three of the five species while the combination of trees per hectare and basal area aid in improvements for one species-specific model. Mixed effect models outperform base and extended model forms for three of the five species. A combined extended mixed effect model is best for one of the species. Weighted regression in the form of 1/dbh (stem diameter at breast height) is applied for three of the five species. Urban and forestland species height-diameter relationships are different with significant p-values 0.03 to less than 0.0001. Coefficients resulting from the fitted equations are documented for future use.

2.2 Introduction

Social, economic and environmental benefits of urban forests are undisputed. Like all trees, urban forests store and sequester carbon thereby reducing the amount of carbon in the atmosphere contributing to global climate change (Nowak 1993; Akbari 2002; Nowak and Crane 2002; Myeong et al. 2005). Unique from typical forestland trees, urban trees have the added benefit of reducing building energy use (McPherson 1994a; Simpson and McPherson 1998; Akbari 2002; Sawka 2013) and removing pollutants from the air (Brack 2002; Nowak et al. 2006; Escobedo and Nowak 2009; Morani et al. 2011). Studies have shown that the urban forests reduce the urban "head-island" effect (Shashua-Bar and Hoffman 2000), mitigate stormwater runoff (Xiao et al. 1998; Gill et al. 2007), increase property values (Sander et al. 2010; Saphores and Li 2012), improve commerce (Wolf 2003; 2005), influence rental rates (Laverne and Winson-Geideman 2003), improve attention spans for students (Tennessen and Cimprich 1995; Faber et al. 2002) and increase recovery rates for patients in hospitals (Ulrich 1984).

Forest structure, composition and health determine the magnitude of these beneficial ecosystem services as well as proximity of the forest to society. Since trees in urban areas are aggregated into society, they can be uniquely positioned to provide a wide range of beneficial services. With such a substantial component of the urban landscape being composed of green infrastructure affecting the 80% of the Nation's population who reside in urban areas, effective urban forestry management that aims to maximize beneficial outcomes while minimizing costs is necessary.

A key component to effective urban forest management is inventory. The state of the current composition, structure and health of the urban forest is necessary in order to devise goals, schedule maintenance, assess progress and make management decisions. Over the past decade, the United States Department of Agriculture (USDA) Forest Service has initiated, for the first time, a pilot urban forest inventory and analyses in several states across the nation. Preliminary strategies for urban forest inventory and analyses at the state-level have been conducted for Indiana (Lake et al. 2006), Wisconsin (Cumming et al. 2007), New Jersey, Tennessee (Nowak et al. 2011), Colorado, California, Oregon, Washington, Alaska, and Hawaii.

Three published pilot urban forest inventory and analyses used i-Tree Eco to analyze urban forest benefits. i-Tree is a peer reviewed software suite developed by the USDA Forest Service and cooperators that analyzes and quantifies urban forest structure, composition and benefits (USDA Forest Service 2012a). It is public domain and has been employed by many cities in and outside of the U.S. these are the first at the state level.

Tree height is an essential component to describing the health and structure of the urban forest. Height is needed to estimate beneficial ecosystem services. Carbon storage, carbon sequestration and building energy reductions rely on tree height and height is a required input variable for i-Tree Eco.

Most inventories collect tree height data however, measuring tree height is time consuming and thus costly (Wang and Hann 1988; Dolph 1989, Hanus et al. 1999; Temesgen and Gadow 2004). In urban areas it can even be dangerous due to busy roads adjacent to trees, or unobtainable due to limited access created by buildings or industrial areas. Therefore, equations that predict height from a given set of variables are useful.

Height equations are useful for predicting missing data or lowing inventory cost by subsampling for height. Height models are commonly used for volume and biomass equations, growth and yield modeling (Garman et al. 1995; Temesgen and Gadow 2004; Sharma and Parton 2007) and estimating site index (Curtis 1969) in forestlands. In urban forests, height models can additionally be used to grow out trees to determine appropriate planting locations or future pruning requirements (Peper et al. 2001a; 2001b).

Allometric functions establish a quantitative relationship between an organism's size and some other attribute so that its size can be predicted when unknown. The relationship of tree height and diameter is well documented for trees and allometric equations that predict height from stem diameter are well developed for forestland tree species (Curtis 1967; Huang et al. 1992; Hanus et al 1999; Temesgen et al. 2006; Sharma and Parton 2007; Gomez-Garcia et al. 2014). However, due to differences in environmental conditions and the resulting disparity between allometric relationships of urban and forestland tree species (Nowak 1994; Close et al. 1996; McHale et al. 2009). Predicting height for urban trees using forestland models is less than ideal.

Urban trees are exposed to environmental conditions that are unlike conditions posed in typical forestlands. A study of sugar maple site characteristics and tree growth by Close et al. (1996) suggests that street trees have reduced growth rates due to prolonged water stress from high transpiration demand and chronic water deficits when compared to the same forestland species. In another case, pruning has a significant impact on tree size (Nowak 1990; Peper et al. 2001). Impermeable surfaces, soil compaction, fertilizer application, watering regimes, pollutions fluxes and pruning are all indicative of urban environments. Environmental variables influence tree growth allocation and phenology indicating that separate allometric equations, aside from those already developed for forestland species, are necessary to accurately estimate urban tree relationships (McHale et al. 2009). Despite these differences, urban forestry is faced with using forestland models simply because models for urban tree attributes do not exist. And because many ornamental species found in urban environments have not been studied, for many of those species a broad forestland model by genera or a model for hardwood or softwood are used instead (Nowak 1993).

For example, the only biomass equations developed specifically for urban trees are those by Pilsbury et al. (1998) for 15 common California trees (McHale et al. 2009). In most cases urban biomass equations are not available and forestland models are used to predict urban tree biomass (Nowak 1993). Biomass equations developed from forestland trees however, overestimate open-grown urban tree biomass by 1.25 (Nowak 1994). To account for this over prediction, biomass estimates are multiplied by a factor of 0.8 (Nowak and Crane 2002) or by 0.9 by Nowak et al. (2002b) in i-Tree. In addition, due to more rapid growth rates from nutrient and water application in urban areas, tree specific gravity used for biomass equations may be different in urban areas compared to forestlands. (McHale et al. 2009). These methods indicate that there are uncertainties in biomass predictions and models developed from urban trees would provide better suited equations. We assume this relationship holds for urban and forestland tree heights as well.

Urban tree modeling is in its beginning stages (McPherson and Peper 2012). As in forestland trees, urban tree height and dbh are strongly correlated (Nowak 1990; Peper et al. 2001a; 2001b). Equations to predict height of three maple species in Rochester and Syracuse, New York were fit to linear and a quadratic functions of dbh by Nowak (1990). He concluded the species warranted separate equations and used the information to grow out trees in order to determine suitable planting locations. Warm-climate street trees in California were used to fit a height-diameter function by Peper et al. (2001a; 2001b). They recommended a logarithmic function with dbh as the predictor variable and note the need for a pruning index to help explain variability in tree heights.

Diameter at breast height is a relatively simple, inexpensive and a conventional forest measurement (Sharma and Parton 2007). For these reasons, models for predicting height include at minimum, dbh as a predictor variable (Larsen and Hann 1987, Hanus et al. 1999).

The relationship between height and diameter is positive and non-linear. Asymptotic equations, those which approach a horizontal line with increasing values on the x-axis, assume the natural curvature of tree height-diameter relationships and do not allow for unrealistic predictions when extrapolating beyond the original data used to develop them due to their asymptotic behavior (Huang et al. 1992). Non-asymptotic equations such as polynomial functions are inadequate for extreme sizes of dbh (Garman et al., 1995). A good height-diameter function, is flexible, passes through the origin, is monotonic with a slope approaching zero as the predictor variable increases, and is fairly simple to fit (Curtis 1969). Asymptotic functions are just that.

Asymptotic equations are commonly fit and used to predict tree height from dbh in forestlands. Some perform better than others depending on the region and species. The commonly recommended equation for forestland height-diameter modeling is the Chapman-Richards equation (Richards et al. 1959; Huang et al. 1992; Temesgen et al. 2006; Sharma and Parton 2007). Equations commonly compared for predicting height for common trees in the western U.S. were developed by Richards et al. (1959), Yang et al. (1978), Ratkowsky (1990) and Hanus et al. (1999).

Incorporating stand-level predictor variables to the base equation (that which includes only dbh) often improves predictive ability of height-diameter models. Large tree basal area (Temesgen et al. 2008), stand level basal area (Temesgen et al. 2006; Newton and Amponsah 2007; Sharma and Parton 2007), crown competition factors (Temesgen et al. 2006; 2008), trees per hectare (Newton and Amponsah 2007; Sharma and Parton 2007), site index (Larson and Hann 1987; Wang and Hann 1988) and average diameter and height of the 40 largest trees (Hanus et al 1999) may improve model performance for forestland tree species. Stand level predictor variables incorporate site quality and competition that can influence tree height. Adding these variables into equations helps explain variation in height and effectively allows the function to shift to suit the data.

Mixed effect models are another approach to improving predictive performance of height-diameter models. The previously described are fixed effect models. Including a random effect into those equations formulates a mixed model. Due to the nature of typical sampling procedures from plots, mixed models deal with the inherit dependence between observations. Data collected on the same plot is likely more similar than data from another plot. Multiple observations on the same plot are not independent and this violates model assumptions. Adding a random effect for stand or plot has been employed to model forestland tree height to deal with this violation. Mixed effect models were preferred over fixed effect models by Robinson and Wykoff (2004), Sharma and Paron (2007) and by Temesgen et al. (2008). A mixed-effect modeling approach requires a subsample of heights in order to predict the random effect allowing for the model to be calibrated to a specific stand or plot (Gomez-Garcia et al. 2014).

The principal objective of this study is to determine the most adequate modeling strategy to predict tree heights for five common urban tree species in the Western states. The objectives of this study are 1) evaluate the relative predictive performance of a variety of height-diameter models 2) evaluate the inclusion of tree and stand level variables in providing better prediction strategies 3) evaluate the inclusion of a random effect in enhancing model prediction performance and 4) determine if separate height-diameter models are needed for trees in urban areas. Further examination of the height-diameter relationships of the five species from forestland and urban forests are explored.

2.3 Methods

Data

Permanent sample plots have been established throughout the U.S. by the USDA Forest Service Inventory and Analysis (FIA) program, starting over 80 years ago (U.S. Department of Agriculture Forest Service 1992). Each plot is located within one of a 2402.62 hectare (5,937 acre) hexagonal cell, uniformly arranged in a grid across the country. Plots are assigned at random location within the cell and are therefore systematically located and evenly distributed. Under objectives of the FIA program, other than pilot studies, plots not meeting definitions of "forested" or not found on "forestland" are not currently sampled. The data for this study came from a pilot project that measured the FIA plots that existed in the urban areas of Washington, Oregon and California. Though most plots did not contain enough cover to meet the definition of forestland, the urban plots often contained trees in addition to other urban features. Urbanized areas are defined by the U.S. Census as areas within the boundaries of cities having a population of 50,000 or more people (U.S. Department of Commerce Bureau of the Census, 2002). This is the first urban data collected from FIA plots in these states and the first urban forest inventory in the region of this scale. A total of 190, 67, and 695 plots comprise the sample from urbanized areas of Washington, Oregon and California respectively (Table 2.1).

Table 2.1. Summary of urban FIA sample by state.

	WA	OR	OR & WA	CA
Total no. plots	190	67	257	695
Total no. trees	1163	298	1461	1871
Plots with trees	126	45	171	382
Proportion of treed plots	66%	67%	67%	55%

Each plot is composed of a cluster of four subplots and each subplot has a nested micro plot (Figure 2.1). Trees between 2.54 cm and 12.6 cm (1 and 4.9 in) in diameter at breast height (dbh; 1.37 m above ground level) were measured on micro plots while all trees larger than 12.6 cm (5 in) were measured on subplots. Each micro plot has a radius of 2.1 meters (6.8 ft) and the four total .0053 hectares (.013 acre) per plot. Each subplot has a radius of 7.3 meters (24 ft) and the four total .0672 hectares (1/6th acre) per plot.

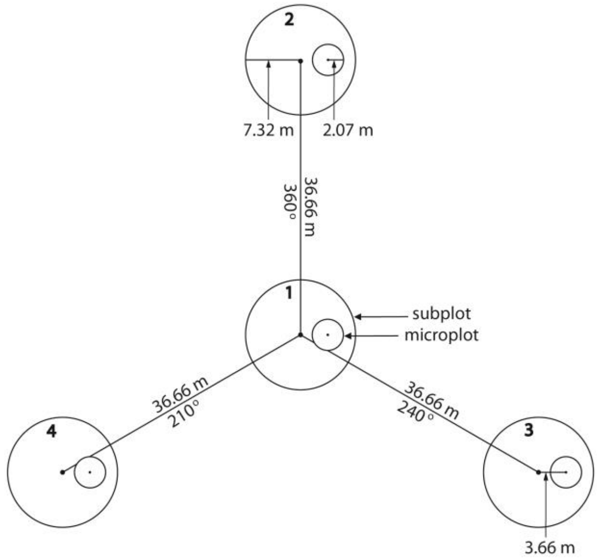

Figure 2.1. Urban forest inventory and analysis plot design layout

Data were collected in 2012 in accordance with the FIA schematic (U.S. Department of Agriculture Forest Service, 2012) along with the protocols of the Forest Health Monitoring program (U.S. Department of Agriculture Forest Service. 2007). Selected variables used for this study include height, diameter, crown light exposure (CLE) and land use. CLE indicates the amount of light the crown receives on a scale from zero to five. It is measured by dividing the crown into four quadrants. One point is given for each quarter that is completely exposed to full light and one point is given for any direct light exposure to the tree center from above. Trees per hectare (TPH) and plot basal area (BA) were calculated from the data [Eq. 2.1] and [Eq. 2.2] and used as additional predictor variables for the extended models investigated.

BA (m^2/ha) is the sum of the cross sectional area of trees from a plot calculated as:

$$BA = \left[\sum_{i=1}^{n} 12.46\pi\left(\frac{dbh_i}{2}\right)^2 + \sum_{j=1}^{m} \pi\left(\frac{dbh_j}{2}\right)^2\right] \qquad [2.1]$$

Where dbhj is tree dbh from of the jth tree from m trees in the four subplots and dbhi is dbh of the ith tree from n trees in the micro plots. Each micro plot tree was expanded by 12.46 to the plot level and plot BA were converted to a per hectare unit.

TPH was calculated for each plot from trees with a dbh greater than 2.5 cm as:

$$TPH = \frac{1}{.06725}\left[\sum_{i=1}^{n} 12.46x_i + \sum_{j=1}^{m} x_j\right] \qquad [2.2]$$

Where x_j is tree basal area from of the *jth* tree from *m* trees in the four subplots and x_i is tree basal of the *ith* tree from *n* trees in the micro plots. Expansion and unit conversion were as described above.

Table 2.2. Summary of tree level data used for h-d modeling.

Species	tree	plot (n)	Diameter (cm) Mean	S.D.	Range	Height (m) Mean	S.D.	Range
Oak spp.	297	30	21.8	13.0	2.1 - 74.2	8.3	3.8	2.1 - 25.9
Douglas-fir	262	28	36.3	23.2	3.8 - 139.2	24.8	11.4	2.7 - 60-7
Red alder	223	21	24.9	12.5	2.6 - 84.9	19.9	6.8	3.0 - 40.8
Big leaf maple	122	13	33.0	16.6	2.5 - 86.0	23.0	7.0	4.3 - 40.0
Western redcedar	98	15	38.3	25.0	4.1 - 114.8	19.6	11.4	3.7 - 60.7

Table 2.3. Summary of stand and tree level variables used in extended h-d models.

Species	Plot basal area (m^2/ha) Mean	S.D.	Range	Crown light exposure Mean	S.D.	Range	Trees per hectare (>2.5cm) Mean	S.D.	Range
Oak spp.	12.9	9.9	1.9 - 41.9	1.5	1.1	0 - 5	516	1233	45 - 6,833
Douglas-fir	31.0	19.9	5.0 - 86.9	2.2	1.5	0 - 5	439	380	60 - 1,535
Red alder	24.7	15.1	3.7 – 63.3	2.2	1.6	0 - 5	485	388	89 - 1,535
Big leaf maple	32.0	26.4	3.7 - 78.2	1.7	1.1	0 - 5	431	414	59 - 1,371
Western redcedar	37.7	26.3	3.4 - 86.9	2.0	1.2	0 - 5	345	305	74 - 1,054

Stem diameter was not collected at breast height (1.37 m) for some trees due to bole irregularities or branching. Height to diameter measurement was recorded in the field and used to impute stem diameter at dbh. Diameter measurements are brought to dbh by allowing for a 1.27 centimeter change in diameter as appropriate for every 1.23 meters of stem length (Avery and Burkhart 2001).

