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Crown width models for woody plant species growing in urban areas of the U.S.

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Abstract
Crown widths of woody plant species growing in urban areas are of considerable importance as an overall indicator of health and also serve as an important factor for assessing leaf area and associated ecosystem services, such as carbon sequestration, air pollution removal, air temperature cooling, and rainfall interception. Unfortunately, assessing crown widths in urban environments is often challenging and time consuming. To help reduce data collection costs and provide consistency over time, models to predict crown widths for urban-grown species were developed using data from 49 cities across the U.S. and Southern Canada. The effort consisted of fitting mixed models for 29 species groups that encompassed 964 species. Cities were considered a random effect and were statistically significant for 22 of the 29 groups. The need for urban-specific crown width models was demonstrated via examination of prediction biases found when applying crown width models based on forest grown trees, where under-prediction up to about 20% was found for the same species growing in urban areas. Application of the models was evaluated by using crown width predictions instead of observed values for calculations of crown leaf area. Mean percent differences in leaf area were about ±10% across most species groups. Further improvements to national-scale urban crown width models should be pursued as additional data become available via i-Tree, Urban FIA, and possibly other sources where data collection protocols are compatible.

Keywords Ecosystem services · Forest inventory · Mixed models · Leaf area · Spatial trend

Introduction

As forest inventories of urban areas become more commonplace, much research is needed to understand phenomena that have only previously been studied in forested settings. Crown characteristics of forest trees, for example, have been actively studied due to their high correlation with tree growth (Chen et al. 2017; Leites et al. 2009), likelihood of mortality (Bussotti and Pollastrini 2017; Morin et al. 2015), probability and behavior of crown fire (Hevia et al. 2018; Mitsopoulos and Dimitrakopoulos 2007), and functional benefits such as air pollution removal (Nowak et al. 2014; Smith 1990). In urban settings, tree crown measurements of woody plant species (hereafter referred to as 'trees' for simplicity) are primarily used to assess crown size and leaf area, and consequent ecosystem services such as carbon sequestration, air pollution removal, air temperature cooling, and rainfall interception (Willis and Petrokofsky 2017; Kardan et al. 2015). Urban corollaries to typical uses of crown information from forested trees include prediction of individual-tree growth and mortality (Nowak et al. 2008; Vogt et al. 2015). Thus, assessments of crown dimensions and condition play a pivotal role in understanding tree functional processes and their interaction with urban environmental conditions.

As with forest-grown trees, urban tree crown attributes are heavily influenced by their local environment. Crown width is

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one important and common tree measurement found in urban forest inventory protocols. Key factors affecting crown width include amount of growing space (Pretzsch et al. 2015) and water/nutrient availability (Gaudio et al. 2017). In forested micro-environments, these factors are primarily constrained by competition from neighboring trees (Sharma et al. 2016; Bragg 2001). Growing space for urban trees may also be affected by nearby trees, as well as buildings and other above-ground formations that place limitations on light availability (Tan and Ismail 2015). These factors, along with surface and below-ground conditions, likely also play a role in water and nutrient availability that affect tree growth (Clark and Kjelgren 1990; Berrang et al. 1985). Tree crowns in urban areas may also be subjected to manipulations such as pruning or other types of damage that produce crown sizes not strictly controlled by natural ecophysiological processes (Fini et al. 2015; Christie and Hochuli 2005).

Despite the numerous factors that affect crown width, statistical models can be developed that predict crown width using tree attribute information. As may be expected, efforts have traditionally focused on forest-grown trees where variables such as tree diameter, total height, height-diameter ratio, height to crown, and crown ratio have been shown to be important predictors (Sharma et al. 2016; Fu et al. 2013; Bechtold 2003). Some models specific to crown width prediction for urban trees have also been presented, with tree diameter being the primary predictor variable (Pretzsch et al. 2015; Troxel et al. 2013; Peper et al. 2001). The use of additional predictor variables has produced mixed success, with some evidence that outcomes may be species-dependent (Blood et al. 2016). In the U.S., McPherson et al. (2016) developed crown width models for street trees using tree diameter as the sole predictor from data encompassing 171 species across 17 cities. However, much additional urban tree data exists from across the urban landscape to allow for considerable expansion of both species inclusion and spatial resolution in modeling efforts. Specifically, the objectives of this study are: 1) develop crown width prediction models applicable to most woody species in urban environments of the U.S., 2) establish appropriate uncertainty statistics in light of inconstant variance and correlated observations, 3) account for species group and city location effects in model calibration, and 4) evaluate the use of model predictions in calculations of urban tree leaf area.

Methods

Data

The data used in this study arise from two sources. The data are primarily (80%) composed of measurements taken in urban inventories following i-Tree protocols (Nowak et al. 2008; i-Tree 2019). Typically, data are collected within randomly located circular plots having a11.34 m radius. Site measurements include vegetation and other ground cover types, as well as land use characteristics. On each plot, woody plants with a minimum stem diameter of 2.54 cm at a height of 1.37 m are recorded as trees. For each tree, species, diameter, height, crown width, height to crown, crown light exposure, and amount of missing crown are recorded (i-Tree 2019).

Additional data (20%) arise from urban inventories initiated by the Forest Inventory and Analysis (FIA) program of the U.S. Forest Service during 2014–2017. The plot design consists of a primary circular plot of 14.63 m radius, within which are four microplots having 2.07 m radius located in each cardinal direction at 3.66 m from plot center (Fig. 1). A myriad of site-level data are collected, such as land use, canopy cover, vegetation cover, and surface cover (U.S. Forest Service 2017). Sample trees having diameter (breast-height or root-collar depending on species) ≥ 12.70 cm were tallied on the primary plot; whereas sample trees with diameter ≥ 2.54 cm and < 12.70 cm are recorded on microplots. Tree-level data collection includes measurements of species, diameter, height, crown width, crown ratio, crown light exposure, and crown dieback (U.S. Forest Service 2017).

The i-Tree and Urban FIA data were combined to provide information covering 49 cities across the conterminous U.S. and southern Canada (Fig. 2). The Canadian cities of Calgary and Toronto were included because of their close proximity to the U.S. border. Due to the large number of species present (964), species groups that generally reflect those developed by the FIA program (U.S Forest Service 2015) were used to facilitate analysis (Online Resource 1). A summary of the 29 species groups is given in Table 1.

A limitation of the combined data is that only variables collected and having identical definition in common to both sources can be utilized. As will be discussed in the subsequent section, the primary variables that were ultimately of interest in this study were crown width, diameter, and total height. Distribution statistics for these variables by species group are shown in Table 2.

