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# Urban tree growth models for two nearby cities show notable differences

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**Abstract**
Reliable models of urban tree growth over time are useful for selecting appropriate species for available planting sites, anticipating future tree maintenance and removal costs, and quantifying the benefits provided by trees. There is a need to develop growth models for multiple cities within the same climate region to understand the degree of variability for the same species in different cities. In this study, we developed tree growth models for 13 common street tree species in Cincinnati, Ohio, USA, based on field data and planting records. These models relate tree age to diameter at breast height. Then we compared the modeled tree growth curves for Cincinnati to analogous models from nearby Indianapolis, Indiana. To estimate how differences in modeled tree growth translate to differences in ecosystem services, we compared annual ecosystem service estimates from Cincinnati and Indianapolis using the i-Tree Eco model. The comparisons showed varying levels of difference between cities; for example, modeled growth curves for *Acer platanoides* were nearly identical, while models for *Pyrus calleryana* differed by > 47% over 35 years of growth. These results advance our understanding of urban tree growth rates by comparing models from two nearby cities, and by underscoring the inherent variability in urban tree growth that will drive attendant differences in the ecosystem services provided by trees.

**Keywords** Diameter at breast height (DBH) · Ecosystem services modeling · i-Tree Eco model · Street trees · Tree age

## Introduction

The urban forest, defined as all trees within an urban area, is an important part of the urban environment. Urban forests provide a wide array of both ecosystem services and ecosystem disservices related to environmental outcomes, human health and social wellbeing, and economics (Escobedo et al. 2011; Dobbs et al. 2014). While the benefits of urban trees are generally thought to outweigh the disservices (McPherson et al. 2005), strategic management of the urban forest can promote ecosystem services and reduce disservices (Lyytimäki and Sipilä 2009). This is especially true for street trees – trees growing in the public right-of-way along streets – because they are distributed broadly throughout a city and they are often managed by one entity such as the municipal government (Hauer and Peterson 2016). Although street trees are less abundant than trees on private property, they are often the most abundant group of trees subject to collective management by the municipality or another entity. Furthermore, street trees are highly visible and more accessible to people compared to trees on private property or in remote areas of parks. As such, the science and management of street trees is an important focus in urban forestry (Mullaney et al. 2015; Galenieks 2017).

A relevant area of inquiry related to street trees is understanding tree growth over time. From a management perspective, it is important to select a tree that is well suited to the space constraints of a planting site (Randrup et al. 2001), for example, so a species that grows to a large diameter is not planted in a narrow tree lawn (Hilbert et al. 2020). In addition, accurately estimating the future sizes of young trees can help urban forest managers plan for future costs associated with tree pruning and removal (McPherson et al. 2016). Beyond these pragmatic management considerations, there has also been a concerted effort to account for benefits and costs associated with urban trees using computer models such as the i-Tree suite of tools (i-Tree 2020). I-Tree models use input tree data such as species and diameter at breast height (DBH) data

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to quantify urban forest structure and estimate ecosystem services provided by trees. For instance, the i-Tree Design model (i-Tree 2020) helps users understand how an existing tree or new planting is expected to perform over time by providing estimates of benefits for the current year and into the future. Communities may use these models to demonstrate the dollar values of benefits provided by their trees as a public engagement tool or as a way to justify urban forestry budgets to decision makers.

Accurate modeling of street tree benefits is important when model estimates are used in science, management, and/or public engagement applications. I-Tree Eco, the flagship i-Tree model, uses a series of modeled relationships to estimate benefits (Nowak et al. 2008; i-Tree 2020). In short, the user inputs tree species and DBH information at minimum, and the model relies on allometric relationships for that species or a similar species to estimate leaf area based on DBH. Leaf area is then used in conjunction with local environmental information like air pollution and rainfall data to estimate environmental benefits provided by the trees. An extension of this is to model benefits over time by using age-to-DBH relationships to model tree growth into the future. More reliable allometric models translating tree age to DBH to leaf area to benefits will lead to more accurate model output that can serve as a basis for strategic and evidence-based urban forest management decisions (McPherson and Peper 2012).