Dbh is calculated if not collected directly in the field using equation [2.3] where Ht_{dbh} is the height of measurement at stem diameter in meters and d is stem diameter in centimetres.

$$dbh = (1.37 - Ht_{dbh}) \times 1.042 + d \tag{2.3}$$

Land use classifications was recorded for each observation and grouped by: agriculture, commercial/industrial, forested, chaparral, park (undeveloped and developed areas as well as cemeteries), residential (single and multi-family structures), transportation (major and limited access roadways with related green spaces) and vacant lots.

Omitted Data

Observations were removed from the data set due to extreme values of height for a given dbh. An outlier with a dbh or 27.4 cm and height of 31.4 meters was identified and removed in the western redcedar data set. One outlier was also removed from the big leaf maple data set due to evidence of over estimation in the field. Few other observations were removed with extreme values although no field or entry misconduct was evident.

Trees with severe top pruning are removed from the data set. In order to estimate the random effects, plots with less than two observations for a given species are removed from the data set as well.

Species Selection

Tree species occurring with the greatest frequency from our sample inventory were chosen for this study. The four most common species sampled in urbanized areas of Oregon and Washington are all native to the region. They include Douglas-fir (*Pseudotsuga menziesii*), red alder (*Alnus rubra*), big leaf maple (*Acer macrophyllum*) and western redcedar (*Thuja plicata*).

California live oak (*Quercus agrifloia*) was the most common tree species sampled in urbanized areas of California. California live oak was combined with data for all oak species encountered in the sample including: canyon live oak (*Q. chrysolepis*), blue oak (*Q. Douglasii*), roble negro (*Q. ilex*), scrub oak (*Q. ilicifolia*), white oak (*Q. lobata*), northern red oak (*Q. rubra*), cork oak (*Q. suber*) and live oak (*Q. virginiana*). Oaks comprised the majority (18.7%) of the sampled trees in California urbanized areas.

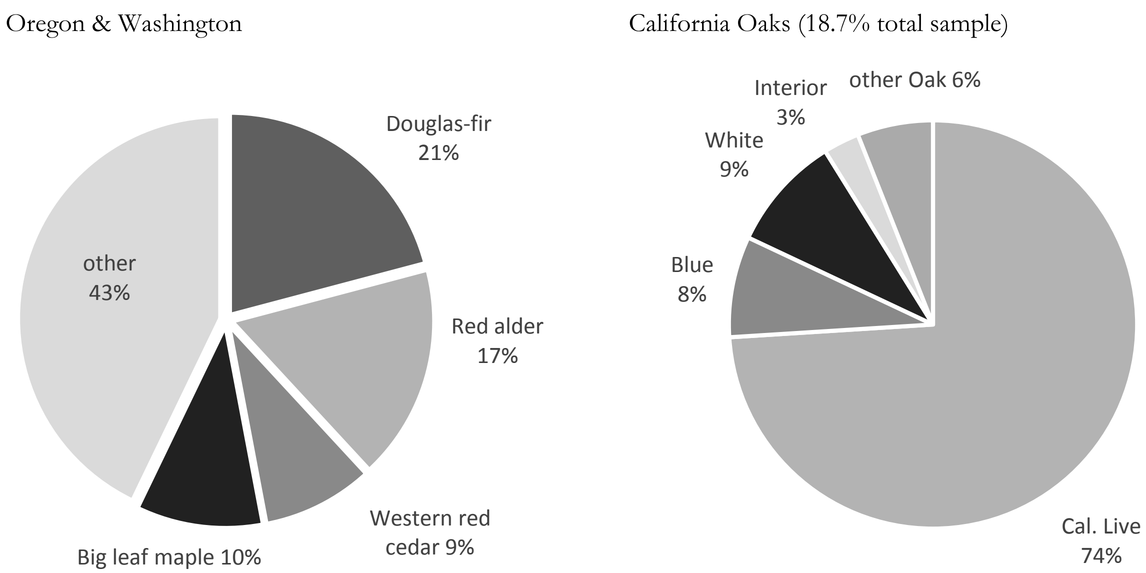

Figure 2.2. Distribution of major urban trees in California and combined Washington and Oregon.

Model Comparison and Selection

We chose to use non-linear asymptotic equations that take the shape of the height-diameter data cloud from the sample data (Figure 2.3). These equations allow for flexibility and do not produce extreme predictions when dbh is large. Four base equations were selected (Table 2.4). These functions are commonly compared and recommended in the literature for predicting tree height for the same species from forestlands in the region (Huang et al. 1992;

Zhang 1997; Temesgen et al. 2008). Where $\widehat{H}$ is predicted height, a, b and c are coefficients and D is dbh.

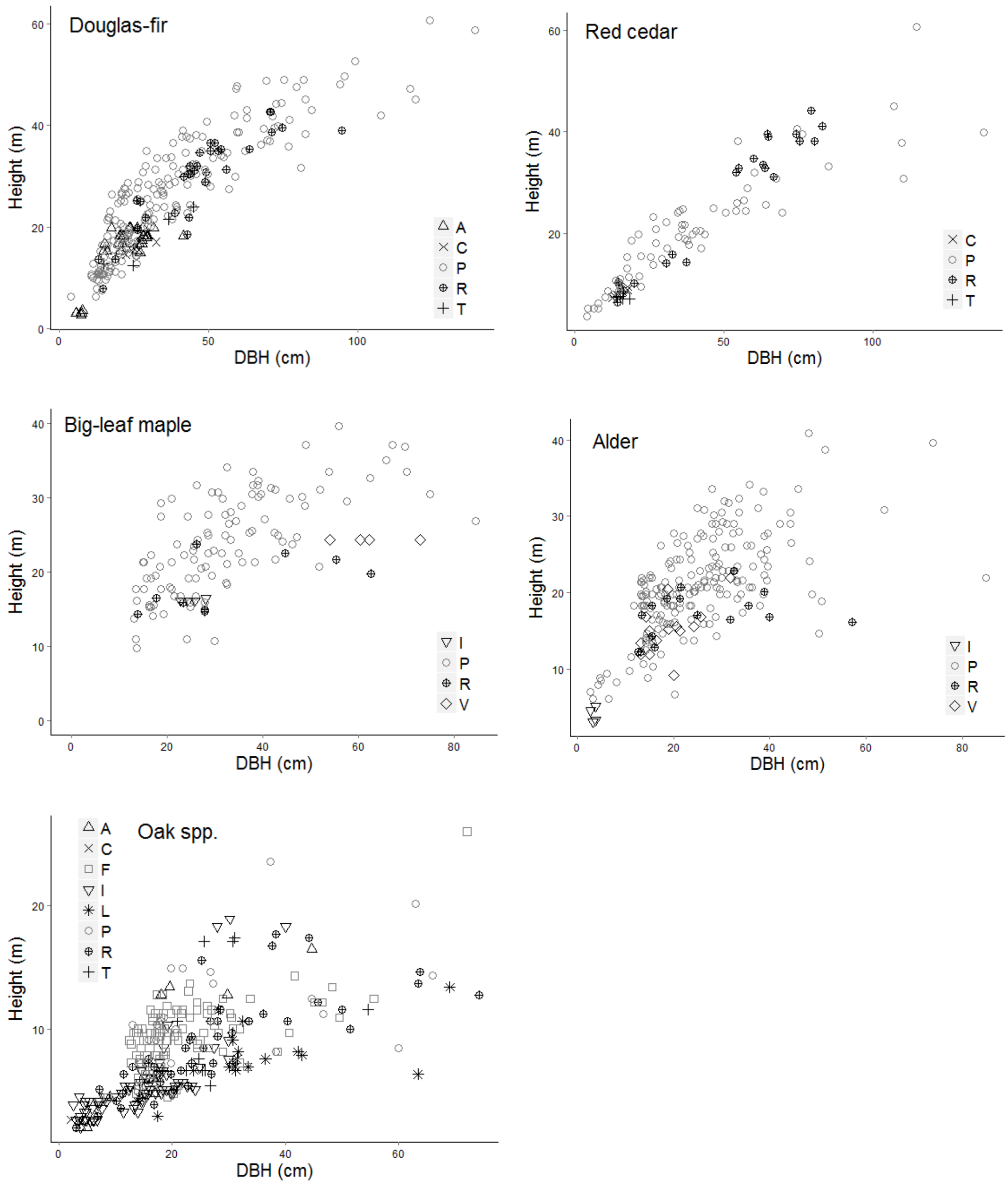

Figure 2.3. Relationship between height and dbh by tree species and land use. Land use is: A=agriculture, C=commercial, F=forested, I=industrial, L=chaparral, P=park, R=residential, and T=transportation.

Table 2.4. List of base non-linear base height-diameter functions.

Eq.	Model form	Source
1.0	$\widehat{H} = 1.3 + a(1 - e^{bD})^{c}$	Richards (1959)
2.0	$\widehat{H} = 1.3 + a(1 - e^{bD^{c}})$	Yang (1978)
3.0	$\widehat{H} = 1.3 + e^{[a + bD^{c}]}$	Hanus (1999)
4.0	$\widehat{H} = 1.3 + e^{[a + \frac{b}{D+c}]}$	Ratkowsky (1990)

Base models are extended to evaluate possible improvements in explanatory power with additional predictor variables (Table 2.5). We evaluate the contribution of BA, TPH and CLE at improving model performance. Where *a*, *a2* and *a3* are coefficients and all other notation is as defined previously.

Table 2.5. List of extended non-linear height-diameter functions.

Eq.	Model form	Description
2.1.1	$\widehat{H} = 1.3 + a + a2 \times CLE + a3 \times BA(1 - e^{bD})^{c}$	Eq. 2.1.0 with CLE and BA
2.1.2	$\widehat{H} = 1.3 + a + a2 \times TPH + a3 \times BA(1 - e^{bD})^{c}$	Eq. 2.1.0 with TPH and BA
2.1.3	$\widehat{H} = 1.3 + a + a2 \times TPH + a3 \times CLE(1 - e^{bD})^{c}$	Eq. 2.1.0 with TPH and CLE
2.2.1	$\widehat{H} = 1.3 + a + a2 \times CLE + a3 \times BA(1 - e^{bD^{c}})$	Eq. 2.2.0 with CLE and BA
2.2.2	$\widehat{H} = 1.3 + a + a2 \times TPH + a3 \times BA(1 - e^{bD^{c}})$	Eq. 2.2.0 with TPH and BA
2.2.3	$\widehat{H} = 1.3 + a + a2 \times TPH + a3 \times CLE(1 - e^{bD^{c}})$	Eq. 2.2.0 with TPH and CLE
2.3.1	$\widehat{H} = 1.3 + e^{[a + a2 \times CLE + a3 \times BA + bD^{c}]}$	Eq. 2.3.0 with CLE and BA
2.3.2	$\widehat{H} = 1.3 + e^{[a + a2 \times TPH + a3 \times BA + bD^{c}]}$	Eq. 2.3.0 with TPH and BA
2.3.3	$\widehat{H} = 1.3 + e^{[a + a2 \times TPH + a3 \times CLE + bD^{c}]}$	Eq. 2.3.0 with TPH and CLE
2.4.1	$\widehat{H} = 1.3 + e^{[a + a2 \times CLE + a3 \times BA + \frac{b}{D+c}]}$	Eq. 2.4.0 with BA and CLE
2.4.2	$\widehat{H} = 1.3 + e^{[a + a2 \times TPH + a3 \times BA + \frac{b}{D+c}]}$	Eq. 2.4.0 with TPH and BA
2.4.3	$\widehat{H} = 1.3 + e^{[a + a2 \times TPH + a3 \times CLE + \frac{b}{D+c}]}$	Eq. 2.4.0 with TPH and CLE

Land use is evaluated as a random variable for mixed effect models. Land use is inserted into the model in varying locations to assess the location most appropriate which allows for a shift in the shape (i.e. asymptote, curvature or steepness) of the function. Because equation [2.0] produced similar fit as the Chapman-Richards model, this model was not adjusted to evaluate mixed effect modeling. Mixed effect modeling methods are evaluated for equations [1.0], [3.0] and [4.0] (Table 2.6). Where b_0 is the random land use effect and all other notation is as defined previously.

Table 2.6. List of height-diameter functions for non-linear mixed models including a random variable (r.v.)

Eq.	Model form	Description
2.1.01	$\hat{H} = 1.3 + (a + b_0)(1 - e^{bD})^c$	Eq. 2.1.0 with r.v. in asymptote
2.1.02	$\hat{H} = 1.3 + a(1 + b_0 - e^{bD})^c$	Eq. 2.1.0 with r.v. in steepness
2.1.03	$\hat{H} = 1.3 + a(1 - e^{bD})^{c+b_0}$	Eq. 2.1.0 with r.v. in curvature
2.3.01	$\hat{H} = 1.3 + b_0 + e^{[a+b_0+bD^c]}$	Eq. 2.3.0 with r.v. in location 1
2.3.02	$\hat{H} = 1.3 + e^{[a+b_0+bD^c]}$	Eq. 2.3.0 with r.v. in location 2
2.3.03	$\hat{H} = 1.3 + e^{[a+bD^{c+b_0}]}$	Eq. 2.3.0 with r.v. in location 3
2.4.01	$\hat{H} = 1.3 + b_0 + e^{[a+\frac{b}{D+c}]}$	Eq. 2.4.0 with r.v. in location 1
2.4.02	$\hat{H} = 1.3 + e^{[a+b_0+\frac{b}{D+c}]}$	Eq. 2.4.0 with r.v. in location 2

Root mean square error (RMSE) and bias are used as a basis for comparing predictive performance of the models. RMSE is a measure of both variance and bias of the estimator. RMSE and bias were calculated from a leave one-out cross validation by plot. The RMSE is not an unbiased estimator of the population variance but when the sample size is large, the bias is small. Models with lower RMSE and bias have better predictive performance. A model's bias is considered a problem if it exceeds 0.50 meters (Temesgen et al. 2006).

RMSE is calculated as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(H_i - \widehat{H}_i\right)^2}{n}} \quad [2.4]$$

Bias is calculated as:

$$Bias = \frac{\sum_{i=1}^{n}\left(H_i - \widehat{H}_i\right)}{n} \quad [2.5]$$

Where H_i is the i^{th} height observation and $\widehat{H}_i$ is the prediction of the i^{th} height observation. The denominator is *n*, the sample size.

Residual plots were also assessed to determine if the model assumptions were upheld. We ensured that the errors were normally distributed with mean zero and equal variance. Predictor variables were evaluated with a t-test for significance.

Parameter Estimation

Equation parameters were estimated with nonlinear least squares using the nls function in R Statistical software (The R Foundation for Statistical Computing 2011) and the package nlme (Version 3.1-117) in R for mixed models. A weight of 1.0/dbh based upon the findings of Larsen and Hann (1987) was used for oak spp., red alder and western redcedar to correct for unequal variance of the residuals. Starting values were obtained from the literature.

Evaluation of Urban and Forestland Tree Height-diameter Relationship

We compare Douglas-fir, red alder, big leaf maple and western redcedar height-diameter relationships from urban and forestland forest types using and indicator variable in non-linear regression analysis. A full model that includes an indicator for urban tree and it's interaction with dbh, is compared with an f-test to the reduced model. The reduced model contains no indicator variable. We used equation [3] for Douglas-fir and equation [4] for the remaining principal species in Oregon and Washington. Forestland and urban oak spp. are not compared because California forestland data is not available.

The equations are presented in Table 2.7. Where h_i is the height of the i^{th} tree, d_i is the dbh of the i^{th} tree, β are coefficients, z_i is the indicator variable ($z_i = 1$ when the i^{th} tree is from an urban forest and 0 when the i^{th} tree is from forestland) and ε_i is random error associated with the i^{th} tree.

Table 2.7. List of full and reduced models used for comparing urban and forestland tree height-diameter relationships.