Analysis

There were few variables in common to both data sources. Apart from the primary variables crown width, diameter, and height, the only relevant tree-level variable for consideration in model development was crown light exposure (CLE, U.S. Forest Service 2017). CLE describes the amount of sunlight the crown receives as categorized by 6 levels ranging from no light to full light (open grown). It was also possible to ascertain if a tree was measured in an area that was considered to function as a forest (FOR, U.S. Forest Service 2017). In these cases, it might be expected that trees would have characteristics similar to those growing in rural forest

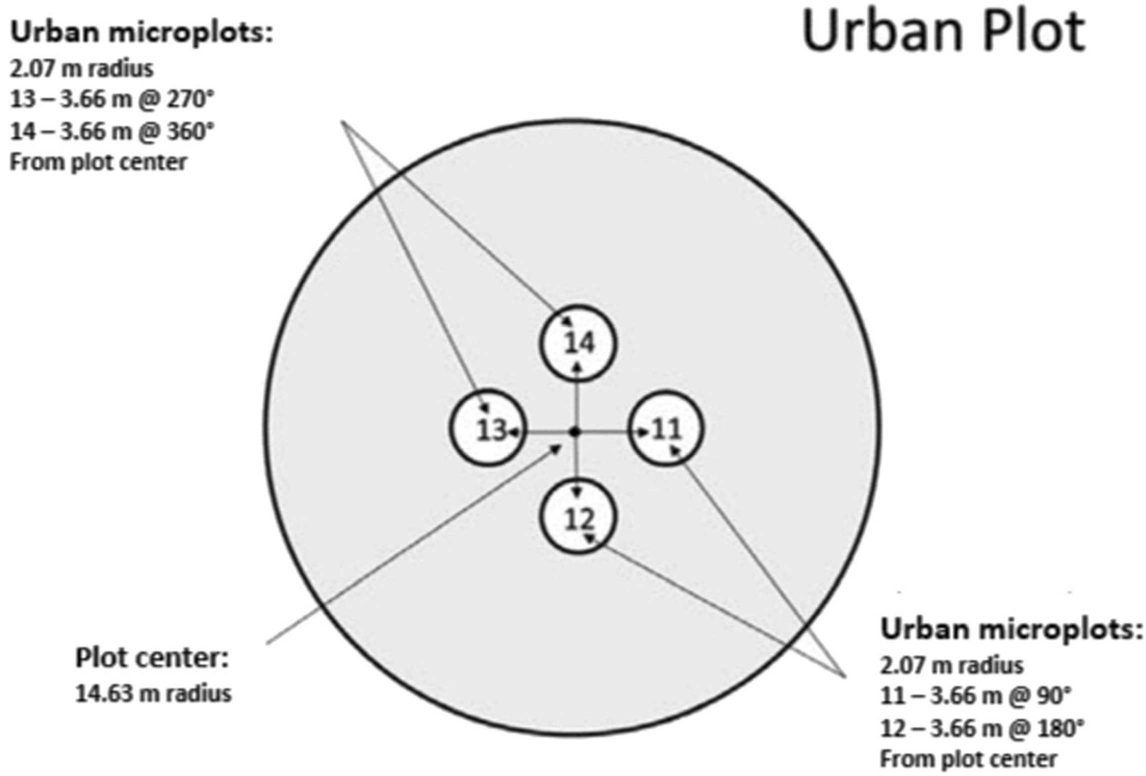

Fig. 1 Urban plot design used by the FIA program

Fig. 2 Map of cities in the U.S. and southern Canada where urban forest inventories were conducted using i-Tree or FIA Urban protocols

Table 1 Species group summary showing number of species and dominant species information for urban inventories in 49 cities (Fig. 2). The star (*) designation indicates the subgroup having diameter measured at root-collar

Group	Description	# spp	Dominant species by frequency		
			Species code	Common name	% of group
1	Loblolly and shortleaf pines	2	PITA	loblolly pine	99.7%
2	Other yellow pines	9	PIVI2	Virginia pine	68.4%
3	Eastern white pine	1	PIST	eastern white pine	100.0%
4	Spruce and balsam fir	6	PIRU	red spruce	80.6%
5	Eastern hemlock	3	TSCA2	Carolina hemlock	99.1%
6	Other eastern softwoods	92	TSME	mountain hemlock	20.6%
7	Woodland softwoods	16	PIMOF	Arizona pinyon pine	98.1%
7*	Woodland softwoods	5	PIED	common pinyon	99.6%
8	Select white oaks	6	QUMU	chinkapin oak	82.3%
9	Select red oaks	8	QULA	Lacey oak	82.1%
10	Other white oaks	8	QUOG	Oglethorpe oak	75.5%
11	Other red oaks	11	QUVE	black oak	34.8%
12	Hickory	20	CACA38	S. shagbark hickory	16.1%
13	Hard maple	6	ACLE	chalk maple	88.6%
14	Soft maple	2	ACSA2	silver maple	62.9%
15	Beech	1	FAGR	American beech	100.0%
16	Sweetgum	1	LIST2	sweetgum	100.0%
17	Tupelo and blackgum	1	NYSY	blackgum	100.0%
18	Ash	9	FRBE	Berlandier ash	66.6%
19	Cottonwood and aspen	17	PONI	Lombardy poplar	68.2%
20	Basswood	4	TIAMC	Carolina basswood	98.3%
21	Yellow-poplar	2	LITU	yellow-poplar	99.9%
22	Black walnut	1	JUNI	black walnut	100.0%
23	Other eastern soft hardwoods	54	MEQU	melaleuca	17.5%
24	Other eastern hard hardwoods	21	ULTH	rock elm	25.5%
25	Eastern noncommercial hardwood	143	PEAM3	avocado	19.7%
26	Woodland hardwoods	18	RONE	New Mexico locust	80.0%
26*	Woodland hardwoods	7	COHO	Bluewood	74.2%
27	Tropical/subtropical hardwoods	259	YUAL	aloe yucca	17.9%
28	Urban-specific hardwoods	215	ZACL	Hercules'club	8.9%
29	Urban-specific softwoods	26	TACU	Japanese yew	53.3%

landscapes. For both CLE and FOR, inclusion in a regression model requires indicator (0,1) variables.

Initial model development proceeded by evaluating the predictive ability of DIA and HT due to their common availability in many urban tree inventories. Evaluation of correlations between these variables and CW suggested a linear model would adequately describe the relationship. As forestry is more complex than rocket science (Bunnell 1999), it was surmised that more intricate phenomena may be present than those accounted for by simply using DIA and HT as individual predictor variables. A typical exploration would include an interaction term in the model as well, i.e., DIA*HT. Further, crown characteristics can also be correlated with tree size relationships in the form of bole taper (Valentine and Gregoire 2001); which suggested inclusion of a taper-based metric such as DIA/HT. To facilitate a linear relationship between DIA/HT and CW, a natural logarithm transformation was used. In summary, the model was specified as:

$$CW_{jk} = \beta_0 + \beta_1 DIA_{jk} + \beta_2 HT_{jk} + \beta_3 DIA_{jk} {*} HT_{jk} + \beta_4 \log\left(\frac{DIA_{jk}}{HT_{jk}}\right) + \epsilon_{jk} \quad (1)$$

The model components are CW_{jk} = crown width (m) in city j for tree k, HT_{jk} = total height (m), DIA_{jk} = diameter (cm), log = natural logarithm, ϵ_{jk} = random error, and β_0 – β_4 = estimated parameters. Further refinement of the model

Table 2 Sample size and summary statistics for crown width (CW, m), diameter (DIA, cm), and total height (HT, m) attributes for 29 species groups across 49 cities. DIA is measured at root collar for groups 7* and 26*; all others at breast height (1.37 m)