As the field of urban forestry has grown, so has the study of tree growth relationships, including age-to-size equations and allometric relationships among tree dimensions (e.g., predicting height based on DBH, predicting leaf area based on leaf crown dimensions). This includes a broadening geographic scope, the development of growth models for more urban tree species, and different statistical approaches for fitting growth curves to predict tree dimensions based on a set of field observations. For example, Peper et al. (2001a, b) developed allometric models for street trees in California cities, in part to address a gap in earlier studies that were geographically focused on cities with cooler climates and shorter growing seasons. More recently, allometric models have been developed for urban trees in diverse geographies such as Denmark (Larsen and Kristoffersen 2002), South Africa (Stoffberg et al. 2009), Italy (Semenzato et al. 2011), South Korea (Yoon et al. 2013), the northeastern US (Troxel et al. 2013), and Great Britain (Monteiro et al. 2016). Various statistical models have been employed including linear regression (including models with polynomial terms) (e.g., Semenzato et al. 2011), logarithmic regression (e.g., Troxel et al. 2013), exponential regression (e.g., Peper et al. 2001a), and power functions (e.g., Yoon et al. 2013). McPherson and Peper (2012) demonstrated that differences in biophysical environment and tree management can lead to differences in tree growth, even for the same species growing in two cities within the same region. This, in turn, can lead to substantial differences in the benefits provided by these trees. In their study, 100 ash trees in Ft. Collins, Colorado, were estimated to grow larger and provide about three times greater benefits over 40 years compared to 100 ash trees in nearby Cheyenne, Wyoming (McPherson and Peper 2012).

McPherson et al. (2016) published the most comprehensive collection of allometric models in terms of both species and geographic scope. They created models for common urban species in 16 climate zones across the US, including 17–22 species per region. Some species were included in multiple regions, but unique models were created for each region to account for the possibility of different tree growth under different climatic conditions. McPherson et al. (2016) developed statistical models to estimate DBH from age in years after planting, and then used DBH to predict height, crown height, crown diameter, and leaf area. They fit six model forms for each model, and selected the best fitting model for each parameter. The approach used by McPherson et al. (2016) forms the basis for modeling age-to-DBH growth curves in this study.

The first goal of this study is to develop age-to-DBH models for common street tree species in Cincinnati, Ohio, where such models have not previously been created. The second goal is to compare the models for Cincinnati to models developed by McPherson et al. (2016) for the same species in nearby Indianapolis, Indiana. This is particularly relevant in light of the substantial differences in tree growth models for the same species across different US climate regions (McPherson et al. 2016), and even for the same species growing in different places within the same climate region (McPherson and Peper 2012). The third goal of this study is to explore how differences in growth models between cities translate to differences in estimated benefits using the i-Tree Eco model. This research has implications for urban forest science and management, primarily by helping to understand the degree of within-region variability in growth rates for common street tree species.

## Methods

### Study area

Cincinnati, Ohio (39.10° N, 84.51° W), is a city of approximately 302,000 residents located in the Lower Midwest region of the US, as defined by McPherson et al. (2016). As described below, our age-to-DBH models from Cincinnati were compared to models from Indianapolis, Indiana, the Lower Midwest reference city studied by McPherson et al. (2016). Cincinnati is approximately 160 km southeast of Indianapolis (39.77° N, 86.16° W). Both Cincinnati and Indianapolis are located in USDA Plant Hardiness Zone 6. Cincinnati's average annual temperature is 12.4 °C (NOAA

NCEI 2020). The average maximum temperature is 30.3 °C in July, and the average minimum temperature is -5.3 °C in January. On average, Cincinnati receives 1,065 mm of annual precipitation (NOAA NCEI 2020). By comparison, Indianapolis has an average annual temperature of 11.8 °C, ranging from a minimum of -6.4 °C in January to a maximum of 29.4 °C in July; Indianapolis receives 1,078 mm of annual precipitation (NOAA NCEI 2020). Street trees in Cincinnati are managed by the Urban Forestry program housed within the City of Cincinnati Parks Department.

## Field data collection

Field data were collected in Cincinnati during the summer of 2014. To construct age-related growth models, we recorded DBH and age for 13 common street tree species (Table 1). Candidate trees were identified using records provided by Cincinnati Parks Urban Forestry staff, as described below. We measured DBH to the nearest 0.1 cm using a diameter tape at a height of 1.37 m (4.5 ft), following the standards of Caris et al. (nd). For multi-stemmed trees, all stems > 2.5 cm (1 inch) at DBH were measured and summed for a total DBH. Multi-stemmed trees that forked at breast height were measured just below the fork and above the butt flare. For trees with shape irregularities, we measured DBH directly above the irregularity where the trunk shape returned to normal.