Eq.	Model form	Description
2.5.0	$h_i = 1.3 + e^{\beta_1+\beta_2 d_i^{\beta_3}+\beta_4 z_i+\beta_5 d_i^{\beta_3} z_i} + \varepsilon_i$	Full Model [Eq. 2.3.0]
2.5.1	$h_i = 1.3 + e^{\beta_1+\beta_2 d_i^{\beta_3}+} + \varepsilon_i$	Reduced Model [Eq. 2.3.0]
2.6.0	$h_i = 1.3 + e^{\beta_1+\frac{\beta_2}{d_i+\beta_3}+\beta_4 * z_i+\beta_5\left(\frac{1}{d_i+\beta_3}\right)} + \varepsilon_i$	Full Model [Eq. 2.4.0]
2.6.1	$h_i = 1.3 + e^{\beta_1+\frac{\beta_2}{d_i+\beta_3}} + \varepsilon_i$	Reduced Model [Eq. 2.4.0]

Forestland data came from a complete set of FIA plots measured from 2002 to 2012 in Oregon and Washington. We use data from plots west of the cascades and no further south than Lane county Oregon for both the urban FIA and forestland FIA data. Damaged trees are not included in the FIA forestland data.

To better understand the significance of these differences, we estimated carbon storage by urban Douglas-fir in urban areas of Oregon and Washington west of the Cascade Range and no further south than Eugen, Oregon. Biomass equations from Zhou and Hemstorm (2010) were used and carbon was derived by multiplying biomass by 0.5. The social cost of carbon is $20.30 per metric ton (Fankhouser 1994). This value is employed in i-Tree. Biomass equations require tree height and dbh. We compared carbon estimates using (1) the observed height, (2) the predicted height using the height-diameter model developed from urban Douglas-fir and (3) the predicted height using the height-diameter model developed from forestland Douglas-fir.

2.4 Results and Discussion

Evaluation of Base Equations

Across each of the five species, base model forms [3.0] and [4.0] are preferred. Model form [3.0] had the lowest RMSE for Douglas-fir while RMSE values for red alder, western redcedar and big leaf maple were the lowest using model form [4.0]. Since each model form produced basically the same RMSE for oak spp. and equation [4.0] lead to the greatest model performance for three of the species, equation [4.0] was selected for oaks. Estimated bias ranged from -0.01 to 0.41 meters for all species although it was big leaf maple with the largest bias. According to Temesgen et al. (2006), a bias less than 0.5 meters is not a problem.

Table 2.8. Base h-d model fit statistics in meters by species. Bold indicates lowest RMSE.

Eq.	Oak spp.*		Douglas-fir		Red alder*		Big leaf maple		Western redcedar*	
	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias
1.0	**2.95**	-0.005	5.00	0.005	5.07	0.159	5.47	0.407	4.99	0.185
2.0	**2.95**	-0.011	5.00	0.003	5.08	0.159	5.47	0.409	5.00	0.190
3.0	2.96	-0.008	**4.96**	0.013	5.07	0.143	5.48	0.411	5.12	0.192
4.0	**2.95**	-0.010	5.01	-0.002	**5.06**	0.150	**5.46**	0.401	**4.82**	0.232

* used weighted regression where $w_i = 1/dbh_i$

Least square regression for prediction relies on the assumption that the random errors associated with each observation are distributed evenly. Douglas-fir and big leaf maple displayed homogeneous variance in their residuals along the predicted values (Figure 2.4). Three of the species, however, displayed an uneven data cloud in residual plots. In each case, variance increases with increasing values of predicted height. Weighted regression was applied as suggested by the literature in the form of 1/dbh to improve residual plots for red alder, western redcedar and oak species (Figure 2.5). Fit statistics can still be compared for weighted regression models if the same weight is applied in each model (Huang et al. 1992). In addition, validating a weighted regression model with weighted heights is appropriate for testing for bias and precision because this method more closely resembles how a model was fit (Larsen and Hann 1987).

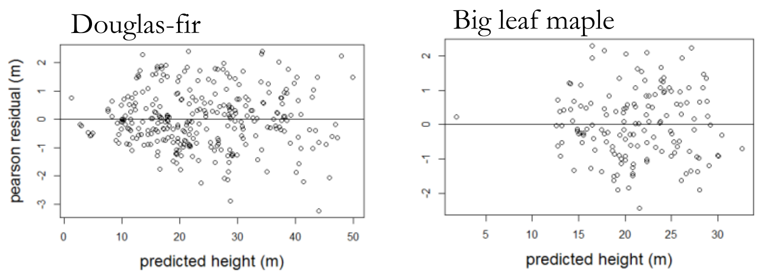

Figure 2.4. Residual plots for Douglas-fir from [Eq. 2.3.0] and big leaf maple from [Eq. 2.4.0] verify homogeneous variance.

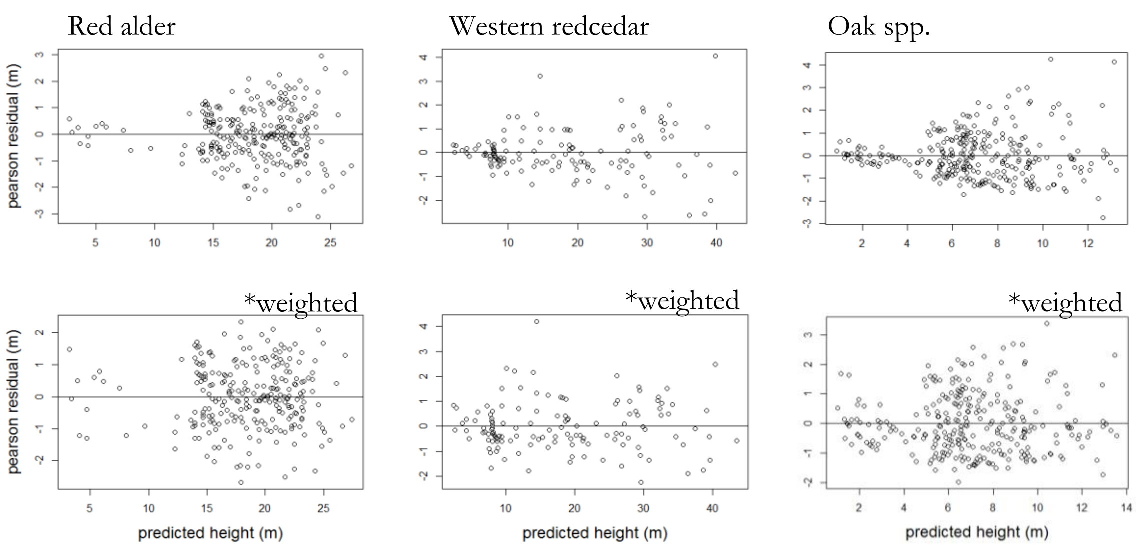

Figure 2.5. Improved residual plots for base equation [2.4.0] by species using weighted regression.

The estimated coefficients from the base equations are provided in Table 2.9. We suggest subsampling tree height and using the data to fit model form [2.3.0] for Douglas-fir or form [2.4.0] for any of the remaining four species. By using localized data, the model can be calibrated to specific height-diameter relationships for a give urban forest. If subsampling is not an option, the coefficients provided could be used with dbh input alone granted heights to be predicted are from an urban forest within the range of the models. For oaks, the range is in urbanized California. For the other four species, the range is in urbanized areas of Oregon and Washington. If additional variables are collected in the field, extended model forms may be more appropriate.

Table 2.9. Estimated parameters a, b and c for base models. All estimated parameters are significantly different from zero ($p < 0.05$).

Equation		[2.1.0]	[2.2.0]	[2.3.0]	[2.4.0]
Oak spp.	a	43.1253	44.2932	3.8694	2.9230
	b	-0.0771	-0.1082	-5.5220	-25.4550
	c	1.1190	1.1585	-0.3542	6.6160
Douglas-fir	a	57.5512	57.3251	4.9164	4.2730
	b	-0.0150	-0.0169	-7.8195	-50.4550
	c	1.0195	1.0377	-0.4301	12.9850
Red alder	a	26.4509	26.6465	3.8654	3.5310
	b	-0.0487	-0.0624	-4.6681	-14.7900
	c	1.0655	1.1000	-0.5265	3.6990
Big leaf maple	a	30.6887	30.7920	3.6870	3.6290
	b	-0.0463	-0.0406	-7.7220	-18.7330
	c	0.9773	0.9350	-0.7570	5.1790
Western redcedar	a	56.9403	60.5514	7.5844	4.3780
	b	-0.0077	-0.0122	-8.9878	-80.1720
	c	1.1061	1.1174	-0.1839	19.9310

Evaluation of Expanded and Mixed-Effect Equations

Base equations [2.3.0] for Douglas-fir and [2.4.0] for the other four principal species performed the best, so extended and mixed effect versions of these forms are chosen for evaluation. Four models were improved with additional explanatory variables and three models are improved with a random effect (Table 2.10 and 2.11).

Table 2.10. Model fit statistics in meters by species for extended and mixed effect versions of Eq. [2.4.0]. Bold indicates lowest overall RMSE.

								Western	
		Oak spp.*		Red alder*		Big leaf maple		redcedar*	
Eq.	Description	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias
	BASE MODEL								
4.0	base	2.95	-0.010	5.06	0.150	5.46	0.401	4.82	0.232
	EXTENDED MODELS								
4.1	CLE & BA	3.26	-0.375	5.17	0.054	**3.82**	0.233	**3.54**	.141
4.2	TPH & BA	2.85	-0.182	5.45	0.040	**	**	4.06	0.140
4.3	CLE & TPH	4.41	-1.345	5.54	0.094	5.80	.551	**	**
	MIXED MODELS								
4.01	r.v. in location 1	3.07	-0.303	4.91	0.060	4.99	0.295	5.07	0.396
4.02	r.v. in location 2	3.59	-0.647	**4.87**	0.070	4.93	0.282	6.15	0.969
4.11	[Eq 4.1] with r.v.				-				
	in location 1	3.47	-0.450	5.10	0.001	3.828	0.230	3.61	0.182
4.12	[Eq 4.1] with r.v.								
	in location 2	4.45	-1.069	5.11	0.002	3.83	0.230	3.61	0.182
4.21	[Eq 4.2] with r.v.								
	in location 1	**2.70**	0.210	-	-	-	-	-	-
4.22	[Eq 4.2] with r.v.								
	in location 2	2.80	0.132	-	-	-	-	-	-

* used weighted regression where $w_i = 1/dbh_i$. ** Unable to converge model, - model not attempted

Table 2.11. Model fit statistics in meters for Douglas-fir using extended and mixed effect modeling versions of Eq. [2.3.0]. Bold indicates lowest overall RMSE.

Eq.	Description	RMSE	Bias
	BASE MODEL		
3.0	base	4.96	0.013
	EXTENDED MODELS		
3.1	CLE & BA	4.86	0.019
3.2	TPA & BA	**	**
3.3	CLE & TPA	4.93	0.040
	MIXED MODELS		
3.01	r.v. in location 1	4.78	0.001
3.02	r.v. in location 2	**4.73**	-0.049
3.03	r.v. in location 3	4.75	-0.032
3.11	[Eq 3.1] with r.v. in location 1	4.76	-0.041
3.12	[Eq 3.2] with r.v. in location 2	4.85	-0.322

** unable to converge model

CLE and BA improve model performance for three of the five species while BA and TPH improve performance for oak spp. red alder is not improved with any combination of predictor variables. RMSE is less for Douglas-fir, western redcedar, big leaf maple and oak models than for base equations indicating that the model is explaining more variability in predicted height. The extended versions, with two variables, also explain more variability in the model than including one alone.

BA and TPH had been used prior for extended models to predict height of forestland tree species. This is the first time CLE was incorporated in a height-diameter model. Exposed crown area is a crude measurement of light availability and Wychoff and Clark (2005) suggested that forest models will be improved by incorporating a variable for crown light exposure. Our results indicate that this is a useful variable to improve model fit statistics. We did not use a crown competition factor (ccfl) commonly employed in forestland height-diameter models because open-grown crown models are not available for urban trees. CLE may be well suited as an indicator of crown competition as it is a more direct measure of competition.

CLE does not however, relay information about other site variables such as obstacles to root growth such as streets and sidewalks, soil nutrients, or soil moisture levels. Other site conditions can be inferred by the measure of BA in meters per hectare or TPH which convey additional information regarding any trees neighboring trees measured on one of the subplots. We expect larger trees and a larger BA in areas with better growing conditions. We also expect more trees, and therefore a larger TPH on sites with better growing conditions. But in urban areas, due to a strong human influence, the quantity of trees on a site and their size may have more to do with land use than site growing conditions. BA more often than TPH improved height-diameter models but weather these explained site conditions, land use practice or the interaction is unclear.

Although the extended versions of base models resulted in improved predictive performance for four of the species, considerations should weigh the cost of additional data collection for only marginal improvements in predictions. Wang and Hann (1988) advise that the additional time required may not support the nominal benefit of the expanded model. However, CLE is a quick measure and TPH and BA can be calculated from any randomized plot design that has dbh for each tree on the plot. Due to the relative ease of collecting and calculating these variables, it is worth the effort to incorporate them into height-diameter models for improved performance. If CLE is not collected, the improvements from BA and TPH, though not as extensive as with CLE, are worth incorporating into the model.

The addition of a random land use variable improved RMSE from the base equation for three species; Douglas-fir, red alder and big leaf maple (Table 2.10 and 2.11). The improved fit statistics from mixed modeling for big leaf maple however, were not greater than the improvements with the extended model version. Mixed models for red alder [Eq. 4.02] and big leaf maple [Eq. 3.02] were the overall best for these species compared to the other equations in this study. The overall best equation for oak is the mixed model with BA and TPH [4.21]. Interestingly, the unextended mixed models [4.01 and 4.02] have no improvement in RMSE and bias from the base equation.

A hierarchical data set of this nature leads to non-independent observations. This is due to the plot structure with multiple observations for a give plot. Trees from the same plot are likely similar to each other and are therefore not independent. Non-independence between the sample units violates ordinary least square assumptions. This is often times the case with forestry data and previous methods (e.g., Temesgen et al. 2008) have incorporated a random stand effect to mitigate this issue.

Land use is used as the random effect in this study. It is reasonable to assume that the structure and composition of the urban forest within each land use type varies less between the same land use and more between different land use types. The variability is not homogeneous across the urban environment. Trees from one land use type are more likely similar to trees from the same land use. For this reason, we chose land use to act as a random variable. Figure 2.6 shows the decrease in variability of the residuals by species and land use when a random land use effect is incorporated into the model.

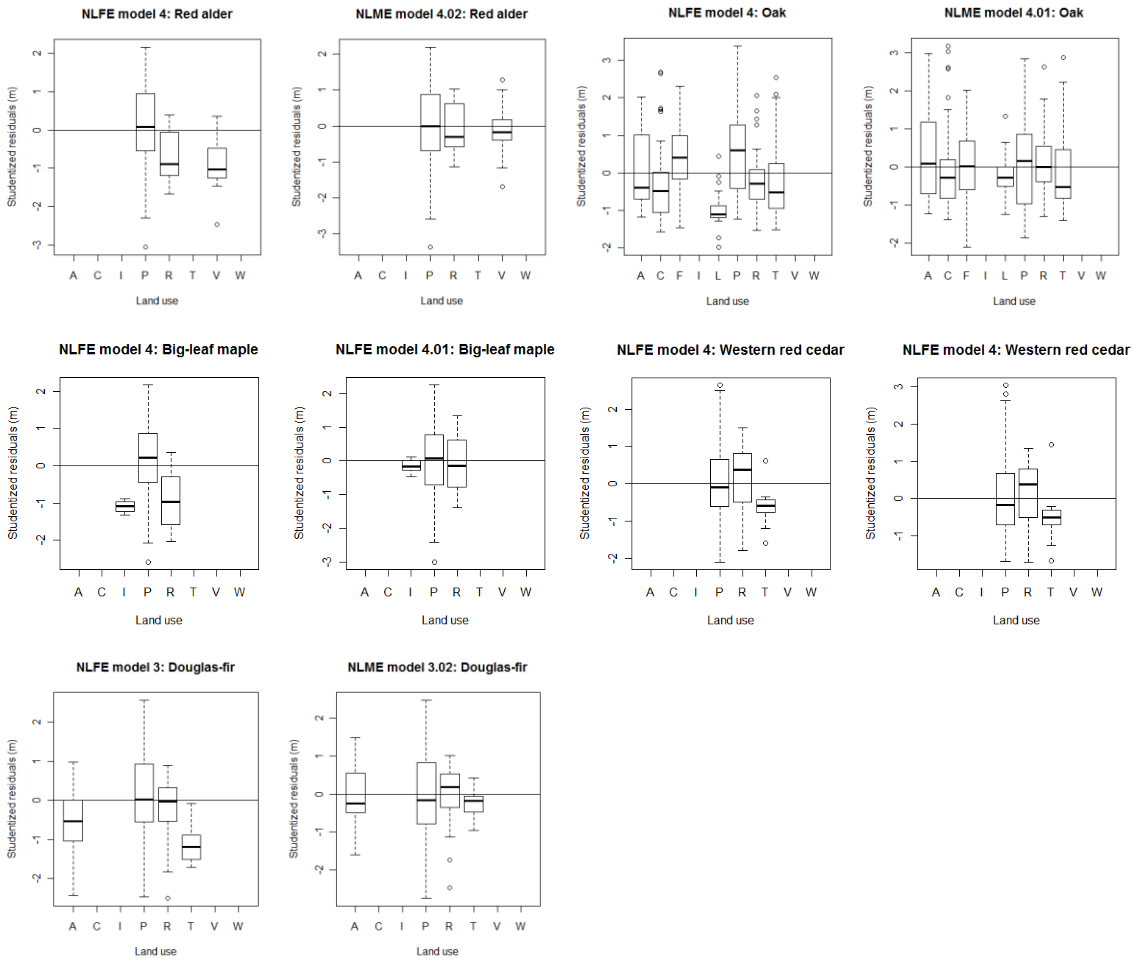

Figure 2.6. Box plot comparison of explained variability between non-linear fixed effect (NLFE) and non-linear mixed effect (NLME) models by species. Land use is: A-agriculture, C-commercial, F-forested, I-industrial, L-chaparral, P-park, R-residential, T-transportation, V-vacant and W-water.