		Minimum			Mean			Maximum			Standard deviation		
Group	n	CW	DIA	HT	CW	DIA	HT	CW	DIA	HT	CT	DIA	HT
1	1168	0.3	2.5	1.2	4.9	24.7	15.6	16.8	86.4	33.5	2.6	13.5	6.2
2	215	0.3	1.5	0.9	6.4	28.2	12.1	17.1	68.6	40.2	3.2	15.7	8.0
3	545	0.9	2.5	1.8	5.3	25.6	12.8	18.0	94.5	32.0	3.2	17.9	8.0
4	284	0.3	1.0	0.3	3.7	18.6	7.3	10.8	63.5	28.7	2.3	13.4	5.0
5	316	0.5	2.5	1.8	4.7	21.3	9.9	16.5	91.4	29.0	2.7	16.1	6.3
6	3114	0.3	0.5	0.3	3.6	17.0	7.3	15.1	154.9	45.7	2.4	14.7	4.9
7	1112	0.3	2.5	0.5	4.2	21.5	6.8	31.9	137.7	19.2	2.1	10.1	2.1
7*	2120	0.3	2.8	1.5	4.1	21.0	6.6	21.5	137.7	15.5	1.8	9.6	1.9
8	896	0.3	2.5	1.8	7.8	30.2	14.9	27.6	131.0	45.1	5.2	24.6	8.4
9	1212	0.3	1.8	1.8	7.7	29.8	14.9	29.9	170.2	50.1	4.6	23.0	7.9
10	1228	0.6	2.5	1.8	7.3	28.9	10.4	28.0	170.2	30.5	3.9	17.4	4.5
11	1150	0.6	2.5	1.8	7.6	29.9	15.2	30.6	138.7	38.0	4.5	21.8	7.0
12	764	0.3	2.5	2.3	6.1	19.9	13.0	26.8	133.3	39.6	3.7	16.7	7.1
13	1431	0.3	2.4	1.5	6.6	22.4	10.2	36.4	109.2	32.3	3.9	18.1	5.1
14	3322	0.3	1.8	0.9	6.1	19.7	12.5	24.4	114.3	35.1	3.5	16.8	6.3
15	735	0.6	2.5	0.6	6.2	16.7	11.2	25.5	127.0	35.4	3.9	20.1	7.7
16	1272	0.3	2.5	1.8	4.8	18.8	13.4	19.5	101.6	37.5	3.0	14.0	6.7
17	457	0.8	2.5	1.5	4.9	14.3	10.3	22.9	69.1	29.0	2.9	11.8	6.2
18	2151	0.3	0.3	0.3	5.4	19.8	10.9	34.0	104.4	36.0	3.5	15.7	5.6
19	2217	0.3	1.5	0.5	2.9	11.7	8.2	24.4	109.5	32.9	2.6	12.4	5.5
20	344	0.3	2.5	0.3	5.5	21.0	10.6	18.3	104.4	30.5	3.7	20.1	5.9
21	684	0.3	2.5	0.9	7.9	33.7	20.2	25.0	132.1	43.6	4.9	27.3	10.7
22	335	0.6	2.5	2.4	7.5	26.4	13.5	23.8	99.8	30.2	4.2	17.1	6.3
23	8784	0.3	0.5	0.8	5.3	17.9	9.9	31.1	180.3	45.1	3.4	15.4	5.4
24	3846	0.3	0.8	0.9	5.3	17.0	8.8	27.6	119.4	39.6	3.4	15.7	5.4
25	5091	0.3	0.5	0.9	4.8	16.3	9.1	24.4	258.1	46.0	3.2	16.0	5.9
26	95	0.3	4.6	1.8	4.6	21.6	7.6	16.6	94.5	26.9	3.0	14.4	4.3
26*	356	0.3	2.8	1.5	5.0	20.5	6.4	14.3	70.6	13.4	2.9	11.4	2.5
27	1097	0.3	2.5	0.5	4.2	17.8	6.6	17.7	159.1	32.0	2.5	17.1	4.3
28	4180	0.3	0.5	0.5	4.5	16.0	6.9	33.1	180.0	81.4	3.4	17.8	4.7
29	105	0.3	2.5	0.3	2.3	12.1	4.6	10.6	55.9	16.5	2.3	11.3	3.4

was attempted by adding FOR and CLE variables as described earlier; however, the anticipated improvements in model performance were not realized and the model shown in [1] was chosen as an appropriate balance of parsimony and prediction accuracy. Examination of the variability of the random errors ($\in_{jk}$) in [1] indicated that heteroscedasticity was present; particularly in the form of increasing variance with increasing tree size. The variance increase appeared to be linear with respect to both DIA and HT such that the error distribution could be adequately described by:

$$\in_{jk} \approx N\left(0, \sigma_e^2\right) \approx N\left(0, \theta_0 + \theta_1 DIA_{jk} + \theta_2 HT_{jk}\right) \quad (2)$$

where $N(0, \sigma^2_e)$ indicates a normal distribution with mean 0 and variance σ^2_e; $\theta_0 - \theta_2$ = estimated parameters.

Models [1] and [2] were used as the basis for a mixed-effects model formulation to account for correlated observations within species groups and individual cities (Gregoire and Schabenberger 1996). The inclusion of random effects parameters also allows for customized calibration for different cities within the species groups. An important consideration when developing mixed models is the placement of the random parameters. After considerable experimentation and examination of regression analysis outcomes, the overall model providing the best fit to the data was specified as:

$$CW_{jk} = \left(\beta_0 + \psi_{0(j)}\right) + \left(\beta_1 + \psi_{1(j)}\right)DIA_{jk} + \left(\beta_2 + \psi_{2(j)}\right)HT_{jk} + \beta_3 DIA_{jk}{*}HT_{jk} + \beta_4 \log\left(\frac{DIA_{jk}}{HT_{jk}}\right) + \in_{jk} \quad (3)$$

where $\psi_{m(j)} \approx N\left(0, \sigma^2_{\psi_m}\right)$

$$\sigma^2_e = \theta_0 + \theta_1 DIA_{jk} + \theta_2 HT_{jk} \quad (4)$$

$\psi_{m(j)}$ are random effect parameters for subject city j, which are assumed to be normally distributed having mean = 0 with variances $\sigma^2_{\psi_m}$ ($m = 0$ to 2). The regression analysis was performed separately for each of the 29 species groups.

Model performance for each species group was quantified using the proportion of variation explained by the model (a pseudo-R^2), root mean squared error (*RMSE*), and mean absolute residual (*MAR*):

$$R^2 = 1 - \frac{\sum\left(CW_{jk} - \widehat{CW}_{jk}\right)^2}{\sum\left(CW_{jk} - \overline{CW}\right)^2} \quad (5)$$

$$RMSE = \sqrt{\frac{\sum\left(CW_{jk} - \widehat{CW}_{jk}\right)^2}{n}} \quad (6)$$

$$MAR = \frac{\sum\left|CW_{jk} - \widehat{CW}_{jk}\right|}{n} \quad (7)$$

where $\widehat{CW}_{jk}$ = predicted value of CW_{jk}, $\overline{CW}$ = mean of observed CW_{jk}, and n = sample size.