Tree age was defined as years since planting. Ages were determined using two separate resources from the Cincinnati Parks Urban Forestry program. First, most tree ages were determined using planting records extending back to 1982. These planting records listed several relevant details including street address, date planted, tree species, and caliper (diameter at 30.5 cm or 1 ft above the ground). Second, we extended our age-to-DBH growth models beyond 1982 using lists of trees slated for removal that were provided each week by Cincinnati Parks Urban Forestry staff. For some of these trees, we visited them before they were removed to measure DBH, and then returned after removal to obtain annual ring counts from the stumps using a hand lens. To reduce aging error introduced by obtaining ages from stumps near the ground as opposed to DBH, we measured diameter on these trees below DBH near 30.5 cm height but above any pronounced flaring at the base. Stump ring counts were only feasible when the stumps were free of rot and a clear ring count could be made in the field.

**Table 1** Summary of species data used to construct age-to-DBH growth models

| Species | Species code | Cincinnati (this study) *n* | age range (years) [b] | DBH range (cm) | selected model | adj $R^2$ | Indianapolis[a] *n* | age range (years) [b] | DBH range (cm) |
|---|---|---|---|---|---|---|---|---|---|
| *Acer campestre* L.<br>Hedge maple | ACCA | 57 | 0–21 | 5.0–29.2 | exponential | 0.77 | - | - | - |
| *Acer platanoides* L.<br>Norway maple | ACPL | 32 | 4–31 | 4.4–33.5 | log-log | 0.76 | 13 | 4–102 | 4.8–98.6 |
| *Acer rubrum* L.<br>Red maple | ACRU | 67 | 0–69 | 4.3–67.4 | linear | 0.91 | 24 | 4–90 | 5.1–100.1 |
| *Acer saccharum* Marshall<br>Sugar maple | ACSA2 | 42 | 0–61 | 3.9–49.8 | quadratic | 0.89 | 14 | 4–105 | 2.5–118.1 |
| *Cercis canadensis* L.<br>Eastern redbud | CECA | 56 | 0–27 | 4.7–33.3 | quadratic | 0.53 | 16 | 4–55 | 2.8–75.4 |
| *Crataegus viridis* L.<br>Green hawthorn | CRVI | 61 | 0–31 | 4.3–22.6 | exponential | 0.72 | - | - | - |
| *Fraxinus americana* L.<br>White ash | FRAM | 70 | 7–128 | 13.8–87.6 | log-log | 0.63 | 23 | 4–102 | 5.1–118.1 |
| *Gleditsia triacanthos* L.<br>Honeylocust | GLTR | 96 | 0–31 | 4.8–57.6 | cubic | 0.69 | 19 | 5–56 | 4.1–113.0 |
| *Liquidambar styraciflua* L.<br>Sweetgum | LIST | 40 | 2–48 | 6.1–63.6 | exponential | 0.81 | - | - | - |
| *Malus* spp. Mill.<br>Crabapple | MA2 | 131 | 0–31 | 2.5–38.2 | exponential | 0.69 | 31 | 0–62 | 4.1–53.8 |
| *Pyrus calleryana* Decne.<br>Callery pear | PYCA | 126 | 1–36 | 5.2–52.8 | log-log | 0.80 | 15 | 1–18 | 2.5–62.0 |
| *Quercus rubra* L.<br>Northern red oak | QURU | 46 | 0–29 | 4.1–40.2 | cubic | 0.95 | 22 | 4–84 | 3.6–129.0 |
| *Syringa reticulata* (Blume) H.Hara<br>Japanese tree lilac | SYRE | 69 | 0–31 | 2.4–26.6 | exponential | 0.72 | - | - | - |

[a] McPherson et al. (2016), data available in Supplemental Table 6 at http://dx.doi.org/10.2737/RDS-2016-0005

[b] Age was defined as years since planting

Ring counts were made along two radii to ensure agreement. We were also granted permission to take increment cores from trees slated for removal. For these trees, we measured DBH and then extracted one or more increment cores at breast height to obtain a rot-free core near the pith. These cores were dried, mounted, and sanded following standard dendrochronological methods (Stokes and Smiley 1996). Annual rings were counted under a microscope to assign an age, and a pith locator was used when the increment core did not include the pith.

For both stumps and increment cores, raw tree ages derived from annual ring counts represented the age of the stem at the pith rather than the number of years since planting, so the raw ages for these observations were reduced by three years to offer a more realistic estimate of the year the tree was planted. This age correction was an approximation, but any error related to the age correction was expected to be small compared to the natural variability in age-related DBH growth. This expectation is supported by Online Resource 1.