Mixed models can be used only when a subset of heights is sampled. The subsample is used to estimate the variance component of the model. In this way, the mixed models allow for model calibration to a specific urban forest providing heightened predictive ability for the stand.

Convergence was an issue for mixed models when land use was not well represented. Land use was aggregated in cases with few observations. Those were aggregated by either (1) combining like land uses or (2) combining the two land uses types with the fewest representatives. Future model fitting should consider using plot or city as the random effect if the data set is unbalanced by land use and with few replicates in a given category. Land use is not well represented and aggregation methods are not clearly interpretable as unlike groups are combined for this study. For example, agriculture was combined with commercial for Douglas-fir and industrial was combined with vacant for red alder.

In addition to correcting for the independence violation, we wanted the model to account for land use and be able to adjust with land use types. While this was achieved (Figure 2.7), the grouping is less than ideal. Future modeling attempts should consider land use type as either a categorical or indicator variable to be included into an extended model.

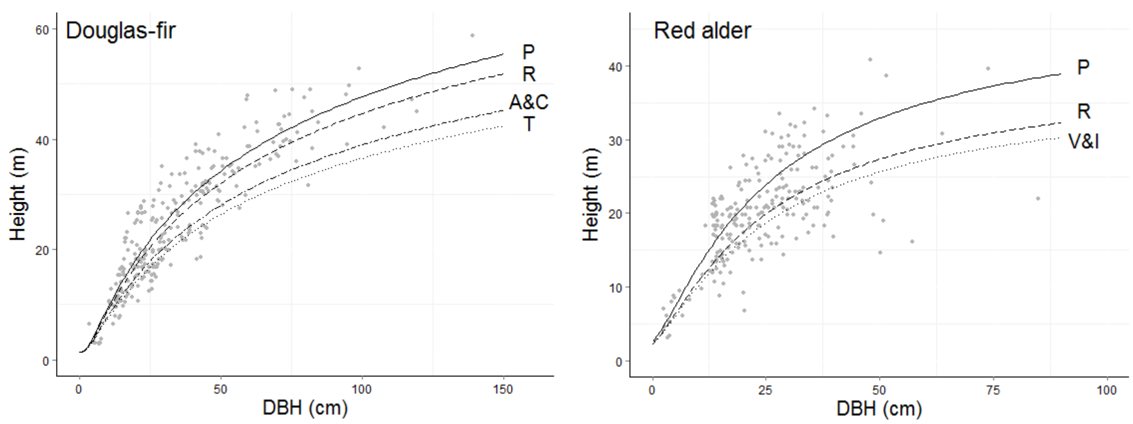

Figure 2.7. Non-linear mixed effect model [2.3.02] for Douglas-fir and [4.02] for red alder allows flexibility between land use types. Land use is: A-agriculture, C-commercial, I-industrial, P-park, R-residential, T-transportation and V-vacant.

Coefficients can be used for starting values for future modeling. It is best to subsample tree height in order to calibrate these equations to a particular urban forest. The coefficients are provided for the best extended and mixed effect model forms (Table 2.12).

Table 2.12. Estimated parameters for selected mixed effect and extended height-diameter models. Where σ_{b0} is the estimated standard error associated with the random effect.

Eq.	Species	a	a2	a3	b	c	σ_{b0}
4.1	Big leaf maple	3.0200	0.0568	.0059	-11.2080	4.7390	-
3.1	Douglas-fir	4.6745	-0.0194	.0018	-8.5989	-0.4986	-
3.02	Douglas-fir	4.5608	-	-	-8.0171	-0.4846	0.1143
4.2	Oak spp.	2.6516	-.0001	.0014	-20.2485	6.4495	-
4.21	Oak spp.	2.5203	-0.0002	0.0161	-13.5258	-0.4089	1.3713
4.02	Red alder	3.3791			-13.9807	3.7336	0.1212
4.1	Western redcedar	4.1070	-0.0438	.0040	-65.5400	11.6380	-

Urban vs. Forestland Trees

Western Washington and Oregon urban trees show differences in height-diameter relationships when compared to the same species in forestlands west of the Cascade Range. We tested for β_4 and β_5 from equations [2.5.0] and [2.6.0] equal to zero with an F-test. Evidence suggests that Douglas-fir, red alder, western redcedar and big leaf maple from urban environments have a different height-diameter relationship than in forestlands with significance level $p < .0001$, $p=.0002$, $p < .0001$ and $p = .0313$ respectively.

Figure 2.8 shows the height-diameter relationship for urban and forestland species. Urban redcedar and big leaf maple have greater heights for a given dbh than in forestlands. However, when dbh is small, these differences are less extreme. The functions for urban and forestland Douglas-fir are nearly the same graphically unit around 30 cm dbh. Urban Douglas-fir is smaller than in forestland grown environments and this disparity grows with increasing dbh.

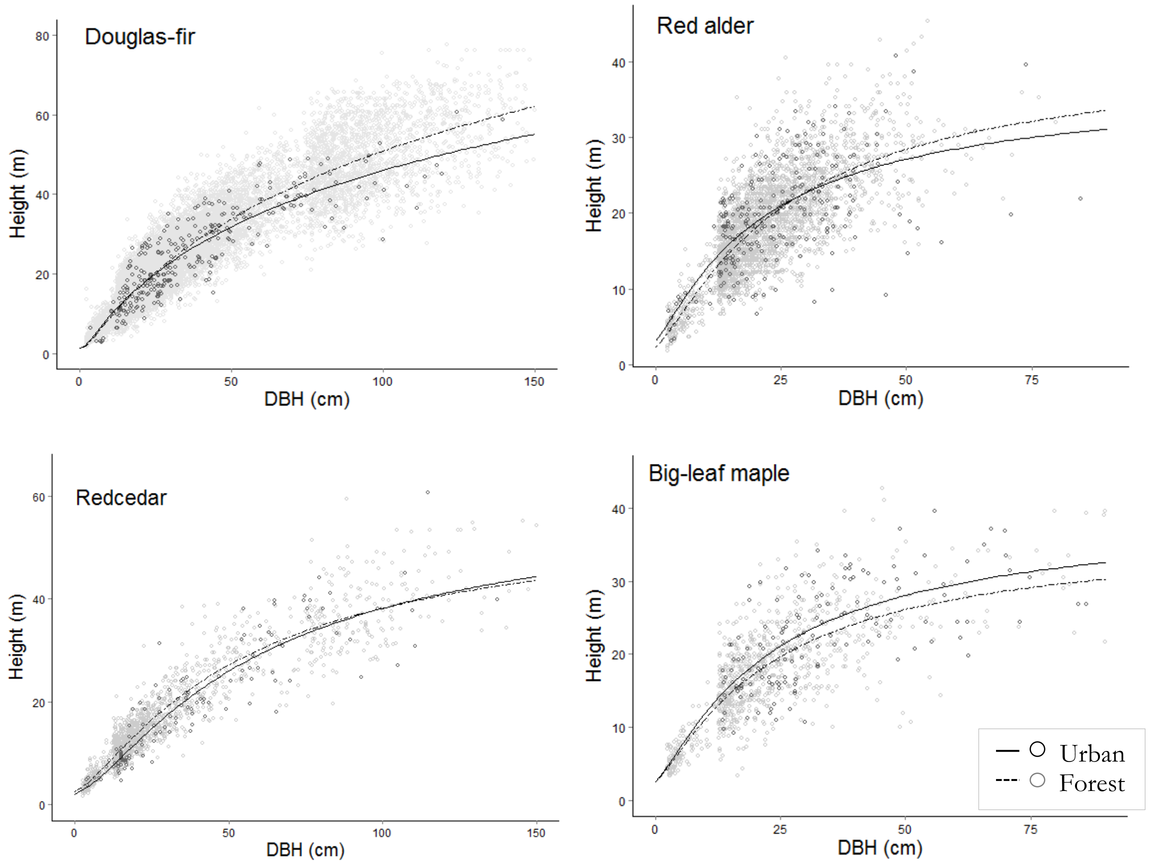

Figure 2.8. Height-diameter relationship with function [Eq. 2.5.0] and [Eq. 2.6.0] for urban and forestland tree species.

Height for urban red alder is smaller for large stem diameters than in forestlands but larger for smaller diameter trees. The urban and forestland functions cross at around 30 centimeters dbh. Younger alders are taller in urban environments until they reach around 30 centimeters dbh at which point, forestland alder has on average greater heights.

The reasons for these differences can only be speculative. Data from urban trees comprises an array of land use and maintenance practices. Whether fertilization, frequent watering, lack of competition or some other factor in urban environments account for differences in height for a give diameter is unknown. Data from forestlands come from a range of ecotypes and land use practices on the west side as well.

Of the 952 urban plots in California, Oregon and Washington, 67 did meet the definition of accessible forest land and were also visited by forest crews. This is due to the urban boundary layer that often included low density areas on the edge of populated suburbs. The inclusion of these plots in both our urban and forestland data set may affect the results however, there are so few plots that the effect is likely minimal especially for highly significant p-values.

Urbanized areas of Oregon and Washington, west of the Cascade Range and no further south than Eugen, Oregon total 516,261 hectares. Carbon storage in this region from Douglas-fir is estimated to be 1,260,996 tons, a $25.6 million dollar gross value (Table 2.13). Using the predicted height from the model developed from urban Douglas-fir in place of that observed, results in a 0.10 ton biomass per hectare under estimate from that using observed values of height. As tree diameter increases, the disparity between biomass estimates increases between prediction methods (Figure 2.9). The difference is much greater, 7 tons per hectare, using the model developed from forestland trees. Using height predicted from the forestland Douglas-fir model over estimates the total carbon estimate by nearly 2 million tons, a $37 million dollar over estimate.

Table 2.13. Biomass and carbon storage estimates from urban Douglas-fir using observed and predicted heights.

.

	Observed $\boldsymbol{H_{obs}}$	Urban Model $\boldsymbol{\widehat{H}_U}$	Forestland Model $\boldsymbol{\widehat{H}_F}$
Mean Biomass (ton/ha) and 95% C.I.	4.89 ± 0.132	4.79 ± 0.126	11.89 ± 0.164
Total biomass (ton)	2,521,992	2,472,482	6,136,371
Total carbon (ton)	1,260,996	1,236,241	3,068,186
Carbon value (million $$)	25.6	25.1	62.3

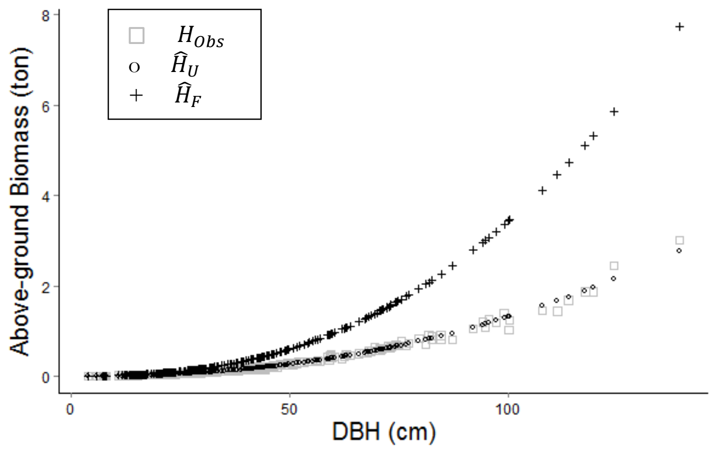

Figure 2.9. Relationship between estimated biomass and dbh from urban Douglas-fir using observed and predicted heights.

Biomass discrepancies into perspective the issue arising from using models developed from forestland trees for urban tree attribute predictions. Average urban Douglas-fir height predicted by the forestland model is 26.13 meters, 1.11 meters greater than that observed. For Douglas-fir, the over prediction in height leads to a 4.89 times (or a 148%) over estimate of tons biomass per hectare leading to further, substantially large, over predictions of carbon and associated monetary values. On the other hand, the 95% confidence interval for tons biomass estimated with the urban model includes the mean estimated from observed values. Although the urban model is under estimating mean biomass per hectare, the difference is not significant at the 95% confidence level.

It should be noted that the biomass equations used for these estimates were developed from forestland Douglas-fir because equations for urban tree biomass do not exist. Biomass, carbon and monetary values are likely overestimated even for estimates using observed data because of the biomass equations. Since urban Douglas-fir height is less than forestland grown Douglas-fir height for a given stem diameter (Figure 2.8), it is reasonable to assume biomass will be as well. Nowak (1994) found that a factor of 0.8 multiplied with urban tree biomass calculated from forestland equations was needed to adjust for this discrepancy. Allometric relationships between height and diameter for the species in this study are different than for the same species in forestlands. Simply multiplying height by a constant shifts the model but does not allow flexibility in shape of the nonlinear curve. By multiplying the predicted height from the forestland model by 0.957, we obtain the same average height of that observed but the shift in the model does not account for the allometric relationship between height and diameter of urban Douglas-fir (Figure 2.10).

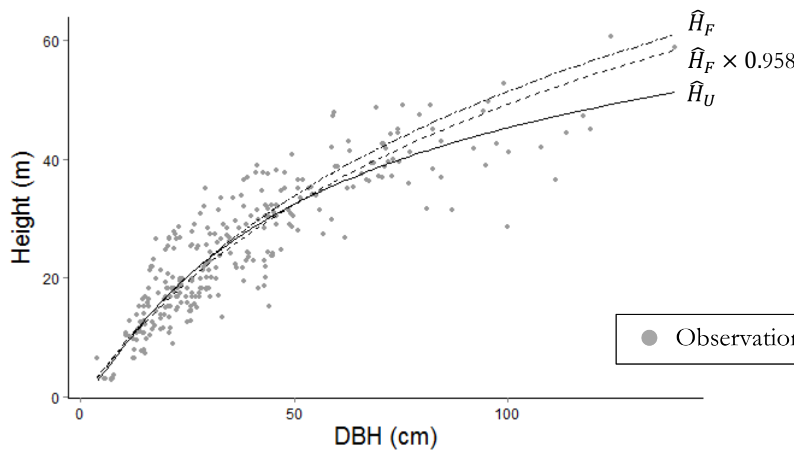

Figure 2.10. Douglas-fir height-diameter relationship: comparing three prediction strategies.

2.5 Conclusion

Height is essential to understanding the structure of the urban forest and a key component to assess the value of urban forests. However, obtaining height is costly and sometime unobtainable. This study assessed the predictive ability of four height-diameter functions commonly applied in forestlands at explaining variability in urban tree height. The best base models were further assessed as extended and mixed effect model versions.