Validation of the model was performed using an enhanced bootstrap approach which assesses the over-optimism in model accuracy that may result from overfitting the model to the data (Harrell et al. 1996). The R^2, *RMSE*, and *MAR* statistics were evaluated in the process. Using R^2 as an example, for each species group this procedure entailed:

1) Fitting model [3] to the original data consisting of n observations and calculating R^2_{app}.
2) Drawing a bootstrap sample of size n with replacement, fitting model [3] using only terms consistent with the significant parameter estimates (as shown in Table 3 below) to these data, and obtaining R^2_{boot}.
3) Applying the fitted model from step #2 back to the original data and calculating R^2_{orig}.
4) Conducting 200 repetitions of steps #2 and #3 and calculating the mean optimism $O = \sum\left(R^2_{boot} - R^2_{orig}\right)/200$.
5) Calculating the optimism-adjusted statistic as $R^2_O = R^2_{app} - O$.

Generally, the implementation of urban tree inventories has accelerated at a pace faster than supporting research needs can be identified and accomplished. For lack of any alternative, models developed from data collected in forested environments are often used. The disadvantage of this approach is that an unknown and potentially large bias in predictions can result due to a number of factors pertaining to different micro- and macro-site conditions. To better understand and justify the need for urban-specific crown width models, forest-based models (Bechtold 2003; Bechtold 2004) were used to predict crown widths for the urban data used in this study. This analysis was performed only for the subset of tree species which were common to both studies. Comparisons were made between observed and predicted values to gauge the effect of using forest-based models in urban environments.

As crown width predictions are often used to replace time-consuming and costly direct measurement, it is important to evaluate how the predictions may alter analytical outputs. A key parameter modeled in the i-Tree software suite is tree leaf area – defined as the total amount of surface area (one-sided) of leaves found on a tree. As the leaf area models depend either directly or indirectly on crown width as one of the input variables (Nowak 1996, 2020), assessments of leaf area were made using both the observed and predicted crown widths. To focus on effects of crown width, default assumptions of average crown dieback of 13% and average percent foliage missing of 13% were used. The calculated leaf areas (m^2) based on observed crown width $\left(\widehat{LA}_{CW}\right)$ and predicted crown width $\left(\widehat{LA}_{\widehat{CW}}\right)$ were used to calculate the mean difference ($\overline{D}$), mean percent difference ($\overline{D}\%$), mean absolute difference ($|\overline{D}|$), and mean percent absolute difference $\left(|\overline{D}|\%\right)$ as compared to the mean $\widehat{LA}_{CW}$ (expressed as $\overline{LA}_{CW}$) for each species group.

$$\overline{D} = \frac{\sum\left(\widehat{LA}_{CW} - \widehat{LA}_{\widehat{CW}}\right)}{n} \quad (8)$$

$$\overline{D}\% = \frac{\overline{D}}{\overline{LA}_{CW}} \; x\ 100 \quad (9)$$

$$\left|\overline{D}\right| = \frac{\sum\left|\widehat{LA}_{CW} - \widehat{LA}_{\widehat{CW}}\right|}{n} \quad (10)$$

$$\left|\overline{D}\right|\% = \frac{\left|\overline{D}\right|}{\overline{LA}_{CW}} \; x\ 100 \quad (11)$$

Table 3 Estimated parameters from [3] and [4]. Intercepts were always retained in the model; similarly estimated parameters β_1 and β_2 were retained if the *DIA*HT* interaction parameter estimate β_3 was significantly different from zero; all other parameter estimates shown were statistically significant at the 95% confidence level

Group	β_0	β_1	β_2	β_3	β_4	θ_0	θ_1	θ_2	$\sigma^2_{\psi_0}$	$\sigma^2_{\psi_1}$	$\sigma^2_{\psi_2}$
1	0.26887	0.21706	0.05721	−0.00355	–	−0.26512	0.08932	0.06089	–	–	–
2	0.63686	0.08472	0.31310	–	–	0.11386	–	0.09640	–	–	0.01218
3	1.22240	0.26890	0.00045	−0.00414	−0.86997	−0.16282	0.08404	–	–	–	0.02622
4	0.60236	0.14731	0.15467	−0.00414	–	0.25101	0.04655	–	–	0.00072	–
5	0.91811	0.15601	0.22104	−0.00347	−0.93469	−0.45151	0.04974	0.17780	–	–	0.00462
6	0.81503	0.12815	0.17060	−0.00134	−0.28382	0.09823	0.04153	0.07040	0.31771	0.00225	0.01707
7	0.27966	0.12481	0.18078	–	–	−0.20351	0.02914	0.24323	–	–	–
7*	0.23035	0.14370	0.12422	–	–	−0.07487	0.06130	–	–	–	–
8	1.67999	0.13469	0.08817	0.00129	–	0.28565	0.14696	–	–	–	0.01359
9	1.35908	0.16661	0.14409	−0.00123	–	−0.32173	0.04744	0.23604	0.20061	0.00049	–
10	0.15256	0.20214	0.20333	0.00241	–	−0.53226	0.06174	0.19591	–	–	–
11	0.92771	0.18969	0.12068	−0.00158	–	−0.33939	0.09692	0.12604	–	0.00062	–
12	1.81689	0.16685	0.06044	–	–	1.61331	0.14678	−0.08505	–	0.00150	–
13	0.38891	0.06271	0.15861	−0.00230	–	0.01515	–	0.38762	–	0.03093	0.11145
14	1.46265	0.00995	−0.01005	−0.00318	–	0.54157	0.14712	–	0.35039	0.04365	0.04531
15	1.95625	0.07069	0.26438	–	0.72412	0.00805	0.17804	0.08709	–	–	–
16	1.43392	0.14489	0.05339	–	–	0.02758	0.08844	0.07348	–	0.00114	–
17	1.59178	0.09983	0.17138	–	0.85449	0.05100	0.16584	–	–	0.00221	–
18	0.89987	0.22704	0.12519	−0.00339	−0.43398	−0.13186	0.12276	0.12748	–	0.00219	0.00975
19	0.29314	0.22682	0.09594	−0.00311	−0.18327	−0.15161	0.07129	0.04302	–	0.00150	–
20	1.42256	0.11728	0.16063	–	–	0.86678	0.07208	–	–	–	0.00986
21	1.25326	0.19692	0.09704	−0.00212	–	0.68759	0.25456	−0.10805	–	–	–
22	1.21121	0.17342	0.12961	–	–	−0.23520	0.23919	–	–	–	–
23	1.31894	0.17904	0.14886	−0.00134	−0.28756	0.47668	0.14225	0.01433	0.23405	0.00124	0.01140
24	1.04849	0.19611	0.20067	−0.00422	–	0.53985	0.19380	−0.03923	0.31784	0.00118	0.00729
25	0.90807	0.13670	0.23432	−0.00166	0.35309	−0.02600	0.13064	0.07932	0.30258	0.00100	0.01051
26	0.83980	0.17540	–	–	–	2.89215	–	–	–	–	–
26*	−0.31517	0.24651	0.22999	−0.00766	–	−0.48536	0.17728	–	–	–	–
27	0.41657	0.09213	0.43246	−0.00265	–	0.14396	0.04365	0.20212	–	–	0.01782
28	0.86620	0.14232	0.28551	−0.00245	–	−0.26134	0.11889	0.17348	0.43134	0.00122	0.01022
29	0.13617	0.06807	0.40388	–	–	−0.15678	0.08557	–	–	–	0.03523