## Tree growth modeling

We largely followed the procedures of McPherson et al. (2016) to develop statistical models for predicting DBH based on tree age. For each species, we fit curves to test the following six models: linear, quadratic, cubic, quartic, log-log, and exponential. The model with the lowest bias-corrected Akaike information criterion (AIC*c*) for each species was selected as the best-fit model; this represents the model that has high explanatory power without being overly complex. AIC*c* was chosen over AIC to accommodate modest sample sizes (Johnson and Omland 2004). The age-to-DBH growth models were fit using R version 3.6.1 (R Core Team 2019) with the packages 'MuMln' (Bartoń 2019), 'DescTools' (Signorell et al. 2019) and 'dvmisc' (Van Domelen 2019). The R code is available as Online Resource 2.

A motivating question in this study was to understand how age-to-DBH models compare for the same species in two different cities within the same climate region. To do this, we plotted best-fit growth curves from Cincinnati (this study) and Indianapolis (McPherson et al. 2016) on the same graph for the nine species in Table 1 that were common to both studies. We then compared the percent difference in DBH over time between the two cities, where percent difference was calculated relative to Cincinnati DBH as:

$$(CincinnatiDBH - IndianapolisDBH)/CincinnatiDBH * 100$$

We limited this comparison to either the maximum age of trees observed in Cincinnati, or the maximum application age range for the species suggested by McPherson et al. (2016), whichever was lower. If models predicted negative DBH values for young trees, these ages were excluded from analysis.

We also plotted a best-fit growth curve for the full US data set from McPherson et al. (2016) using every individual tree from each species that had a valid age and DBH value, regardless of US region. We fit growth curves using the same procedure we used for Cincinnati. Relative to tree growth models for Cincinnati and Indianapolis, we expected that larger sample sizes from the broader US could lead to reduced uncertainty in growth models, but US models may also deviate from Lower Midwest models due to influences of trees in other US regions growing under different climatic conditions.

## Comparing environmental benefits across locations

To explore how differences in estimated DBH between Cincinnati, Indianapolis, and US growth models translate into differences in estimated environmental benefits, we simulated tree growth scenarios using the i-Tree Eco model (i-Tree 2019). I-Tree Eco is a USDA Forest Service tool that uses tree data inputs, a database of tree growth equations, and location-specific data about weather and air pollution to estimate benefits provided by urban trees. These benefits include annual estimates of carbon sequestration, avoided storm water runoff, and air pollution removal. Each of these estimated benefits is expressed in both raw units and monetary values (USD) per year. I-Tree Eco also estimates structural value, which is a compensatory value representing the cost of replacing the tree with a similar tree. The model can estimate benefits for individual trees based on species and DBH.

To understand how modeled benefits change according to a tree's age, we used the age-to-DBH models developed for each species to estimate DBH for each year over the modeled time period for that species (i.e., the lower value of either the maximum age observed in our Cincinnati data set or the maximum application age suggested by McPherson et al. (2016)). This was done separately for the three locational data sets of Cincinnati, Indianapolis, and the US as a whole. We entered each species-year-location combination into i-Tree Eco as a separate tree with the appropriate modeled DBH for that year. This allowed us to model the annual benefits of a tree of each species according to its predicted DBH at that age. We plotted these i-Tree Eco estimates of benefits at several snapshots in time to visualize how differences in age-to-DBH models translate to differences in annual environmental benefits provided by the trees. Note that all trees were entered into the same i-Tree Eco project using Cincinnati weather and pollution data, so observed differences are attributable to differences in the three age-to-DBH models for that species (Cincinnati, Indianapolis, and US) and not different weather and pollution conditions. We also plotted structural value by species for each of the three locations at the end of the species' modeled time period to visualize the effects of variations in age-to-DBH models.

## Results

We determined age and DBH for a total of 893 trees from 13 common street tree species in Cincinnati (Table 1). Of these observations, 92% were based on planting records, 5% were based on stump ring counts, and 3% were based on increment cores. The data set is available as Online Resource 3. The form of the best-fit model for predicting DBH from tree age varied by species (Table 1; Figs. 1 and 2). Of the 13 species models selected, five were exponential, three were log-log, two were quadratic, two were cubic, and one was linear (Table 1). In general, the Cincinnati field data from this study have larger sample sizes but smaller age ranges and DBH ranges compared to Indianapolis data from McPherson et al. (2016) for the same species (Table 1).