The overall best equation, in terms of lowest RMSE and low bias for big leaf maple and western redcedar was extended model form [2.4.1]. The overall best equations for oak spp., Douglas-fir and red alder were mixed effect model forms [2.4.21], [2.3.02] and [2.4.02] respectively. CLE and BA improved base equations for Douglas-fir, western redcedar and big leaf maple while TPH and BA improved the base equation for oak spp. No extended model version improved the base equation for red alder. The overall best equation for oak spp. was an extended and mixed effect model form. Improvements from a mixed model exceeded improvements from the extended model form for Douglas-fir.

Height-diameter models exist for the same species in forestlands but due to differences in environmental conditions forestland and urban tree allometric relationships differ. We compared the height-diameter relationship of forestland and urban trees for Douglas-fir, red alder, western redcedar and big leaf maple west of the Cascade Range in Oregon and Washington. Urban and forestland height-diameter relationship is statistically different with significance values of $p < .0001$, $p = .0002$, $p < .0001$ and $p = .0313$ respectively.

An unprecedented opportunity to investigate the relationship of urban tree height and stem diameter for major species across a variety of land use types throughout West coast urban areas arose through analysis of this urban FIA data set. The models and coefficients reported are the only species-specific height-diameter models developed for these urban trees in the region. This is the first large scale-modeling attempt for urban tree height prediction.

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3 Predicting largest crown width and height to crown base for major urban tree species in urbanized areas of the western pacific states.

3.1 Abstract

Height to crown base and crown radius are important variables for growth, carbon, pollution and ladder fuel modeling that have not been well modeled specifically for urban trees. Although regional equations are developed to model common forestland tree species attributes in the west, conditions arising from the urban environment pose a divergence in urban tree allometry from typical forestlands. Forestland models are not as suitable as models developed specifically to predict urban tree attributes.

Selected crown radius and height to crown base equations are fitted for live oak (*Quercus agrifolia*), Douglas-fir (*Pseudotsuga menziesii*), red alder (*Alnus rubra*), western redcedar (*Thuja plicata*) and big leaf maple (*Acer macrophyllum*) tree species in urbanized areas of Washington, Oregon and California. Data used to fit selected models come from an urban forest inventory based on protocols set by the USDA Forest Service, Enhanced National Forest Inventory Analysis (FIA) and Forest Health Monitoring program (FHM).

Model forms and predictor variables are evaluated to improve root mean square error and bias. Diameter at breast height, the squared diameter at breast height, an indicator for suppressed and park tree, tree height, the natural log of basal area, height to crown base and percent permeable surface covariates improved linear models for predicting largest crown width. A non-linear exponential equation with a squared term is better suited than a logistic function for predicting height to crown base for live oak. For predicting height to crown of live oak trees, diameter to height ratio, the log basal area, diameter at breast height and an indicator for suppression are the best predictor variables with a root mean square error of 1.8 meters. For largest crown width prediction, best models resulted in root mean square error values between 1.6 to 1.9 meters. Weighted regression in the form of 1/diameter breast height is employed to correct heteroskedasistity of model error terms.

3.2 Introduction

Social, economic and environmental benefits of urban forests are undisputed. Like all trees, urban forests store and sequester carbon thereby reducing the amount of carbon in the atmosphere contributing to global climate change (Nowak 1993; Akbari 2002; Nowak and Crane 2002; Myeong et al. 2005). Unique from typical forestland trees, urban trees have the added benefit of reducing building energy use (McPherson 1994a; Simpson and McPherson 1998; Akbari 2002; Sawka 2013), removing pollutants from the air (Brack 2002; Nowak et al. 2006; Escobedo and Nowak 2009; Morani et al. 2011), reducing the urban 'heat island' effect (Shashua-Bar and Hoffman 2000), increasing property values (Sander et al. 2010; Saphores and Li 2012), improving commerce (Wolf 2003; 2005) and mitigating stormwater runoff (Xiao et al. 1998; Gill et al. 2007). It is due to the proximity of trees to buildings, pollution sources and human traffic that urban trees are uniquely positioned to provide much of the US population with benefits essential to the livability of urban environments.

Tree canopy is the single most important urban forest asset in providing social, environmental and economic benefits (Nowak, 1996). Canopy affects building heating and cooling energy use, is the site of pollution removal and carbon sequestration, and constitutes aesthetic value. Branches and leaves that comprise the tree canopy block wind and create shade allowing near-by buildings to limit wintertime heating and summertime cooling energy consumption. Leaves are the sites of stomatal conductance where airborne pollutants are absorbed and removed from the atmosphere. Carbon dioxide enters trees through stomata, is broken down by the photosynthetic process. The carbon is assimilated into the biomass of the tree while oxygen is released. Rainwater is intercepted by canopy to slowly enter runoff channels and attenuate stormwater pollution entering water channels. Canopies are esthetically pleasing and create habitable refuge for many avian species. Urban tree canopies are important structural components of our urban forests and are therefore of interest to resource managers (Marshall et al. 2003).

Crown dimensions provide a great amount of information about the structure, health and benefit of the urban forest. They can be used to estimate crown cover, crown volume and solar, rainwater and wind interception potential. Hence, it is common to measure crown dimensions for urban trees. Unfortunately, crown measurements are relatively time consuming and sometimes difficult to collect in urban environments. Crowns can extend into streets with unsafe traffic conditions, adjacent properties where permissions may be an issue, or above or below rooftops where crown edges are unseen either by ground or aerial views. Somewhat accurate ocular estimates may be made in these cases. Typically two measurements are collected to find an average and this is time consuming and can sometimes prove difficult when working in urban areas.

The height to crown base (HCB), the point at which the crown begins on the stem or similarly, the crown ratio (CR), the proportion of the stem which carries the canopy, is important information that is also relatively time consuming to collect. Several methods are used to collect this information. If hypsometers are employed, some distance from the stem is needed to determine the height of the live crown base. Again, issues may arise with safety, permissions or blocked lines of sight and as with any measurement, there are costs associated with additional field time.

When this information is unobtainable or simply not available as in growth predictions, models for predicting these variables can be useful. In urban areas, tree crown modeling is limited for crown diameter and not published for HCB or CR.

Peper et al. (2001a) were able to predict crown diameter as a function of diameter at breast height (dbh) using a logarithmic regression function for 16 species in Santa Monica, California. Sample sizes were small, ranging from 27 to 33 roadsides trees. Root mean square errors (RMSE) ranged from 0.12 and 0.22 meters and adjusted coefficients of determination between 0.57 and 0.95. Peper et al. (2001b) used the same methods for 12 common street trees in Modesto, California results similar to Santa Monica. Martin et al. (2012) fit linear regression equations to predict crown width of three open-grown oak species common to the south using dbh and a quadratic term for dbh. Adjusted coefficient of determination values between 0.91 and 0.96. RMSE values are not presented. Polynomial equations were used by Troxel et al. (2013) for common urban tree species in New Haven, CT in northeastern U.S. to establish allometric relationships between age, dbh, crown diameter and crown volume.

In urban areas, modeling attempts for HCB have not been published but information for forestland HCB modeling is abundant. HCB and the related CR have been modeled across multiple regions in North America and for a variety of species (Rijal et al. 2012).

Nonlinear HCB model comparison commonly occur in the literature and the logistic form is most often preferred (e.g., Ritchie and Hann 1987; Zumrawi and Hann 1999; Hanus et al. 2000; Rijal et al. 2012). The logistic equation has the benefit of being constrained so that predictions more closely resemble the biological relationships with the predictor variables, producing better fit statistics compared to other nonlinear forms and being easy to interpret compared to modes with squared expressions (Ritchie and Hann 1987). The logistic equation can be constrained so that CR cannot exceed 1 or be below zero, or to not allow HCB to be greater than the tree height. Soares and Tome (2001) suggested the 'Richards" function, a form of the logistic with constrained parameters which later was employed and recommended by Rijal et al. (2012).

At minimum, the logistic equation includes height and dbh as explanatory variables but additional covariates are often included to improve model performance. Explanatory variables can be thought of as three types; those which describe the tree size, competition or environmental conditions (Temesgen et al. 2005). Among those commonly used in forestlands are tree height (H), diameter to height ratio (DHR), crown competition factor (ccf), ccf for large trees (ccfl), basal area (BA), BA for larger trees (BAL), site index (SI) and climatic site index (CSI). Rijal et al. (2012) found H, DHR, CCF, BAL and CSI to be the most suitable and Zumrawi and Hann (1999) found SI to be an insignificant contributor. Size variables may be better at explaining variability than competition type variables because size variables intrinsically reflect measures of competition (Temesgen et al. 2005).

Crown diameter equations are linear and at minimum include dbh as the single independent variable as well. They are well represented in the forestry literature. Commonly a quadratic term for dbh is also added along with additional independent variable to aid in better predictive performance.

Similar to this study, Bechtold (2004) used the Forest Health and Monitoring (FHM) data set to develop regional largest crown width (LCW) models for stand-grown trees in the Western states (CA, CO, ID, NV, OR, UT, WA, WY). They found stem diameter (D), quadratic stem diameter (D^2), live-crown ratio (CR), stand-level basal area (BA), and Hopkins bioclimatic index (HI) to be the most well suited predictor variables. Earlier however, Gill et al. (2000) had found only modest improvements with extended models. Sattler and LeMay (2011) fit crown length and LCW equations simultaneously using system equations to improve model predictive ability. Crown width and length are related. Each influences the other and therefore a systems approach improves predictive performance and ensures logical consistency.

In the literature, maximum crown width (MCW) is used when describing crown width models which were fit with observations from open-grown trees. Open-grown trees are assumed to not be in competition for resources and therefor represent the maximum size a crown can achieve for a given species. LCW models are fit with data from stand-grown trees in less than ideal growing conditions.

Crown dimensions can be important components for forest growth and yield modeling in forestlands (Soares and Tome 2001; Temesgen et al. 2005; Rijal et al. 2012). Crown size, in terms of foliage area or weight, determines growth capacity (Ritchie and Hann 1987). Crown dimensions can be used to estimate crown cover, crown volume and solar, rainwater and wind interception potential. Biomass and hence, carbon are an important reason for modeling crown volume. Additionally, HCB is a critical component influencing initiation and propagation of a crown fire making HCB and important consideration for fire management (McAlpine and Hobbs 1994). In urban areas, the single most important forest asset in providing social, environmental and economic benefits is the crown (Nowak, 1996). Since HCB is not a common measurement for forest inventory (McAlpine and Hobbs 1994; Soares and Tome 2001; USDA Forest Service 2012b), HCB or CR models are useful.

Although these models are developed for many forestland species, conditions arising from the urban environment suggest differences in allometric relationships between forestland and urban trees. Urban trees are exposed to environmental conditions that are unlike conditions posed in typical forestlands. One large difference in urban areas is the potential less light competition as planting densities are much less than in forestlands (McHale et al. 2009). The authors also point out that urban trees receive fertilization and water. A study of sugar maple site characteristics and tree growth by Close et al. (1996) suggests that street trees have reduced growth rates due to prolonged water stress from high transpiration demand and chronic water deficits when compared to the same forestland species. In another case, pruning has a significant impact on tree size (Nowak 1990; Peper et al. 2001a; 2001b). Human manipulation of the environment has a large influence on tree growth allocation and phenology indicating that separate allometric equations, aside from those already developed for forestland species, are necessary to accurately estimate urban tree relationships (McHale et al. 2009). Despite these differences, urban forestry is faced with using forestland models simply because models for urban tree attributes do not exist. And because many ornamental species found in urban environments have not been studied, more broad forestland models by genera or for hardwood or softwood are used instead (Nowak 1993).

The objective of this study is to develop LCW and HCB prediction models for urban Douglas-fir (*Pseudotsuga menziessii*), live oak (*Quercus agrifolia*), western redcedar (*Thuja plicata*), red alder (*Alnus rubra*) and big leaf maple (*Acer macrophyllum*), the principal tree species found in urbanized areas of Washington, Oregon and California.

3.3 Methods

Data

Permanent sample plots have been established throughout the U.S. by the USDA Forest Service Inventory and Analysis (FIA) program, starting over 80 years ago (U.S. Department of Agriculture Forest Service, 1992). Each plot is located within one of a 2402.62 hectare (5,937 acre) hexagonal cell, uniformly arranged in a grid across the country. Plots are assigned at random location within the cell and are therefore systematically located and evenly distributed. Under objectives of the FIA program, other than pilot studies, plots not meeting definitions of "forested" or not found on "forestland" are not currently sampled. The urban tree data for this study came from a pilot project that measured the FIA plots that existed in the urban areas of Washington, Oregon and California. Though most plots did not contain enough cover to meet the definition of forestland, the urban plots often contained trees in addition to other urban features. Urbanized areas are defined by the U.S. Census as areas within the boundaries of cities having a population of 50,000 or more people (U.S. Department of Commerce Bureau of the Census, 2002). This is the first urban data collected from FIA plots in these states and the first urban forest inventory in the region of this scale. A total of 190, 67, and 695 plots comprise the sample from urbanized areas of Washington, Oregon and California respectively (Table 3.1).

Table 3.1. Summary of urban FIA sample by state.

	WA	OR	OR & WA	CA
Total no. plots	190	67	257	695
Total no. trees	1163	298	1461	1871
Plots with trees	126	45	171	382
Proportion of treed plots	66%	67%	67%	55%

Each plot is composed of a cluster of four subplots and each subplot has a nested micro plot (Figure 3.1). Trees between 2.54 cm and 12.6 cm (1 and 4.9 in) in diameter at breast height (dbh; 1.37 m above ground level) were measured on micro plots while all larger trees were measured on subplots. Each micro plot has a radius of 2.1 meters (6.8 ft) and the four total .0053 hectares (.013 acre) per plot. Each subplot has a radius of 7.3 meters (24 ft) and the four total .0672 hectares (1/6th acre) per plot.

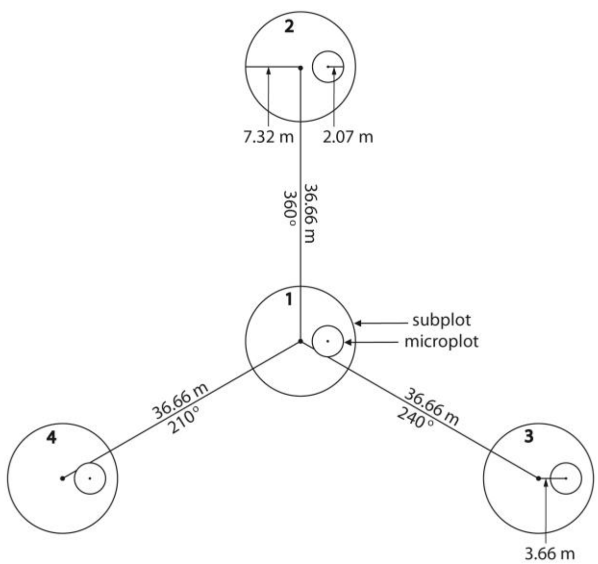

Figure 3.1. Urban forest inventory and analysis plot design layout.

Data were collected in 2012 in accordance with the FIA schematic (U.S. Department of Agriculture Forest Service, 2012) along with the protocols of the Forest Health Monitoring program (U.S. Department of Agriculture Forest Service. 2007). Selected variables from the inventory used for this study include crown diameter, uncompacted crown ratio (CR), stem diameter, crown light exposure (CLE), percent permeable, impermeable and herbaceous surface, and land use types. Land use classification was recorded for each observation and grouped by: agriculture, commercial/industrial, forested, chaparral, park (undeveloped and developed areas as well as cemeteries), residential (single and multi-family structures), transportation (major and limited access roadways with related green spaces) and vacant lots.

We assessed the suitability of several variables for explaining variation in LCW or HCB. For LCW, we examined size variables: dbh, and its quadratic form, stem height (H), HCB, CR, diameter to height ratio (DHR), competition variables: plot basal area (BA), the natural log BA, trees per hectare (TPH), CLE, a suppression indicator and environmental variables: percent permeable (Perm), impermeable (Imper) and herbaceous (Herb) surface in the plot and indicators for park, or west of the Cascade Range. For HCB models, we access all of these same variables as well as LCW but not HCB. Several variables are calculated from the data.

CLE indicates the amount of light the crown receives on a scale from zero to five. It is measured by dividing the crown into four quadrants. One point is given for each quadrant that is completely exposed to full light and one point is given for any direct light exposure to the tree center from above. An indicator for suppression (Sup) was designated from CLE for each tree where Sup is one when CLE is less than two and zero otherwise.