Results

Estimated fixed-effects parameters for models [3] and [4] are given in Table 3, where missing values indicate parameter estimates not significantly different from zero at the 95% confidence level; with the exception of intercepts (β_0, θ_0), which were always retained regardless of statistical significance. The estimated β_1 parameter was always significant and positive in sign, which agrees with the biological intuition that tree crown width increases as diameter increases. Similar outcomes were generally found for tree height as well, with positive β_2 suggesting that taller trees support larger crown widths. The β_3 parameter associated with the interaction term *DIA*HT* was usually negative when statistically significant. For these species groups, predictions of crown width decrease slightly with increasing height for a given diameter value. Viable explanations include taller trees being unable support so much crown that they become too 'top-heavy', or perhaps overall crown size is similar to shorter trees but taller trees tend to have a more vertical distribution (vs. horizontal). The exception to this trend was species group 8 (Select white oaks), which had a positively valued β_3. An examination of the data suggests this outcome was due to the largest diameter trees only being intermediate in height, such that height increases at a given diameter were associated with increasing crown sizes. Finally, the taper-based metric of (log) DIA/HT only provided

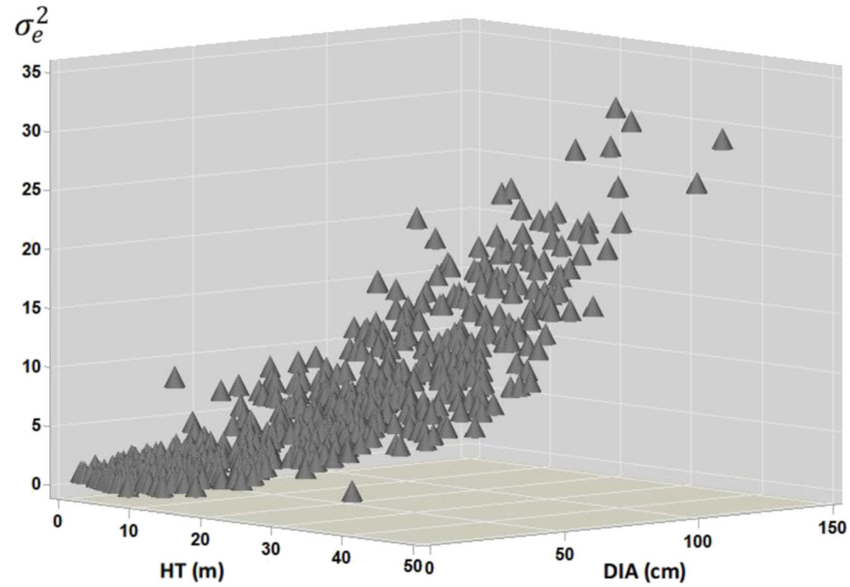

Fig. 3 Expected model error variance from [4] for Yellow-poplar (group 21)

significant information for about one-third of the groups, i.e., the statistical significance of β_4. Further, there was inconsistency in the sign of β_4 among species groups (Table 3). Negatively valued β_4 for some groups (Eastern white pine (3), Eastern hemlock (5), Other eastern softwoods (6), Ash (18), Cottonwood and aspen (19), and Other eastern soft hardwoods (23)) resulted in smaller crown width predictions as trees increasingly favored diameter growth in relation to height; whereas the reverse was true for other groups (Beech (15), Tupelo and black gum (17), and Eastern noncommercial hardwoods (25)) with $\beta_4 > 0$.

Model error variances [4] were largely driven by diameter, where increases in diameter resulted in increases in error (Table 3). For Other yellow pines (2) and Hard maples (13), diameter was not a statistically significant driver of error variance; however, increased error was associated with taller tree heights. Generally, greater tree size as measured by either diameter or height produced larger estimates of error variance. Exceptions were noted for Hickory (12), Yellow-poplar (21), and Other eastern hard hardwoods (24), where increasing height at a given diameter reduced variance. Figure 3 illustrates the general trend of error variance as a function of tree size.

The inclusion of cities as random parameters in the model showed there was a statistically significant city effect for 22 of the 29 species groups (Table 3). Essentially, there are two parts to assessing whether the city effect should be included. First, there is an assessment of which term(s) in the model should contain a random component. In studies where this decision is not dictated by an a priori experimental design, this exercise entails evaluation of various alternative model formulations from which a final model can be chosen. Subsequently, the inclusion of a random parameter in the model is predicated on the variance of the random effects across cities being statistically different from zero ($\sigma^2_{\psi_0}, \sigma^2_{\psi_1}, \sigma^2_{\psi_2}$ in Table 3). Note there exists a distribution of random effect values – for some cities the effect can be relatively large, while for others the effect may be small. For this study, a complete listing of random effects by species group and city is provided in Online Resource 2. When the random effect is not significant, its numerical value is considered to be zero.

The model goodness-of-fit to the data exhibited large variation among the 29 species groups, where the ranges were: R^2 (0.53–0.84, mean 0.73), *RMSE* (0.93–2.63, mean 1.71), and *MAR* (0.66–1.93, mean 1.21) (Table 4). Model validation results were generally promising, with optimism-adjusted fit statistics (R^2_O, $RMSE_O$, MAR_O) showing only slight deterioration (Table 4). For comparative purposes, the bounds of these statistics were: R^2_O (0.52–0.82, mean 0.71), $RMSE_O$ (1.13–2.65, mean 1.79), and MAR_O (0.71–1.94, mean 1.26). Generally, the species groups with relatively small sample sizes exhibited the largest losses, as the small samples are more likely to be overfitted.

The application of crown width models developed from forest-grown trees (Bechtold 2003, 2004) generally showed underprediction of crown widths for urban trees (Table 5). The magnitude of differences was highly dependent on the species group, where some groups exhibited 1.0% or less difference (Loblolly and shortleaf pine (1) and Eastern noncommercial hardwoods (25)) while others exceeded 15.0% (Other yellow pines (2), Spruce and balsam fir (4), Hard maple (13), Soft Maple (14), Beech (15), Tupelo and blackgum (17), and Black walnut (22)). The Other yellow pines group was most notable in terms of percent difference (21.5%). The remaining notable results were for the species groups Eastern hemlock (5) and Other white oaks (10), where the forest-based crown widths were on average predicted to be slightly larger than those found in urban settings. Again, this outcome is likely due to differences in the data sources which at least partially arise

Table 4 Original and optimism-adjusted fit statistics [5–7] for 29 species groups