The similarity of age-related growth models from different locations varied by species (Figs. 1, 2 and 3). For example, age-to-DBH curves for *Acer rubrum* were very similar for Cincinnati and Indianapolis, but the US curve was markedly different (59, 57, and 121 cm at 60 years since planting, respectively; Fig. 3). On the other hand, age-to-DBH curves for *Gleditsia triacanthos* were similar for Cincinnati and the US, while modeled DBH for Indianapolis remained much lower over time (37, 37, and 16 cm at 25 years since planting, respectively; Fig. 3). The percentage differences between modeled DBH for Cincinnati and Indianapolis are given in Table 2. For all nine species, projected diameters for Cincinnati models are larger than Indianapolis at 5 and 10 years since planting when trees are relatively small. Some of these large discrepancies persist over time (e.g., *Pyrus calleryana*, *Gleditsia triacanthos*), while others reverse such that modeled DBH for Indianapolis outpaces Cincinnati (*Acer saccharum, Fraxinus americana*). The DBH estimates

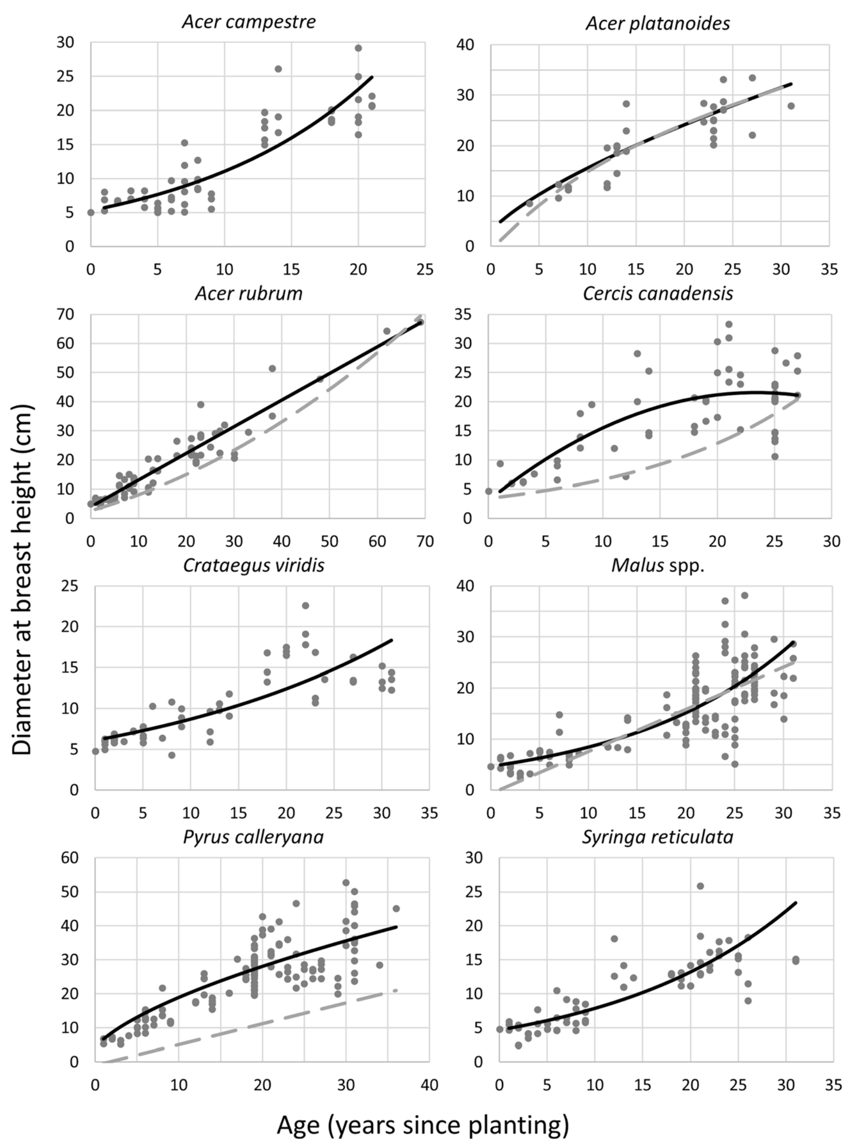


**Fig. 1** Age-to-DBH growth models for small- and medium-statured trees. Solid lines represent models for Cincinnati, and dots represent individual trees used to construct the models. For comparison, dashed lines represent models developed for Indianapolis by McPherson et al. (2016)