BA (m^2/ha) is the sum of the cross sectional area of trees from a plot calculated as:

$$BA = \left[\sum_{i=1}^{n} 12.46\pi \left(\frac{dbh_i}{2}\right)^2 + \sum_{j=1}^{m} \pi \left(\frac{dbh_j}{2}\right)^2\right] \qquad [3.1]$$

Where *dbhj* is tree dbh from of the *jth* tree from *m* trees in the four subplots and *dbhi* is dbh of the *ith* tree from *n* trees in the micro plots. Each micro plot tree was expanded by 12.46 to the plot level and plot BA were converted to a per hectare unit.

TPH was calculated for each plot from trees with a dbh greater than 2.5 cm as:

$$TPH = \frac{1}{.06725}\left[\sum_{i=1}^{n} 12.46x_i + \sum_{j=1}^{m} x_j\right] \qquad [3.2]$$

Where x_j is tree basal area from of the *jth* tree from *m* trees in the four subplots and x_i is tree basal of the *ith* tree from *n* trees in the micro plots. Expansion and unit conversion were as described above.

Height to crown base (HCB) is calculated as:

$$HCB_i = H_i - CR_i(H_i) \tag{3.3}$$

Where HCB_i is the height to crown base of the *ith* tree, H_i is the height of the *ith* tree and CR_i is the uncompacted crown ratio of the *ith* tree.

Largest crown width (LCW) is calculated as the quadratic mean diameter by:

$$LCW_i = \sqrt{\frac{D_{i1}^2 + D_{i2}^2}{2}} \tag{3.4}$$

Where LCW_i is the largest crown width of the *ith* tree, D_{i1} is the largest crown diameter from the *ith* tree and D_{i2} is the crown diameter 90° from D_{i1} of the *ith* tree.

Diameter height ratio (DHR) is calculated as:

$$DHR_i = \frac{dbh_i}{H_i} \tag{3.5}$$

Where *DHRi* is the diameter to height ratio of the *ith* tree.

Stem diameter was not collected at breast height (1.37 m) for some trees due to bole irregularities or branching. Height to diameter measurement was recorded in the field and used to impute stem diameter at dbh. Diameter measurements are brought to dbh by allowing for a 1.27 centimeter change in diameter as appropriate for every 1.23 meters of stem length (Avery and Burkhart 2001).

Dbh is calculated if not collected directly in the field using equation [3.6] where Ht_{d_i} is the height of measurement at stem diameter in meters and d_i is stem diameter in centimetres.

$$dbh_i = \left(1.37 - Ht_{d_i}\right) \times 1.042 + d_i \qquad [3.6]$$

The data comes from a diverse array of land use and management practices and from open-grown and competitively-grown conditions. Observations with severe top pruning or a lack of crown were removed. Outliers outside the data cloud were identified ocularly and removed from the data set.

Species Selection

Tree species occurring with the greatest frequency from our sample inventory were chosen for this study. The four most common species sampled in urbanized areas of Oregon and Washington are all native to the region. They include Douglas-fir (*Pseudotsuga menziesii*) at 21%, red alder (*Alnus rubra*) at 17%, big leaf maple (*Acer macrophyllum*) at 10%, and western redcedar (*Thuja plicata*) at 9%. California live oak (*Quercus agrifolia*) was the most common tree species at 14% of the sample in urbanized California. The sample ranged from 121 to 278 trees (Table 3.2). A summary of the principal variables from this study is in Table 3.3.

Table 3.2. Summary of observations used for LCW and HCB models.

	Tree	Plot (n)
Douglas-fir	278	57
Coastal live oak	259	38
Red alder	226	38
Western redcedar	121	36
Big leaf maple	132	27

Table 3.3. Summary of LCW, HCB and dbh variables used for crown models.

	Largest crown width (m)			Height to crown base (m)			Dbh (cm)		
Species	Mean	S.D.	Range	Mean	S.D.	Range	Mean	S.D.	Range
Douglas-fir	6.98	3.35	1.7 - 19.1	11.09	8.14	0.03 - 38.3	38.85	24.8	3.8 - 139.2
Coastal live oak	4.99	3.09	0.3 - 16.8	3.15	2.83	0.02 - 20.70	21.9	14.5	2.1 - 102.9
Red alder	6.88	2.64	1.4 - 13.5	10.09	5.54	0.03 - 27.20	24.3	12.1	2.6 - 84.8
Western redcedar	7.07	2.98	1.4 - 14.2	3.48	4.40	0.05 - 24.69	37.6	27.0	4.1 - 137.2
Big leaf maple	9.43	3.06	2.3 - 17.7	12.05	6.52	0.24 - 26.21	34.2	17.1	2.5 - 91.7

Model Comparison and Selection

The models evaluated are common equations used for forestland tree species in the region. LCW is modeled linearly or non-linearly when the quadratic term for dbh is included. For each of the urban species, LCW has generally a linear relationship with dbh although some relationships show signs of a non-linear relationship (i.e. western redcedar) (Figure 3.2).

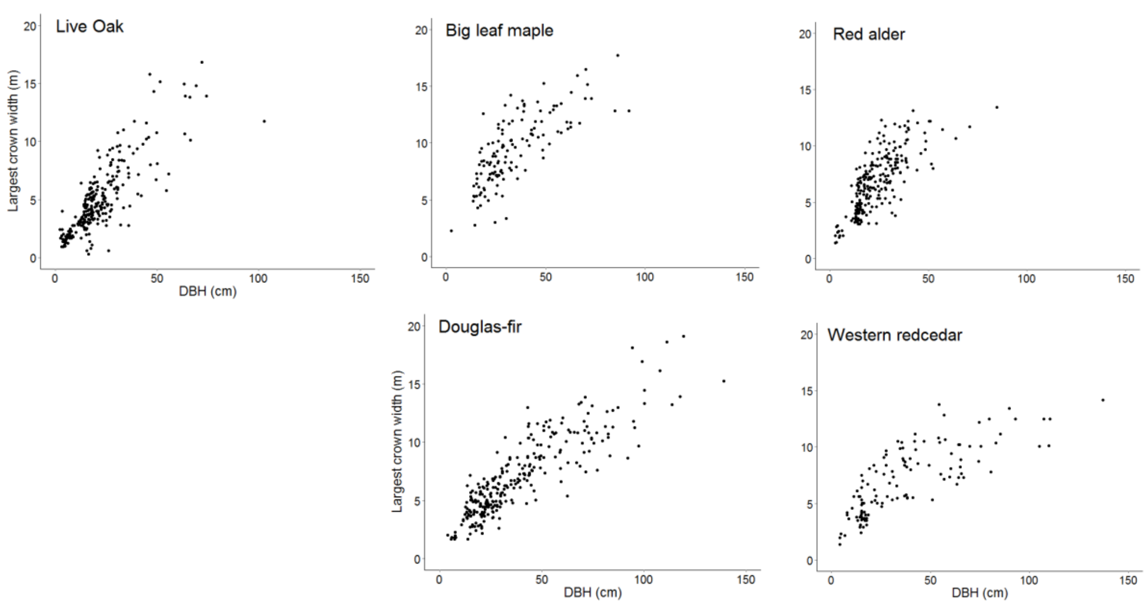

Figure. 3.2. Relationship of LCW and dbh by species.

The general model form for LCW is given in equation [3.1.0] where x_i is the *ith* explanatory variable, b_i is the associated coefficient with the *ith* explanatory variable and k is the number of explanatory variables. At minimum, x_i includes dbh.

$$\widehat{LCW} = \sum_{i=1}^{k} b_i x_i \qquad [3.1.0]$$

For HCB, a logistic model form is most often recommended in the literature. Here we compare the logistic [Eq. 3.2.0] and exponential [Eq. 3.3.0] non-linear models as in Rijal et al. (2012).

$$\widehat{HCB} = \frac{H}{\left[1 + \mathrm{a} * \exp\left(-c \sum_{i=1}^{k} b_i x_i\right)\right]^{1/m}} \qquad [3.2.0]$$

$$\widehat{HCB} = H\left[1 - \mathrm{a} * \exp\left(-c\left(\sum_{i=1}^{k} b_i x_i\right)^{\mathrm{w}}\right)\right] \qquad [3.3.0]$$

Where H is stem height, a and c are parameters set to 1, m is a parameter set to 0.5 [Eq. 3.2.1] or set to 6 [Eq. 3.2.2], w is a parameter set to 2 [Eq. 3.3.1] or set to 10 [Eq. 3.3.2], and all else is a defined earlier.

HCB and dbh are positively correlated though extremely variable (Figure 3.3). We fit HCB models only for live oak in this study. I similar relationship exists between HCB and DHR for live oak (Figure 3.4).

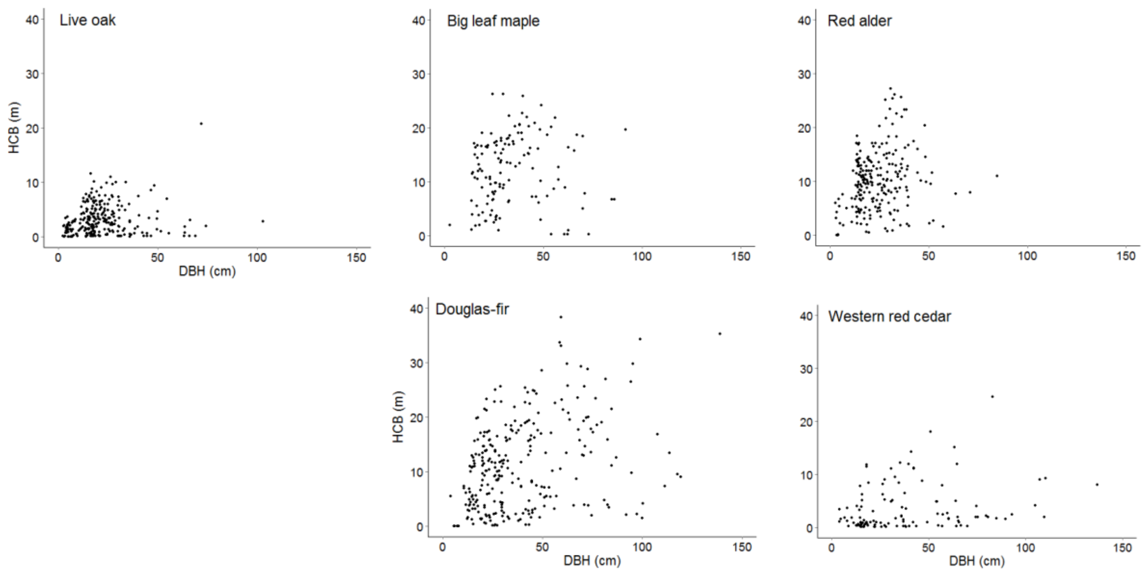

Figure 3.3. Relationship between HCB and dbh by species.

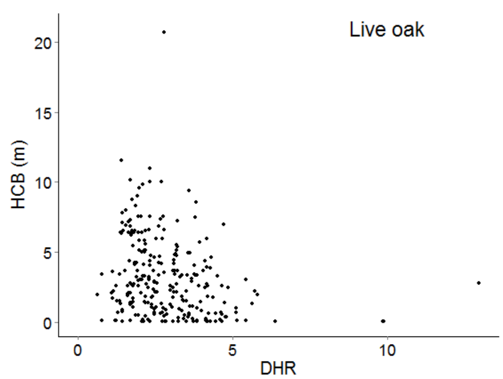

Figure 3.4. Relationship between HCB and DHR for live oak.

Crown width and length are naturally associated with each other (Sattler and LeMay 2011). In a process known as epinastic control, lateral branch growth is maintained by the terminal leader. The degree of epinastic control varies by species. On the other hand, lateral branches, and the amount of potential light absorption, influence terminal growth. As a result, crown length and width are playing a part in the growth of one another and therefor their size. This indicates that each would serve well as predictor variables in these predictive models. Because HCB is a function of crown length and stem height, it too has a natural association with crown width. We follow the methods of Sattler and LeMay (2011) to devise a system of nonlinear simultaneous equations for LCW and HCB to try to further improve model fit statistics.

First we fit linear models for LCW and HCB with the same predictor variables. The variables chosen are those which produce the best fit for LCW modeling. These new variables, LCW_1 and HCB_1 are added to the best LCW and HCB models so that LCW_1 is a predictor for HCB and HCB_1 is a predictor variables for the LCW model.

Root mean square error (RMSE) and bias, are used as a basis for comparing predictive performance of the models. RMSE is a measure of both variance and bias of the estimator. RMSE and bias were calculated from a leave one-out cross validation by plot. The RMSE is not an unbiased estimator of the population variance but when the sample size is large, the bias is small. Models with lower RMSE and bias have better predictive performance.

RMSE is calculated as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_i - \widehat{Y}_i\right)^2}{n}} \qquad [3.7]$$

Bias is calculated as:

$$Bias = \frac{\sum_{i=1}^{n}\left(Y_i - \widehat{Y}_i\right)}{n} \qquad [3.8]$$

Where Y_i is the i^{th} LCW or HCB observation and $\widehat{Y}_i$ is the prediction of the i^{th} LCW or HCB observation. The denominator is *n*, the sample size.

Residual plots were also assessed to determine if the model assumptions were upheld. We ensured that the errors were normally distributed with mean zero and equal variance. Predictor variables were evaluated with a t-test for significance.

Parameter Estimation

Parameters were estimated with nonlinear least squares using the lm and nls function in R Statistical software (The R Foundation for Statistical Computing 2011) and the package nlme (Version 3.1-117) in R for non-linear models. A weight of 1.0/dbh was applied in some cases to correct for unequal variance of the residuals. Starting values were obtained from the linear models.

3.4 Results and Discussion

Evaluation of LCW Models

Largest crown width was predicted from dbh with simple linear regression. RMSE values ranged from 1.66 to 2.06 meters and the adjusted coefficient of determination (R^2) ranged from 0.57 to 0.76 (Table 3.4). RMSE values decreased and adj. R^2 increased with larger sample sizes. The greatest model performance, with lowest RMSE, highest adj. R^2 and low bias, was seen for Douglas-fir. Douglas-fir was also the most represented species in the sample with 278 observations from 57 plots.

Table 3.4. Fit statistics for base models [Eq. 3.1.0] including dbh as the only explanatory variable for predicting LCW.

Species	RMSE (m)	Bias (m)	Adj. R^2
Douglas-fir	1.66	-0.02	0.76
Coast live oak	1.78	-0.07	0.71
Red alder	1.84	-0.01	0.69
Western redcedar	1.96	0.00	0.61
Big leaf maple	2.06	0.04	0.57

For each species, additional explanatory variables improved model performance (Table 3.5). The quadratic form of dbh is the best variable for improving model performance overall. Dbh^2 improved RMSE for four of the five species. Improved RMSE values range between 2 and 10% better than the base model. CLE also improved model performance.

Three of the five species LCW predictions were improved with CLE, however, the indicator for suppression derived from CLE, surpassed those improvements. Suppression improved model fit for four species, of which red alder RMSE was improved by 10% from the base equation. Tree height and the natural log of BA are both good explanatory variables as well. An indicator for park improves model fit only for western redcedar, however; the improvement is relatively large. RMSE was improved by 7%. Of the three surface covers, a variable for percent permeable influenced LCW the most though the improvement was moderate, ranging from 0.5 to 3.8%. An indicator for Cascade west made no improvement for any species. HCB and DHR improve model fit moderately while TPH is poorly suited as an explanatory variable for these urban species as no improvements were made with its addition. Size and competition variables seem to be more important than site specific environmental factors at influencing LCW. This may be due to size already explaining environmental conditions as size relies on growing conditions.

Table 3.5. RMSE and percent improvement (Imp.) from base equation by explanatory variable and species. Bold indicates three most improved for a species.