Group	R^2	R^2_0	RMSE	$RMSE_0$	MAR	MAR_0
1	0.558	0.554	1.698	1.705	1.310	1.315
2	0.805	0.773	1.394	1.518	1.078	1.179
3	0.817	0.790	1.350	1.457	0.954	1.017
4	0.794	0.759	1.034	1.127	0.762	0.821
5	0.688	0.637	1.534	1.676	1.138	1.227
6	0.777	0.757	1.132	1.184	0.776	0.807
7	0.442	0.426	1.545	1.550	0.853	0.855
7*	0.576	0.568	1.160	1.174	0.769	0.771
8	0.824	0.803	2.174	2.304	1.544	0.620
9	0.785	0.773	2.147	2.208	1.551	1.595
10	0.725	0.719	2.034	2.065	1.348	1.357
11	0.773	0.757	2.141	2.226	1.536	1.582
12	0.738	0.709	1.918	2.030	1.356	1.412
13	0.755	0.732	1.920	2.017	1.278	1.329
14	0.737	0.722	1.795	1.854	1.298	1.333
15	0.762	0.759	1.924	1.940	1.373	1.379
16	0.694	0.682	1.653	1.691	1.223	1.245
17	0.715	0.684	1.556	1.648	1.124	1.175
18	0.707	0.683	1.913	1.993	1.299	1.344
19	0.794	0.771	1.198	1.262	0.689	0.711
20	0.842	0.817	1.452	1.581	1.073	1.161
21	0.717	0.713	2.628	2.651	1.930	1.944
22	0.684	0.678	2.367	2.399	1.753	1.772
23	0.698	0.684	1.853	1.897	1.283	1.304
24	0.690	0.665	1.868	1.942	1.303	1.344
25	0.725	0.708	1.693	1.751	1.193	1.225
26	0.688	0.697	1.692	1.739	1.328	1.360
26*	0.602	0.594	1.840	1.862	1.368	1.379
27	0.646	0.615	1.506	1.576	1.068	1.104
28	0.757	0.735	1.666	1.746	1.109	1.145
29	0.827	0.720	1.932	1.238	0.659	0.813

from the particular environments the sample trees were growing in. The general inference from this comparison is that use of forest-based models for prediction of urban tree crown width is not recommended.

The use of predicted crown widths instead of observed crown widths for calculations of leaf area per i-Tree methods (Nowak 1996, 2020) showed a range of mean percent differences ($\overline{D}\%$) of approximately ±10% across the species groups (Table 6). An exception was group 29 (Urban-specific softwoods) where the difference was nearly 23%. This result should be interpreted in the context of group 29 having substantially smaller crowns than the other groups, such that the relatively unexceptional $\overline{D}$ of 4.13 m^2 translates into a large percentage difference. The mean absolute percent differences $\left(\left|\overline{D}\right|\%\right)$ varied from about 20–35% among groups; with the exceptions of group 7 (Woodland softwoods) having much smaller values of $\left|\overline{D}\right|\%$ near 7% and group 29 being considerably larger at about 47%. These outcomes suggest that possibly the leaf area models for Woodland softwoods are only marginally responsive to crown width and may be more heavily influenced by other inputs such as crown length (which would remain the same each tree regardless of the predicted or observed crown width input). Conversely, the leaf area models for Urban-specific softwoods appear to be highly sensitive to the crown width value such that relatively minor differences between observed and predicted crown width translate into large changes in calculated leaf area.

Discussion

As is consistently found in other crown width modeling efforts, DIA was the principal predictor variable. Although its use in other studies has been sporadic, HT was also found to be an important predictor for many species groups. The inconsequential improvements from additional predictors FOR and CLE suggested tree size and form variables may already manifest these influences. For example, open-grown trees would tend to have large CLE, but also have relatively large DIA/HT values. Similarly, competition within forested environments (FOR) tends to produce smaller DIA/HT relationships due to smaller CLE. Further research is needed to understand the numerous inter-related factors influencing tree growth across the gradient of social-ecological conditions encountered in urban and forest environments. Additionally, future availability of a broader suite of consistent urban tree data may lead to modeling refinements. For example, inclusion of variables such as crown ratio and height-to-crown may improve predictive accuracy (Sharma et al. 2016; Bechtold 2003).

A key discussion point is to put this research in the context of previously published crown-width models for urban trees. The breadth of this study is considerably larger than other analyses in terms of number of cities (49 cities; Fig. 1) and species coverage (964 species; Online Resource 1). In comparison, McPherson et al. (2016) used street tree data from 17 cities and 171 species, and Blood et al. (2016) data comprised 97 species across 12 locations in the Southeastern U.S. Most other efforts have been confined to limited spatial extent and/or species coverage (Russell and Weiskittel 2011; Sánchez-González et al. 2007; Marshall et al. 2003; Peper et al. 2001). Other notable methodological differences include:

1) Approaches to accounting for spatial trends: In this study, random effects parameters were employed to account for differences among cities; with statistical hypothesis test outcomes providing the basis for inclusion in the models (Blood et al. 2016). An alternative approach is to fit

Table 5 Results of using crown-width models based on forest-grown trees applied to trees growing in the urban environment. Notational definitions are $\overline{CW}$ = mean of observed data (m), $\widehat{\overline{CW}}_F$ forest-based model prediction (m), and n = sample size. Species in groups 7 and 26–29 were not present in the forest-based models

Group	n	$\overline{CW}$	$\widehat{\overline{CW}}_F$	% difference
1	1026	5.32	5.27	1.0
2	180	7.23	5.67	21.5
3	394	6.39	5.62	12.0
4	175	5.08	4.28	15.8
5	200	5.90	6.05	−2.5
6	1307	5.01	4.54	9.4
8	657	9.43	8.91	5.4
9	912	9.12	8.20	10.1
10	1133	7.64	7.69	−0.7
11	929	8.75	8.35	4.6
12	285	8.06	7.32	9.2
13	879	8.51	7.06	17.0
14	1945	7.91	6.37	19.5
15	268	9.91	8.37	15.6
16	799	6.00	5.43	9.6
17	214	6.89	5.71	17.1
18	1386	6.82	5.95	12.8
19	275	7.28	6.26	14.0
20	195	7.55	6.73	10.9
21	483	9.90	8.57	13.4
22	269	8.57	7.12	16.9
23	4953	6.92	6.58	4.9
24	1632	7.29	6.57	9.9
25	1821	6.43	6.41	0.3

models separately to subsets of the data corresponding to each location or region (McPherson et al. 2016). The latter approach is often implemented without consideration of whether the spatial disaggregation of the data is appropriate, can result in relatively small sample sizes, and possibly introduce model-overfitting issues. Conversely, if done effectively, these data subsets may reduce model error via grouping of trees having similar characteristics and thus minimizing error due to spatial variability (Westfall 2015).

2) Species inclusion and applicability: In this study, all species present in the data were included in the analyses and were aggregated into 29 species groups. Because the sampling is area-based, it can be argued that the frequency of any given species is approximately in proportion to its presence in urban areas – thus a 'self-weighting' occurs for the species-level influence in the group-level model. Many studies have developed models at the species-level. In some cases, this approach may give rise to issues similar to spatial partitioning, i.e., relatively small sample sizes and increased likelihood of model overfitting. The advantage of species-level models may be to reduce error by eliminating inter-species variation not accounted for via model predictor variables.