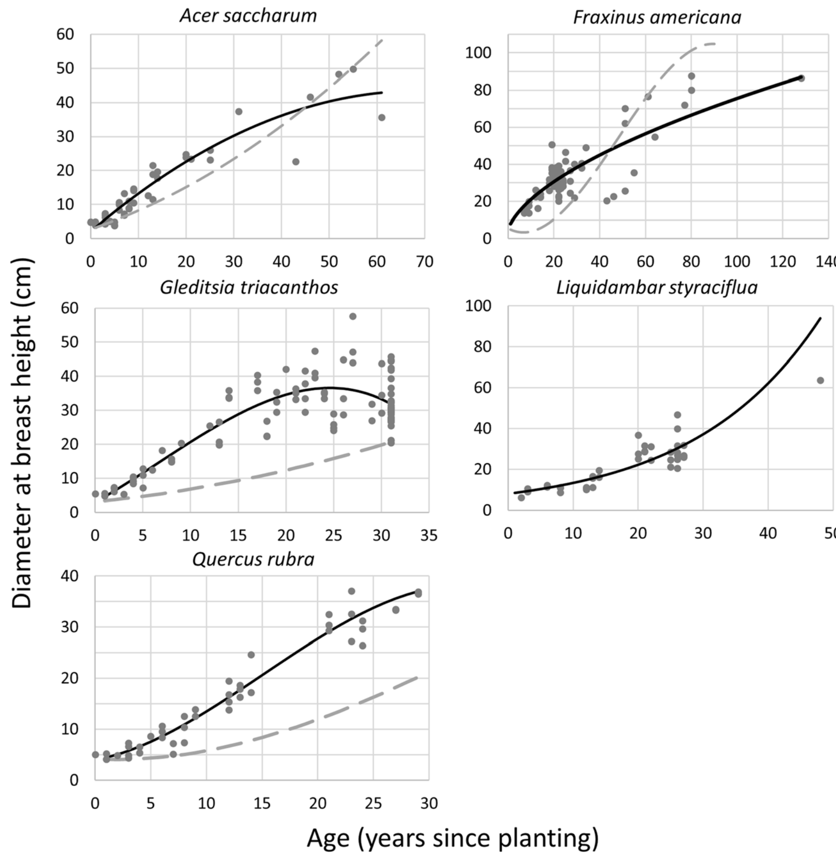


**Fig. 2** Age-to-DBH growth models for large-statured trees. Solid lines represent models for Cincinnati, and dots represent individual trees used to construct the models. For comparison, dashed lines represent models developed for Indianapolis by McPherson et al. (2016)

over time for *Acer platanoides* are almost identical for Cincinnati and Indianapolis (Fig. 1; Table 2).

The i-Tree Eco estimates of environmental benefits show differences according to location that are similar, but not directly proportional, to differences in DBH (Fig. 3). For example, DBH of *Acer rubrum* at 60 years since planting is 106% larger for the US data set compared to Cincinnati, but estimated annual benefits are only 73% greater. Conversely, discrepancies in structural value are proportionally larger than differences in DBH (Fig. 3).

## Discussion

Tree growth equations are important for the science and management of street trees. For example, understanding how large a tree could grow over time can help managers avoid conflicts between paved surfaces and trees that are too big for their planting sites. One contribution of this study is generating age-to-DBH models for Cincinnati, where such models had not been previously developed. The models are likely to be more reliable for some species than others, because the quality of model fit varies by species, as indicated by adjusted $R^2$ values ranging from 0.53 for *Cercis canadensis* to 0.95 for *Quercus rubra* (Table 1). Moreover, taxa including *Gleditsia triacanthos*, *Malus* spp., and *Pyrus calleryana* exhibited pronounced heteroskedasticity, or increasing variability in observed DBH with increasing age (Figs. 1 and 2). While this heteroskedasticity was not surprising given the findings of earlier studies (e.g., Semenzato et al. 2011; McPherson et al. 2016), it does indicate that age-to-DBH models are less reliable for projecting the DBH of individual trees at more advanced ages. We suggest that species growth models could potentially be refined by accounting for characteristics of the individual trees used to develop those models, such as their variety or cultivar, site conditions, and pruning history.

Another primary contribution of this study is comparing models for the same species in two nearby cities within the same region. This allows us to begin evaluating how well an age-related growth model performs outside of the city for which it was developed. Monteiro et al. (2016) made similar comparisons across cities in Great Britain; the main difference is that our models included age and DBH while that study analyzed allometric relationships among tree dimensions (DBH vs. height, DBH vs. crown width, etc.) but not age. Here, we saw that models for all nine species included in both cities predicted larger DBH for Cincinnati compared to Indianapolis for the first ten years (Table 2). Given the similar climatic conditions in the two cities, it is unlikely that these differences were driven by climate, but the cause of this