Explanatory Variable		Douglas-fir		Live oak *		Red Alder*		Western redcedar		Big leaf maple	
		RMSE	Imp.	RMSE	Imp.	RMSE	Imp.	RMSE	Imp.	RMSE	Imp.
Size	dbh^2	1.63	**1.81**			1.68	**8.70**	1.9	**3.06**	1.98	**3.88**
	H			1.73	**2.81**	1.78	3.26			1.96	**4.85**
	HCB	1.65	0.60								
	DHR			1.74	**2.25**			1.95	0.51	2.02	**1.94**
	CR	1.63	**1.81**	1.76	1.12	1.81	1.63				
Competition	BA			1.75	1.69	1.8	2.17	1.94	1.02		
	ln(BA)			1.73	**2.81**	1.79	2.72	1.86	**5.10**		
	TPH										
	CLE	1.66	0.00	1.76	1.12	1.69	**8.15**			2.05	0.49
	Sup	1.61	**3.01**	1.75	1.69	1.66	**9.78**			2.05	0.58
Environmental	Park							1.82	**7.14**		
	West			-	-						
	Imper.	1.66	0.00	-	-	1.83	0.54				
	Herb.	1.64	1.20	-	-	1.77	3.80				
	Perm.	1.66	0.00	-	-	1.77	3.80	1.95	0.51		

* weighted regression; - no data; blank cell indicates no improvement

Whether a tree comes from a park or not is a major environmental variable influencing LCW for western redcedar but for no other species. A large portion of the data came from park trees. Since parks were so well represented and because trees from parks are assumed to be under less stress with better growing conditions then trees in other urban areas, we wanted to know if this was influential. Western redcedar LCW is larger in parks than in the combined remaining land use types of commercial, residential and transportation. In parks, the mean LCW of western redcedar is 7.76 m ± 2.85 compared to 6.21 m ± 2.96 western redcedar outside of parks. This difference is statistically significant (p-value < 0.0001).

Western redcedar is also unique in that it is the only species that LCW is not influenced by CLE or suppression. These variables made no improvement to the model because western redcedar tolerates shade. Red alder and live oak are shade intolerant, big leaf maple and Douglas-fir are intermediate and western redcedar is tolerant (USDA Plants Profile Data Base 2014). Since western redcedar is shade tolerant, it is within reason that CLE and suppression do not influence LCW.

The dbh^2 term is highly useful for predicting LCW for all species except live oak. Squared terms are difficult to interpret but the lack of influence from dbh^2 may coincide with the relatively linear relationship of live oak LCW with dbh compared to the other species (Figure 3.2).

Table. 3.6. Fit statistics for the best species-specific LCW models, accompanying explanatory variables and percent improvement (Imp.) from base equation.

Species	Explanatory Variables	RMSE (m)	Bias (m)	Adj. R^2	Imp.
Douglas-fir	dbh, dbh^2, sup, HCB, Perm	1.57	-0.02	0.76	5.42
Coastal live oak*	dbh, log(BA), sup, H	1.70	0.14	0.76	4.49
Red alder*	dbh, dbh^2, sup, perm	1.55	0.00	0.76	15.76
Western redcedar	dbh, dbh^2, park	1.69	0.04	0.72	13.78
Big leaf maple	dbh, dbh^2, sup, H	1.92	0.03	0.63	6.80

* weighted regression

Extending the model by including several explanatory variables further improves model performance (Table 3.6). We selected top performing variables for final models and the final overall best combinations include between 3 and 5 variables. Compared to the RMSE for the base model, improvements in RMSE with the extended model forms are between 4.5 and 15.8%. The overall lowest RMSE values range from 1.55 to 1.92 meters using the extended models with three or more variables. Adjusted R^2 values are between 0.63 for big leaf maple and 0.76 for Douglas-fir. Bias is extremely minimal except for a moderate 0.14 meter bias for live oak which is 8% of the RMSE.

Although, CLE improved LCW predictions for three species, we did not attempt to include this variable in an extended model version because the indicator for suppression was a direct function of CLE and suppression has a greater influence on improved model performance. This reasoning was employed for BA and its natural log as well. If log(BA) was used, BA was not.

On several attempts at model building, a variable that was significant became insignificant with the addition of another covariate. This is because the variables are correlated. Because the variables are correlated, a portion of variability in LCW being explained by the variables is shared. Depending on how much is shared, or how correlated two variables are, determines if the addition of one or the other will explain additional variation in the predicted variables; LCW in this case. For example, the natural log of BA for western redcedar improves model performance by 5% when using just dbh and log(BA) in the model. However, when log(BA) is included in the best extended model for western redcedar in Table 3.6, the variable is no longer significant (p-value = 0.11) and RMSE improvement drops form 14% to 9%. This is due to any or each of the other three variables already in the model explaining variability in LCW.

Evaluation of HCB Models

HCB predictions were attempted for live oak using several modeling strategies. The base form of urban live oak HCB is better modeled with DHR than with dbh alone (Figure 3.7). RMSE values are around 2.5 meters using dbh compared to 2.3 meters using DHR. This is an 8 to 11% improvement depending on equation. Since DHR is calculated with information from both dbh and height, it is explaining more variability in HCB than dbh alone. The model bias is larger using DHR than dbh however, 0.1 meters is not large.

Table. 3.7. Fit statistics for live oak HCB base models including either dbh or DHR as single explanatory variables. Percent improvement (Imp.) is relative to base model with dbh alone. Bold indicates best RMSE value.

	dbh		DHR		
Eq.	RMSE (m)	Bias (m)	RMSE (m)	Bias (m)	Imp.
3.2.1	2.548	-0.032	2.330	0.113	8.58
3.2.2	2.505	-0.049	2.340	0.091	6.59
3.3.1	2.595	-0.026	**2.316**	0.125	10.75
3.3.3	2.537	-0.037	2.333	0.109	8.03

The best base model form is equation [3.3.1] with DHR as the single explanatory variable. Interestingly, this model form was the worst when using only dbh (RMSE = 2.60) but the best using DHR. To ensure this equation was the best for model building, other variables were evaluated (Appendix C). Equation [3.3.1] consistently performed above the other equations. We used DHR as the starting model and added variables to further improve fit statistics.

To assess contributions of each potential variable to explaining HCB variability, we start first by adding one at a time with DHR. From there we choose the best performers and built the model until RMSE values no longer improved. Since the variables are correlated to some degree, those that improved the model initially when coupled with DHR alone, may not have when three, four or five variables were combined.

The natural log of BA contributed the most. It improved the base model (that with dbh alone) by 25% (Table 3.8). An indicator for suppression improved RMSE by 21% and CLE made a 19% improvement from the base model. LCW and H are not suitable as predictor variables. They made no improvement in the model and actually increased RMSE values. The natural log of BA was more suitable than BA and the suppression indicator more suitable than CLE. Although BA and CLE improved model performance, because the variables derived from them performed better, they were not used for model building. We were able to ultimately improve the model by nearly 30% from the base dbh model. The combination of DHR, the natural log of BA, an indicator for suppression and dbh lowered the RMSE to 1.83 meters. This is the best model form for predicting live oak HCB in our study. Still the bias is larger but 0.26 meters is only 2.36% of the mean HCB for live oak. To verify that the function was indeed better, we acquired fit statistics from [Eq. 3.2.1] incorporating the same variables and confirmed that is still did not perform as well. Using [Eq. 3.2.1] the RMSE was worse at 1.867 but the bias was better at -0.012 meters.

Table 3.8. Fit statistics for live oak HCB [Eq. 3.3.1] by explanatory variable used. Percent improvement (Imp.) is relative to the base model [3.3.1] with dbh alone.

	RMSE (m)	Bias (m)	Imp. (%)
DHR, BA	2.128	-0.116	17.98
DHR, ln(BA)	1.947	0.018	24.95
DHR, CLE	2.096	0.150	19.22
DHR, sup	2.037	0.128	21.49
DHR, LCW	2.680	0.271	-3.28
DHR, H	2.617	0.265	-0.86
DHR, log(BA), sup	2.098	-0.043	19.13
DHR, log(BA), sup, dbh	1.834	0.209	29.33

Simultaneous LCW and HCB Equations

The best predictive model for live oak LCW was achieved by using dbh, log(BA), height, and a suppression indicator variable. These variables were therefore chosen for first-stage nonlinear models of LCW and HCB in the first step for the simultaneous system of equations ([Eq. 3.4.0] and [Eq. 3.5.0]).

$$\widehat{LCW_1} = b_0 + b_1 dbh + b_2 \log(BA) + b_3 Sup + b_4 H \quad [3.4.0]$$

$$\widehat{HCB_1} = b_0 + b_1 dbh + b_2 \log(BA) + b_3 Sup + b_4 H \quad [3.5.0]$$

Each of the variables in the first-stage models was significant (p-value < 0.01) from equation [3.4.0] and [3.5.0]. Weighted regression was employed in both models. The residuals for the HCB_1 model displayed hederoskedasticity even with weighted regression. These new variables, LCW_1 and HCB_1 were then incorporated into the best equations determined previously for the second step in the simultaneous system fitting.

$$\widehat{LCW} = b_0 + b_1 dbh + b_2 \log(BA) + b_3 Sup + b_4 H + b_5 \widehat{HCB_1} \qquad [3.6.0]$$

Equation [3.6.0] made no additional improvements to model performance from the already establish LCW predictive equation. With the addition of HCB_1, height was no longer significant nor was HCB_1 itself. By adding HCB_1, the RMSE changed from 1.70 to 1.72 meters. This was no improvement from the best model but was still a 3.37% improvement from the base simple linear equation. The additional effort of the system equations is not necessary when the simpler method of multiple-linear regression proves a better model fit.

The best HCB prediction model was determined earlier to be the [Eq. 3.3.1] coupled with DHR, log(BA), dbh and the suppression indicator. We found no improvement using this equation with these variables and the addition of LCW_1 in the system equations method. RMSE was 1.93 for the systems approach compared to the already determined best equation providing an RMSE of 1.83 and bias of 0.21 meters previously. However, when we used these same variables incorporated into model form [3.2.1] we were able to improve RMSE of the already determined best equation. Equation [3.7.0] improved the original base equation with an RMSE value of 1.80 meters.

$$\widehat{HCB} = \frac{H}{[1 + \exp - \left(b_0 + b_1 DHR + b_2 \log(BA) + b_3 dbh + b_4 Sup + b_5 \widehat{LCW_1}\right)]} \qquad [3.7.0]$$

Although HCB is a function of crown length, the relationship between HCB and LCW does not as closely follow a concomitant relationship as with crown width and crown length. No clear trend was observed in plots of HCB and LCW (Figure 3.5) and their correlation was only 0.08. On the other hand, crown length and LCW are have a strong relationship with a correlation factor of 0.65 and clear graphical trend (Figure 3.5). The strategies from Sattler and LeMay (2011) are not useful for HCB and LCW modeling likely because the two variables are not closely associated. However, this method may improve model performance and logical consistency for live oak LCW and crown length modeling instead.

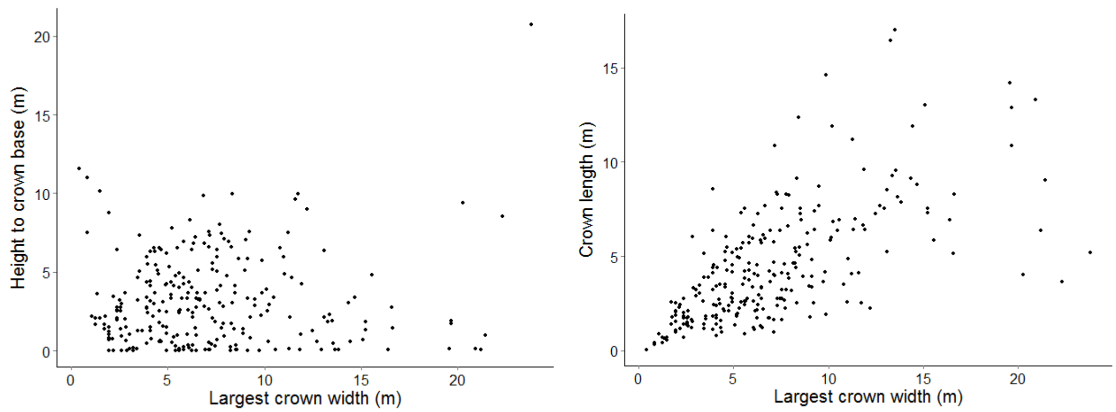

Figure 3.5. Relationship of live oak LCW to HCB and crown length.

We saw no improvement in live oak LCW models and only marginal improvements in predictive HCB models. Urban live oak, HCB and LCW modeling is not improved by fitting simultaneous equations.

Weighted Regression

Least square regression for prediction relies on the assumption that the random errors associated with each observation are distributed evenly. Big leaf maple, western redcedar and Douglas-fir displayed homogeneous variance in their residuals along the predicted values (Figure 3.6). Coastal live oak and red alder displayed an uneven data cloud in residual plots and weighted regression was employed. Weighted regression was applied as suggested by the literature in the form of 1/dbh to improve residual plots (Figure 3.7). Fit statistics can still be compared for weighted regression models if the same weight is applied in each model (Huang et al. 1992). In addition, validating a weighted regression model with weighted heights is appropriate for testing for bias and precision because this method more closely resembles how a model was fit (Larsen and Hann 1987).

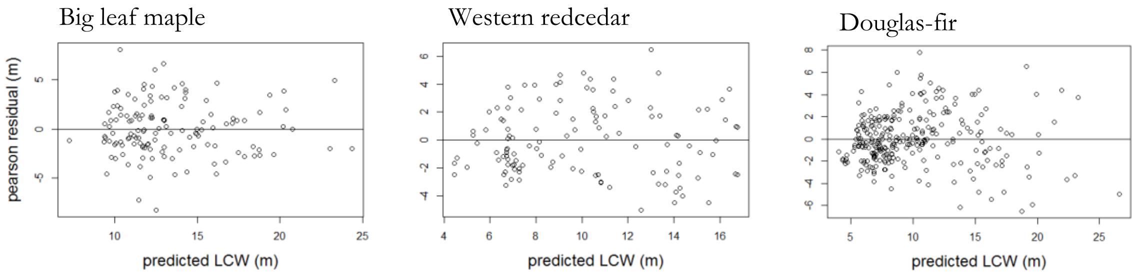

Figure 3.6. Residuals plotted against predicted LCW by species for model with dbh and dbh^2.

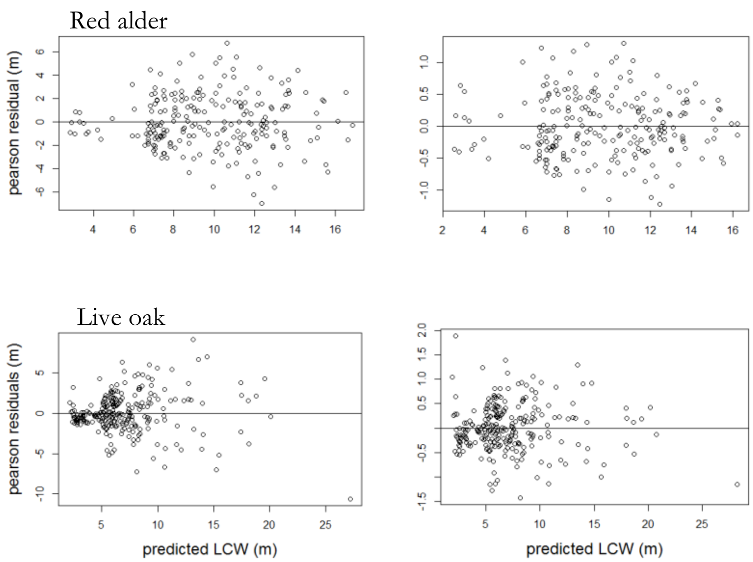

Figure 3.7. Unweighted (right) and weighted in the form $w_i=1/dbh_i$ (left) residuals plotted against predicted LCW by species.

HCB models for coastal live oak displayed hetroskedasisity as well. The same weight of 1/dbh was applied to the HCB equation for coastal live oak. We found that a weight in the form of 1/dbh was better than other suggestions of 1/dbh^2 (Figure 3.6).

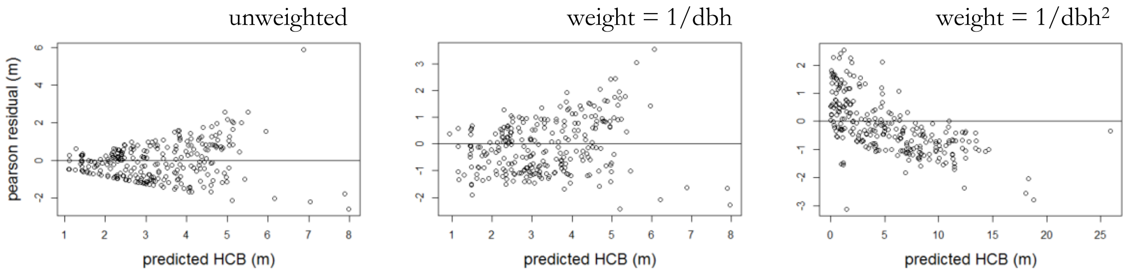

Figure 3.8. Weighted and unweighted residuals plotted against predicted HCB for live oak.