3) Modeling considerations: Perusal of the literature shows a wide range of approaches to modeling crown width, particularly in the forms of the models and the predictor variables used. Some studies compared a number of model types for each species and selected the best fit as the final model (McPherson et al. 2016; Blood et al. 2016; Peper et al. 2014; Troxel et al. 2013). While the intent is to find the best model for the data, only validation with independent data will reveal whether this approach truly produces the most accurate models or whether the result is model overfitting to the data. Another key modeling consideration is exclusion criteria, which removes certain observations from the data. One approach is to exclude species having small sample sizes (Blood et al. 2016). Monteiro et al. (2016) employed a number of criteria to omit certain sample trees – including those of small size

Table 6 The mean difference ($\overline{D}$, m^2) mean percent difference ($\overline{D}\%$), mean absolute difference ($|\overline{D}|$, m^2) and mean percent absolute difference ($|\overline{D}|\%$) between i-Tree leaf area calculations based on observed crown widths and those from predicted crown widths

Group	$\overline{D}$	$\overline{D}\%$	$\lvert\overline{D}\rvert$	$\lvert\overline{D}\rvert\%$
1	10.93	7.56	47.72	32.98
2	2.42	2.33	19.31	18.59
3	6.75	4.30	40.06	25.51
4	0.66	0.74	27.75	31.39
5	1.98	1.14	42.52	24.54
6	4.07	4.36	28.63	30.65
7	0.18	2.96	0.46	7.54
7*	0.14	2.22	0.45	7.33
8	2.34	1.30	41.56	23.07
9	0.17	0.08	47.02	23.31
10	−1.58	−1.05	35.96	23.91
11	−4.60	−1.83	60.91	24.24
12	8.25	4.14	45.84	23.01
13	9.81	4.38	54.49	24.34
14	2.56	1.14	59.15	26.23
15	0.44	0.18	72.83	30.22
16	−15.58	−9.87	51.81	32.83
17	−0.36	−0.35	37.7	36.44
18	3.14	2.57	38.15	31.15
19	0.89	0.43	49.93	24.19
20	−3.83	−1.80	48.87	22.88
21	−40.28	−8.95	147.10	32.70
22	17.73	4.61	108.78	28.25
23	2.95	1.70	50.55	29.08
24	1.73	1.89	29.80	32.59
25	1.28	1.35	30.25	31.79
26	0.06	1.65	0.39	10.36
26*	0.03	0.94	0.49	13.17
27	1.25	1.89	21.20	32.00
28	6.43	8.37	24.17	31.47
29	4.13	22.91	8.51	47.22

or abnormal allometry. Similarly, McPherson et al. (2016) eliminated observations that were deemed outliers based on residual plots. These data exclusion methods produce domains that may be subject to poor model extrapolation in practical applications, e.g., calculating predictions for excluded species or tree sizes. These differences in data reduction methods also make it difficult to compare model goodness-of-fit statistics across studies.

The need for urban-specific crown width models has been demonstrated here via application of forest-based models (Bechtold 2003, 2004) to urban trees. The empirical results generally confirmed the supposition that urban trees would exhibit wider crowns for a specified tree diameter (Table 5). Thus, the misguided use of forest-based models would likely produce systematic underestimation of crown width in urban assessments. Crown width is often used to evaluate growing space requirements (Dahlhausen et al. 2016; Pretzsch et al. 2015), where prediction biases could have a long-term detrimental effect due to erroneous planning decisions. Crown width also plays an integral role in estimation of crown or leaf area – from which many ecosystem service metrics are calculated, e.g., rainfall interception, shading/cooling effects, carbon sequestration, and air pollution amelioration (Nowak et al. 2016; Gómez-Baggethun and Barton 2013). Thus, the use of urban-specific crown width models is imperative to avoid underestimating the contributions of urban trees to environmental health and human well-being.

The i-Tree software suite uses calculated values of leaf area to provide estimates of various eco-system services such as rainfall interception and air pollution removal (Nowak et al. 2008). Substitution of predicted crown widths in the leaf area estimation process should generally have little effect on i-Tree outputs; however, the realized differences would also depend on the species present and their relative frequency (Table 6). The average absolute prediction errors are relatively large, which suggests a high level of variability in the data. This variability manifests in two general ways: 1) trees that are small as described by dbh and height, but have uncharacteristically large crowns, and 2) conversely, trees that would be considered large-sized based on dbh and height attributes, however the crowns are divergently small. In the former case, trees with abnormally large crowns likely are growing in conditions with little competition for light where crown expansion is essentially uninhibited. Small crowns relative to tree size may occur due to storm damage, pruning, or simply overall poor tree health. Thus, crown widths for urban trees tend to be more highly variable than forest-grown counterparts which makes accurate model prediction more elusive.

Application of the modeling results is fairly straightforward for cities (and associated species occurence) included in the data used for this analysis. Use of the models outside this domain will require further consideration. For situations lacking lack specific treatment from this study, perhaps the simplest approach would be to adopt the model parameters that are 'closest' to the city/species being considered. Several situations may be present under this implementation: 1) the species group is known, but no random effect exists for the new city, 2) the city random effect is known, but the species is new and lacking group assignment, or 3) both city and species are new, with no city random effect and no species group assignment. The latter is perhaps the most troubling as it requires assumptions for both city and species group effects. Regardless, practitioners employing this approach should be aware that bias in model predictions is unknown and possibly large. In contrast, random effects may be predicted for cities/species groups not in the original data; however, this would require collection of new data in order to perform the calculations. Prediction of random effects for new observations has been well-addressed in the statistical literature (Vonesh and Chinchilli 1997) and forestry-specific applications are also sufficiently documented (Trincado and Burkhart 2006, Westfall 2010). These publications and references therein are recommended to practitioners desiring to predict random effects for new observations.

Conclusion

Ultimately, practitioners need to ascertain whether statistical models are adequate for their specific uses. The crown width models presented herein extend the species and geographic coverage beyond those found in other published studies. The analytical results allow for comparison with both forest- and urban-based crown width models that may be found in the literature. Generally, localized models tend to outperform those that have wider application; however, the use of city-based random effects in this study may produce comparable prediction accuracy at local scales. Thus, the possibility of using prediction models in lieu of field-measured crown widths may be considered. Although there has been ongoing advancement of urban crown width modeling, it seems clear that continued research is needed. A topic worthy of further investigation is assessment of alternative methods to account for spatial variability, such as the use of latitude/longitude/elevation or other continuous variables that reflect different growing environments. As efforts such as i-Tree and Urban FIA continue to expand data availability in both spatial extent and consistency of protocols for field measurements, the ability to further increase the accuracy of national-scale crown width models seems highly plausible.

References

Bechtold WA (2003) Crown-diameter prediction models for 87 species of stand-grown trees in the eastern United States. South J Appl For 27(4):269–278
Bechtold WA (2004) Largest-crown-width prediction models for 53 species in the western United States. West J Appl For 19(4):245–251
Berrang P, Karnosky DF, Stanton BJ (1985) Environmental factors affecting tree health in New York City. J Arboric 11(6):185–189
Blood A, Starr G, Escobedo FJ, Chappelka A, Wiseman PE, Sivakumar R, Staudhammer CL (2016) Resolving uncertainties in predictive equations for urban tree crown characteristics of the southeastern United States: local and general equations for common and widespread species. Urban For Urban Green 20:282–294
Bragg DC (2001) A local basal area adjustment for crown width prediction. North J Appl For 18(1):22–28
Bunnell F (1999) Forestry isn't rocket science – it's much more complex. Forum (Publication of the Association of British Columbia Professional Foresters) 6(1):7
Bussotti F, Pollastrini M (2017) Traditional and novel indicators of climate change impacts on European forest trees. Forests 8(4):137
Chen C, Weiskittel AR, Bataineh M, MacLean DA (2017) Evaluating the influence of varying levels of spruce budworm defoliation on annualized individual tree growth and mortality in Maine, USA and New Brunswick, Canada. For Ecol Manag 396:184–194
Christie FJ, Hochuli DF (2005) Elevated levels of herbivory in urban landscapes: are declines in tree health more than an edge effect? Ecol Soc 10(1)
Clark JR, Kjelgren RK (1990) Water as a limiting factor in the development of urban tree plants. J Arboric 16(8):203–208
Dahlhausen J, Biber P, Rötzer T, Uhl E, Pretzsch H (2016) Tree species and their space requirements in six urban environments worldwide. Forests 7(6):111
Fini A, Frangi P, Faoro M, Piatti R, Amoroso G, Ferrini F (2015) Effects of different pruning methods on an urban tree species: a four-year-experiment scaling down from the whole tree to the chloroplasts. Urban For Urban Green 14(3):664–674
Fu L, Sun H, Sharma RP, Lei Y, Zhang H, Tang S (2013) Nonlinear mixed-effects crown width models for individual trees of Chinese fir (Cunninghamia lanceolata) in south-Central China. For Ecol Manag 302:210–220
Gaudio N, Gendre X, Saudreau M, Seigner V, Balandier P (2017) Impact of tree canopy on thermal and radiative microclimates in a mixed