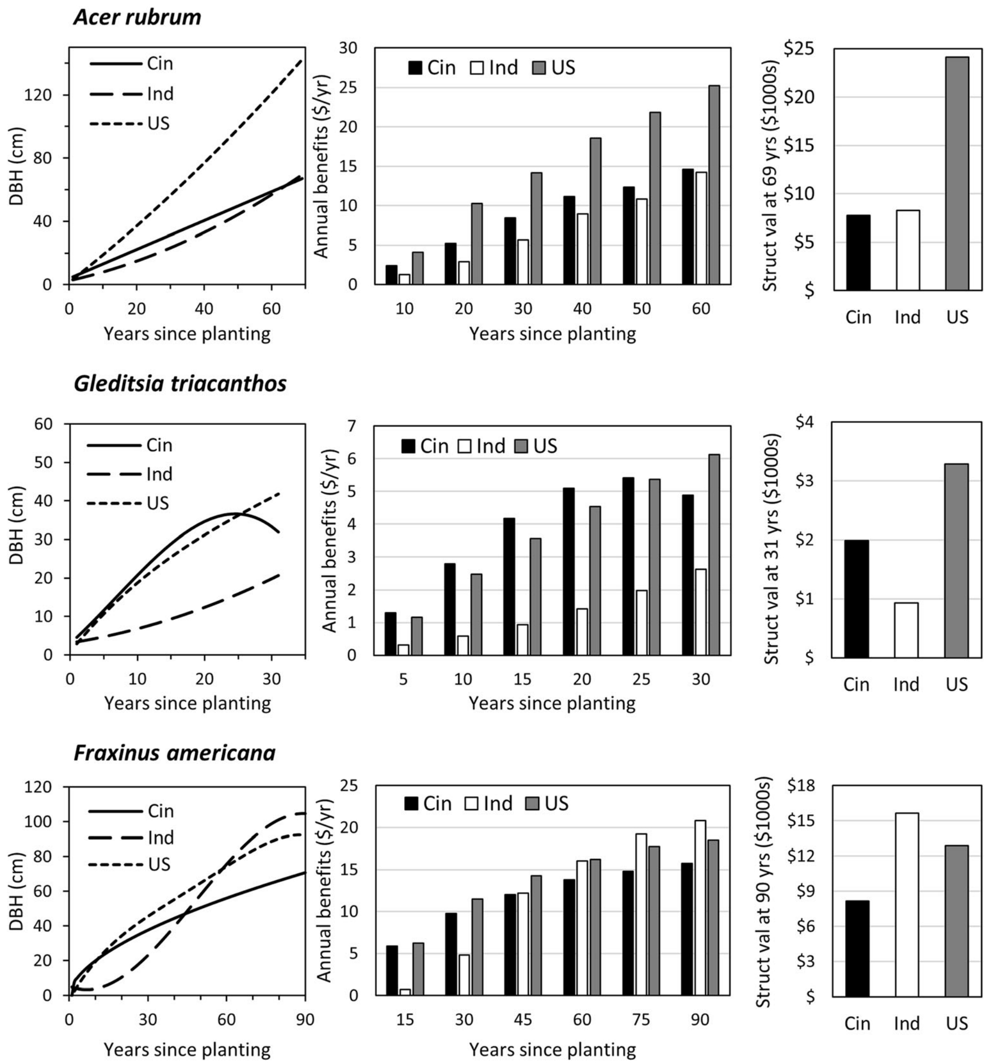


**Fig. 3** Comparisons for select species using data from this study for Cincinnati (Cin), and data from McPherson et al. (2016) for Indianapolis (Ind) and all data compiled nationwide (US). (Left) Best-fit growth curves. (Center) i-Tree Eco estimates of annual benefits provided by a tree of a given age, based on the projected diameter at breast height (DBH) from the growth curves at left. (Right) I-Tree Eco estimates of structural value of a tree at the end of the modeled time period based on projected DBH

systematic difference in modeled DBH is unclear. This difference could be an artifact of the size distributions of trees that were sampled in each city. Or, because these are municipally managed trees, it could be attributable to differences in arboricultural practices between the two cities. For example, if Cincinnati routinely plants larger caliper trees than Indianapolis, it would make sense that young trees are larger and the percent differences diminish with age. Alternatively,