3.5 Conclusion

Urban forest canopy is a major provisionary component for beneficial ecosystem services. The canopy is the source of pollution and carbon removal and the principal structure for creating shade and blocking wind to decrease building energy reduction. The structure of the canopy indicates forest health and its area is a performance benchmark in most urban forest management plans. Information regarding tree crown dimensions is a vital component for successful urban forest management driven by maximizing beneficial ecosystem services.

When crown related information is unattainable or costly, predictive models can be employed. This study developed species-specific regional models for predicting largest crown width and height to crown base for the five most common trees in urbanized areas of Washington, Oregon and California.

We found LCW and HCB can be predicted using several predictor variables. After dbh, dbh^2 and the indicator for suppression contributed the most to improving LCW model performance although final selected HCB was improved with a suppression indicator as well. Suppressed live oak tend to have a larger LCW and smaller HCB. It was DHR that made the greatest contribution to explaining live oak HCB predictions. It was the exponential function that provided the best fit statistics rather than the logistic function as is most often recommended by the literature found for forestland HCB modeling.

The data set came from a wide range of land used types across a broad region. The heterogeneity within the environment is expected to impose upon the heterogeneity within the forest population. RMSE values between 1.6 to 1.9 meters for predicting LCW and of 1.8 meters for predicting live oak HCB are good considering the variability in the population itself.

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4.0 General Conclusions

A key component to effective urban forest management is an inventory of the resource. To determine management goals and devise activities for meeting those goals it is necessary to understand the extent of the resource. Whether a Farm Bill passes revisions to mandate an urban forest inventory by the federally implemented FIA program seems inevitable. However, funding is an issue as always. The urban FIA projects in the works (Baltimore, Austin, and the state of Wisconsin) all have state or city backing. In the west, clients of FIA are mostly forest based and do not want scarce resources spent on urban efforts. Near future urban work in the west will likely involve something in California as interest seems strongest there.

Numerous pilot inventories have already been conducted in preparation for the future Urban Forest Inventory and Analysis (UFIA). Is the cluster plot foot print appropriate in urban environments? Is the sampling intensity providing an accurate representation of the forest resource in US cities? How often do urban forest plots need to be sampled? These are important questions for moving forward with UFIA.

The sampling design developed for monitoring forestlands may not be appropriate for urban forests. Urban areas are a patchwork or land use types ranging from transportation corridors to residential areas to parks. The degree of maintenance varies from land use type. The amount of trees themselves vary by land use. Urban environments are extremely heterogeneous and green infrastructure is exposed to the resulting wide range of conditions. It is reasonable to assume these conditions impose a range of stressors and influence the urban forest to be relatively variable even among the same species.

In this study we saw variability in the form of RMSE values between 2.7 to 4.9 meters for tree height, 2.2 to 2.7 meters for largest crown width and of 1.8 meters for live oak height to crown base. If these allometric relationships were less variable, more precise predictions could be obtained but it is not possible to change the intrinsic variation in the urban forest type. Due to the variety of growing conditions across the heterogenic urban landscape, more precise predictions are difficult. The natural variation of the urban forest cannot be changed, but the models can be more flexible to account for variability.

The answer is not simply increasing the sample size. A more intensified sample inventory will be beneficial but if the range of urban land use is not represented, the heterogeneity in the population will not be accurately captured and understood. In this study, park trees were disproportionally represented. Most observations came from park trees not because more plots landed in parks, but because there are simply more trees in parks. Transportation corridors and residential areas were also well represented by urban trees but other land use types such as commercial and industrial were not. Few trees exist in industrial and commercial zones. The UFIA should move toward increasing sample intensity but in a way that allocates sampling efforts to represent the full variety of the urban landscape.

Since few observations came from trees aside from those inhabiting park, residential and transportation corridors, it may not be appropriate to use models developed from the UFIA for all trees inhabiting other land use types in cities. We saw in this study that western redcedar park tree LCW was different than the grouped remaining land use types in the sample. However, this was not the case for the other four species. Whether allometric relationships differ between land use types and by what degree they differ is unknown. The FIA sampling design may not be capable at accommodating urban tree model modeling across all land uses unless (1) the model is flexible enough to shift by land use or (2) allometric relationships are similar enough between land use types for the same species that additional variation is not present. I assume however, the latter may be the case for some land use types but not for other due to the heterogeneity in urban environments. Future studies should investigate the allometric relationships of the same urban species between land use types.

Forest management regimes differ among cities. Although the climate is generally the same throughout Pacific Northwest, or Northwestern or Southwestern California regions, the degree of installation and maintenance may differ. Biomass models from Zhou and Hemstrom (2010) for forestland Douglas-fir are regional. For example, there is one specifically for Douglas-fir west of the Cascade Range in Oregon and Washington and another for the east side of the states. Due to the influence of management on urban trees, regional equations may need to be more finely focused than in forestlands. Perhaps the western region urbanized areas of Oregon and Washington is not enough. It would be interesting to compared allometric relationships of urban trees across management types. This may be across entire cities, jurisdictions, socioeconomic gradients or between different sized cities.

The underlying question is, what is influencing urban forest structure and how does structure shift under these influences? If we can better understand this, we can develop better models and obtain more accurate estimates of the ecosystem services provided by our urban forest and ultimately improve urban forest management to maximize those benefits.

Urban forestry is fairly new compared to what was traditionally considered forestry. It has been gaining attention as knowledge about the breadth of benefits, aside from timber value from trees, has become better understood. Urban forest structure influences function resulting in beneficial ecosystem services. This is why understanding forest structure at the individual tree level is important. Models are a tool for understanding these structural attributes and allometric relationships. They are tools to aid in effective urban forest management necessary for maximizing the benefit of this essential forest resource.

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APPENDIX A: Map of urban FIA plot locations in Oregon and Washington

APPENDIX B: List of h-d models attempted with fit statistics (m) and ranking.

Where ht2 is total tree height minus 1.3 (m2), DBH, BA and CLE are as defined in chapter 2, TPH is for trees with dbh > 12.7 cm, TPH2 is calculated for trees with dbh > 2.5, the coefficient holders are a, a1, a2, a3, b, and c, and the random effect of land use is noted by b0 and b1. Blank cells were not attempted and bold indicates lowest RMSE. * unable to converge validation, ** unable to converge model, *** used weighted regression

R Equation Form	Eq.	Description	Douglas-fir RMSE	Douglas-fir Bias	Red Alder*** RMSE	Red Alder*** Bias	Western red cedar*** RMSE	Western red cedar*** Bias	Big leaf maple RMSE	Big leaf maple Bias	Oak Spp.*** RMSE	Oak Spp.*** Bias
Chapman-Richards Models												
ht2~a*(1-exp(b*DBH))^c	1	BASE	5.00	0.005	5.07	0.159	4.99	0.185	5.47	0.407	2.95	-0.005
Extended models:		EXTENDED MODELS										
ht2~(a1+a2*CLE+a3*BA)*(1-exp(b*DBH))^c	1.1	CLE & BA	4.88	0.000	5.19	0.060	3.55(2)	0.081	3.90	0.233	3.24	-0.036
ht2~(a1+a2*TPH2+a3*BA)*(1-exp(b*DBH))^c	1.2	TPH2 & BA	4.99	0.005	5.44	0.075	4.15	0.073	4.24	0.181	2.93	-0.286
ht2~(a1+a2*CLE+a3*TPH2)*(1-exp(b*DBH))^c	1.3	CLE & TPH2	4.98	0.029	5.52	0.150	4.87	0.329	5.63	0.268	3.85	-0.663
ht2~(a1+a2*CLE+a3*TPH)*(1-exp(b*DBH))^c	1.4	CLE & TPH	4.99	-0.095	4.99	0.252	4.77	0.038	4.79	-0.134	3.37	0.266
ht2~(a1+a2*TPH+a3*BA)*(1-exp(b*DBH))^c	1.5	TPH & BA	5.03	-0.092	5.09	0.211	4.07	-0.174	4.45	-0.040	3.62	0.151
Mixed models:		MIXED MODELS										
ht2~(a+b0)*(1-exp(b*DBH))^c	1.01	asy	4.80	0.114	4.88(2)	0.108	4.08	0.041	4.94	0.307	3.04	-0.250
ht2~a*(1+b0-exp(b*DBH))^c	1.02	steep	4.86	0.104	4.92	0.078	4.22	-0.014	5.01	0.307	**	**
ht2~a*(1-exp(b*DBH))^(c+b0)	1.03	curve	4.87	0.140	4.98	-0.031	4.38	-0.056	**	**	**	**
ht2~(a+b0)*(1-exp(b*DBH))^(c+b1)	1.04	2 random	4.95	0.077	-	-	*	*	*	*	-	-
ht2~(a1+a2*CLE+a3*BA+b0)*(1-exp(b*DBH))^c	1.11	extended	4.77	-0.085	5.13	0.056	3.61(3)	0.126	3.90	0.233	**	**
Yang Models												
ht2~a*(1-exp(b*DBH^c))	2	BASE	5.00	0.003	5.08	0.159	5.00	0.190	5.47	0.409	2.95	-0.011
Extended models:		EXTENDED MODELS										
ht2~(a1+a2*CLE+a3*BA)*(1-exp(b*DBH^c))	2.1	CLE & BA	4.89	-0.004	5.20	0.058	3.55(2)	0.080	**	**	3.25	-0.372
ht2~(a1+a2*TPH2+a3*BA)*(1-exp(b*DBH^c))	2.2	TPH2 & BA	5.00	0.000	5.44	0.082					2.92	-0.276
ht2~(a1+a2*CLE+a3*TPH2)*(1-exp(b*DBH^c))	2.3	CLE & TPH2	4.99	0.026								
ht2~(a1+a2*CLE+a3*TPH)*(1-exp(b*DBH^c))	2.4	CLE & TPH	5.00	-0.098			5.69	0.760				
ht2~(a1+a2*TPH+a3*BA)*(1-exp(b*DBH^c))	2.5	TPH & BA	5.04	-0.099								
Hanus Models												
ht2~exp(a + b*DBH^c)	3	BASE	4.96	0.013	5.07	0.143	5.12	0.192	5.48	0.411	2.96	-0.008
Extended models:		EXTENDED MODELS										
ht2~exp(a1+a2*CLE+a3*BA+b*DBH^c)	3.1	CLE & BA	4.86	0.019	5.18	0.047	3.64	0.071	3.84(3)	0.234	3.27	-0.381
ht2~exp(a1+a2*TPH2+a3*BA+b*DBH^c)	3.2	TPH2 & BA	**	**	**	**	4.18	0.085	**	**	2.87	-0.202
ht2~exp(a1+a2*CLE+a3*TPH2+b*DBH^c)	3.3	CLE & TPH2	4.93	0.040	5.54	0.088	4.89	0.299	5.70	0.288	4.43	-1.365
ht2~exp(a1+a2*CLE+a3*TPH+b*DBH^c)	3.4	CLE & TPH	**	**	4.99	0.284	4.82	0.111	4.81	-0.179	3.30	0.222
ht2~exp(a1+a2*TPH+a3*BA+b*DBH^c)	3.5	TPH & BA	**	**	**	**	**	**	4.43	-0.046	3.56	0.081
Mixed models:		MIXED MODELS										
ht2~b0+exp(a+b*DBH^c)	3.01	asy	4.78	0.001	4.93	0.066	*	*	5.01	0.302	**	**
ht2~exp(a+b0+b*DBH^c)	3.02	steep	**4.73**(1)	-0.049	4.89(3)	0.045	*	*	4.96	0.289	3.63	-0.687
ht2~exp(a+b*DBH^(c+b0))	3.03	curve	4.75(2)	-0.032	4.92	0.023	**	**	**	**	**	**
ht2~exp(a+(b+b0)*DBH^c)	3.04	other	4.76 (3)	0.009	4.92	0.020	*	*	**	**	*	*
ht2~b0+exp(a1+a2*CLE+a3*BA+b*DBH^c)	3.11	extended	4.76 (3)	-0.041	5.12	0.005	3.77	0.155	3.84(3)	0.234	3.44	-0.466
ht2~exp(a1+a2*CLE+a3*BA+b0+b*DBH^c)	3.12	extended	4.85	-0.322	5.12	-0.025	3.77	0.155	3.84(3)	0.234	4.51	-1.111
Ratowski Models												
ht2~exp(a+b/(DBH+c))	4	BASE	5.01	-0.002	5.06	0.150	4.82	0.232	5.46	0.401	2.95	-0.010
Extended models:		EXTENDED MODELS										
ht2~exp(a1+a2*CLE+a3*BA+b/(DBH+c)	4.1	CLE & BA	4.89	-0.001	5.17	0.054	**3.54**(1)	0.141	**3.82**(1)	0.233	3.26	-0.376
ht2~exp(a1+a2*TPH2+a3*BA+b/(DBH+c)	4.2	TPH2 & BA	**	**	5.45	0.040	4.06	0.140	**	**	2.86(3)	-0.197
ht2~exp(a1+a2*CLE+a3*TPH2+b/(DBH+c)	4.3	CLE & TPH2	4.98	0.026	5.54	0.094	**	**	5.80	0.551	3.86	-1.050
ht2~exp(a1+a2*CLE+a3*TPH+b/(DBH+c))	4.4	CLE & TPH							4.80	-0.178		
ht2~exp(a1+a2*TPH+a3*BA+b/(DBH+c))	4.5	TPH & BA							4.41	-0.049	3.62	0.146
Mixed models:		MIXED MODELS										
ht2~b0+exp(a+b/(DBH+c))	4.01	asy	4.82	0.060	4.91	0.060	5.07	0.396	4.99	0.295	3.07	-0.303
ht2~exp(a+b+b0/(DBH+c))	4.02	steep	4.78	0.020	**4.87**(1)	0.070	6.15	0.969	4.93	0.282	3.59	-0.647
ht2~b0+exp(a1+a2*CLE+a3*BA+b/(DBH+c))	4.11	extended	4.79	0.027	5.10	-0.001	3.61(3)	0.182	3.828	0.230	3.47	-0.450
ht2~exp(a1+a2*CLE+a3*BA+b0+b/(DBH+c))	4.12	extended	4.78	-0.043	5.11	0.002	3.61	0.182	3.83(2)	0.230	4.45	-1.069
ht2~b0+exp(a1+a2*TPH2+a3*BA.p+b/(DBH+c))	4.21	extended									**2.70**(1)	0.210
ht2~exp(a1+a2*TPH2+a3*BA+b0+b/(DBH+c))	4.22	extended									2.80(2)	0.132

APPENDIX C: Fit statistics for height to crown base (HCB) models attempted.

	Eq. 2.1			Eq. 2.2			Eq. 3.1			Eq. 3.2		
	RMSE	Bias	Imp.	RMSE	Bias	Imp.	RMSE	Bias	Imp.	RMSE	Bias	Imp.
D+DHR	2.53	0.17	0.60	2.53	0.12	-1.11	2.52	0.19	2.88	2.53	0.16	0.16
D+BA	2.43	-0.36	4.70	2.61	-0.54	-4.15	2.37	-0.31	8.53	2.51	-0.44	1.19
D+log(BA)	2.22	-0.20	12.95	2.31	-0.34	7.77	2.19	-0.16	15.49	2.24	-0.24	11.56
D+CLE	2.18	0.07	14.35	2.20	0.02	12.22	2.21	0.08	14.96			
D+sup							2.15	-0.02	17.30			
DHR+BA	2.16	-0.02	15.12	2.32	-0.03	7.33	2.13	-0.12	17.98	2.21	-0.22	12.76
DHR+ln(BA)	1.96	-0.02	23.18	2.03	-0.11	18.81	1.95	0.02	24.95	1.98	-0.04	21.99
DHR+CLE				2.08	0.08	17.09	2.10	0.15	19.22	2.07	0.11	18.42
DHR+sup							2.04	0.13	21.49	2.04	0.11	19.57

Coastal live oak fit HCB model fit statistics. RMSE and bias are in meters and Imp. is percent improvement from the base model form which includes dbh (cm) as the only explanatory variable. Blank cells were not attempted. For equations see chapter 3.