temperate forest: a new statistical method to analyse hourly temporal dynamics. Agric For Meteorol 237:71–79
Gómez-Baggethun E, Barton DN (2013) Classifying and valuing ecosystem services for urban planning. Ecol Econ 86:235–245
Gregoire TG, Schabenberger O (1996) A non-linear mixed effects model to predict cumulative bole volume of standing trees. J Appl Stat 23:257–271
Harrell FE, Lee KL, Mark DB (1996) Tutorial in Biostatistics: Multivariable prognostic models. Stat Med 15:361–387
Hevia A, Crabiffosse A, Álvarez-González JG, Ruiz-González AD, Majada J (2018) Assessing the effect of pruning and thinning on crown fire hazard in young Atlantic maritime pine forests. J Env Manage 205:9–17
i-Tree (2019) Eco Field Guide v6.0. https://www.itreetools.org/resources/manuals/Ecov6_ManualsGuides/Ecov6_FieldManual.pdf Accessed 28 October 2019
Kardan O, Gozdyra P, Misic B, Moola F, Palmer LJ, Paus T, Berman MG (2015) Neighborhood greenspace and health in a large urban center. Sci Rep 5(11610)
Leites LP, Robinson AP, Crookston NL (2009) Accuracy and equivalence testing of crown ratio models and assessment of their impact on diameter growth and basal area increment predictions of two variants of the Forest vegetation simulator. Can J For Res 39(3):655–665
Marshall DD, Johnson GP, Hann DW (2003) Crown profile equations for stand-grown western hemlock trees in northwestern Oregon. Can J For Res 33(11):2059–2066
McPherson EG, van Doorn NS, Peper PJ (2016) Urban tree database and allometric equations. Gen. Tech. Rep. PSW-GTR-253. Albany, CA: U.S. Department of Agriculture, Forest Service, Pacific southwest Research Station. 86 p
Mitsopoulos ID, Dimitrakopoulos AP (2007) Canopy fuel characteristics and potential crown fire behavior in Aleppo pine (*Pinus halepensis* mill.) forests. Ann For Sci 64(3):287–299
Monteiro MV, Doick KJ, Handley P (2016) Allometric relationships for urban trees in Great Britain. Urban For Urban Green 19:223–236
Morin RS, Randolph KC, Steinman J (2015) Mortality rates associated with crown health for eastern forest tree species. Env Monit Assess 187:87
Nowak DJ (1996) Estimating leaf area and leaf biomass of open-grown urban deciduous trees. For Sci 42(4):504–507
Nowak DJ (2020) Understanding i-tree: summary of programs and methods. Gen. Tech. Rep. NRS-GTR-____. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, northern Research Station. ___ p. (In press)
Nowak DJ, Crane DE, Stevens JC, Hoehn RE, Walton JT, Bond J (2008) A ground-based method of assessing urban forest structure and ecosystem services. Arboric Urban For 34:347–358
Nowak DJ, Hirabayashi S, Ellis E, Greenfield EJ (2014) Tree and forest effects on air quality and human health in the United States. Env Pollut 193:119–129
Nowak DJ, Hoehn RE, Bodine AR, Greenfield EJ, O'Neil-Dunne J (2016) Urban forest structure, ecosystem services and change in Syracuse, NY. Urban Ecosyst 19(4):1455–1477
Peper PJ, McPherson EG, Mori SM (2001) Equations for predicting diameter, height, crown width, and leaf area of San Joaquin Valley street trees. J Arboric 27:306–317
Peper PJ, Alzate CP, McNeil JW, Hashemi J (2014) Allometric equations for urban ash trees (Fraxinus spp.) in Oakville, southern Ontario, Canada. Urban For Urban Green 13(1):175–183
Pretzsch H, Biber P, Uhl E, Dahlhausen J, Rötzer T, Caldentey J, Koike T, Van Con T, Chavanne A, Seifert T, Du Toit B (2015) Crown size and growing space requirement of common tree species in urban centres, parks, and forests. Urban For Urban Green 14(3):466–479
Russell MB, Weiskittel AR (2011) Maximum and largest crown width equations for 15 tree species in Maine. North J Appl For 28(2):84–91
Sánchez-González M, Cañellas I, Montero G (2007) Generalized height-diameter and crown diameter prediction models for cork oak forests in Spain. For Syst 16(1):76–88
Sharma RP, Vacek Z, Vacek S (2016) Individual tree crown width models for Norway spruce and European beech in Czech Republic. For Ecol Manag 366:208–220
Smith WH (1990) Forests as sinks for air contaminants: vegetative compartment. In: Air pollution and forests. Springer, New York, pp 147–180
Tan PY, Ismail MRB (2015) The effects of urban forms on photosynthetically active radiation and urban greenery in a compact city. Urban Ecosyst 18(3):937–961
Trincado G, Burkhart HE (2006) A generalized approach for modeling and localizing stem profile curves. For Sci 52:670–682
Troxel B, Piana M, Ashton MS, Murphy-Dunning C (2013) Relationships between bole and crown size for young urban trees in the northeastern USA. Urban For Urban Green 12:144–153
U.S. Forest Service (2015) FIA database description and user guide for urban, version 10 https://wwwfiafsfedus/library/database-documentation/urban/current/FIADB_user%20guide_urban_10_2015pdf Accessed 28 October 2019
U.S. Forest Service (2017) National urban FIA plot field guide. Version 71 https://wwwnrsfsfedus/fia/urban/field-guides/national/National%20UFIA%20FIA%20FG-71pdf Accessed (28 October 2019)
Valentine HT, Gregoire TG (2001) A switching model of bole taper. Can J For Res 31:1400–1409
Vogt JM, Watkins SL, Mincey SK, Patterson MS, Fischer BC (2015) Explaining planted-tree survival and growth in urban neighborhoods: a social–ecological approach to studying recently-planted trees in Indianapolis. Landsc Urban Plann 136:130–143
Vonesh EF, Chinchilli VM (1997) Linear and nonlinear models for the analysis of repeated measurements. Marcel Dekker, New York, 560 p
Westfall JA (2010) New models for predicting diameter at breast height from stump dimensions. North J Appl For 27(1):21–27
Westfall JA (2015) Spatial-scale considerations for a large-area forest inventory regression model. Forestry 88(2):267–274
Willis KJ, Petrokofsky G (2017) The natural capital of city trees. Science 356(6336):374–376