**Table 2** Percent difference in modeled DBH between Cincinnati and Indianapolis at 5-year intervals. Percent difference was calculated relative to Cincinnati DBH, so positive (negative) values indicate that modeled DBH was larger (smaller) for Cincinnati than for Indianapolis. Blank cells are beyond the modeled time period for that species

| | Years since planting | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Species | 5 | 10 | 15 | 20 | 25 | 30 | 35 | 40 | 45 | 50 |
| *Acer platanoides* | 20.7 | 4.6 | 0.3 | -0.7 | -0.4 | 0.2 | | | | |
| *Acer rubrum* | 38.7 | 37.9 | 35.5 | 32.5 | 29.2 | 25.7 | 22.1 | 18.5 | 14.8 | 11.0 |
| *Acer saccharum* | 25.9 | 15.3 | 8.7 | 3.0 | -2.4 | -7.9 | -13.7 | -19.9 | -26.6 | -34.1 |
| *Cercis canadensis* | 52.6 | 57.0 | 51.7 | 39.2 | 16.7 | | | | | |
| *Fraxinus americana* | 76.3 | 81.6 | 76.0 | 65.8 | 53.3 | 39.7 | 25.7 | 11.9 | -1.3 | -13.5 |
| *Gleditsia triacanthos* | 59.5 | 67.3 | 67.7 | 64.4 | 56.8 | 40.6 | | | | |
| *Malus* spp. | 45.0 | 10.2 | -3.4 | -4.3 | 1.9 | 11.7 | | | | |
| *Pyrus calleryana* | 84.7 | 73.2 | 65.8 | 60.1 | 55.4 | 51.3 | 47.7 | | | |
| *Quercus rubra* | 42.4 | 57.1 | 59.4 | 57.1 | 51.8 | | | | | |

the cities could prefer different varieties or cultivars of the same species that may grow at different rates and to different mature sizes. While the data at hand do not point to the reason for differences among cities, the salient point is that we did observe differences between Cincinnati and Indianapolis models, and some of these differences were substantial (Figs. 1 and 2; Table 2).

The differences in age-to-DBH growth models drove notable differences in structural value and estimated benefits (Fig. 3). The differences are not surprising, given that we observed differences in modeled DBH in the three locations, and i-Tree Eco uses species and DBH inputs to estimate these benefit values. However, the magnitude of the observed differences was unexpected, particularly for *Gleditsia triacanthos* (Fig. 3). This analysis stresses that ecosystem services modeling for urban trees is highly dependent on model equations that translate observed species and DBH inputs into estimates of derived tree metrics (especially leaf area), and ultimately to estimates of benefits (Nowak et al. 2008). Model outputs from i-Tree Eco should be interpreted with care if these modeled relationships among DBH, leaf area, and benefits are not reliably portable across cities in the same region. Note that the i-Tree model developers are candid about these limitations (Nowak et al. 2008; i-Tree 2019), but model users may not always understand the model's assumptions and limitations.

There are limitations to this study that should be considered when interpreting our findings. We generally followed the statistical modeling techniques outlined by McPherson et al. (2016) to facilitate more straightforward comparisons of tree growth models between Cincinnati and Indianapolis, and it is possible that we overlooked better fitting statistical models. While our sample sizes were larger than those used by McPherson et al. (2016) (Table 1), we did not locate trees across the full age range for each species. For example, see the gap in observations between 27 and 48 years for *Liquidambar styraciflua*, and the maximum observed age of 29 years for *Quercus rubra*, a species that can potentially live much longer in the urban environment (Fig. 2). Our technique for adjusting tree ages from samples obtained using stump ring counts introduced a small degree of variation from models based on measurements from standing trees alone (Online Resource 1), but the impact of this error was minor because only 5% of samples were obtained using stump ring counts. Finally, our field observations did not include additional tree measurements such as tree height or crown width that would have been useful for more fully capturing tree size dimensions and for improving the accuracy of i-Tree Eco benefits estimates (i-Tree 2019).

Our results point to the need for continued refinement of species growth models to better understand the sources of inconsistencies between cities. For example, it is unclear if the substantial differences in curves for *Pyrus calleryana* in Cincinnati vs. Indianapolis (Fig. 1) were driven by differences in field sampling (sample sizes, size class distribution, unintentional inclusion of outliers), growing conditions (e.g., soil volumes, soil quality, light availability), climate, pollution, municipal arboricultural practices, or other factors. Development of these models is becoming increasingly feasible with the growing availability of past tree planting data from local governments and other organizations, especially as more cities have moved from paper records to digital records that can be easily shared. Producing additional tree growth models and reconciling the models among neighboring cities will help make projections of future tree growth and attendant benefits more reliable. This will ultimately help urban foresters make informed decisions about street tree planting and management with an eye toward promoting ecosystem services.

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**Data availability** Online Resource 3.

**Code availability** Online Resource 2.

## Compliance with Ethical Standards

**Conflicts of interest/Competing interests** None.

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