A framework for integrating high-resolution trees in urban energy use models

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Abstract

Urban vegetation is known to be effective in mitigating the Urban Heat Island (UHI) effect and reducing building energy use, specifically that associated with cooling. However, to quantify urban trees' cooling effect, the influence of their characteristics on cooling effectiveness and the corresponding building energy use needs to be assessed quantitatively and reflected in energy simulation efforts. In this study, a modelling framework is introduced to facilitate the integration of high-resolution geometries for trees in urban energy simulation models. A preliminary study of this modelling framework showed that our enhanced tree models can predict cooling loads that are as much as 2.2% lower than those predicted with the simplified tree models that are typically used. This enhancement in modelling can address current shortcomings for predicted and actual energy consumption of buildings.

Key Innovations

- A comprehensive set of tree-related factors that have previously been established as important for cooling demand of buildings is identified.
- All of these previously identified tree-related factors are integrated into this enhanced modelling framework.

Practical Implications

The modelling framework introduced in this study supports development of high-resolution tree models for urban energy use studies. This framework can be used to address frequently observed differences between predicted and actual energy loads of buildings, and lead to more realistic energy consumption predictions using urban energy simulation tools.

Introduction

In most urban areas the temperature at the heart or the canter of the city is higher than suburban and surrounding near-urban areas. This phenomenon is typically referred to as the Urban Heat Island (UHI) effect (O'Malley et al., 2015). Rapid urban expansion is exacerbating the UHI phenomenon and causes higher urban energy consumption in order to cool buildings, or when cooling is not possible it leads to lower thermal comfort with significantly increased risks to human health (Rosenzweig et al., 2011; Tan et al., 2016; Wang & Akbari, 2016). In addition, UHI effects are also amplified by the effects of climate change in many warm and humid regions, so the ability to mitigate against the impact of that can also diminish the negative effects of climate change.

Urban vegetation (specifically trees) can play a significant role in UHI mitigation and adaption (Yumino et al., 2015). Trees alter local climates within urban areas through (1) shading, which reduces the amount of radiant energy absorbed and stored by built surfaces; (2) evapotranspiration, which converts liquid water in plants to vapour, thereby cooling the air; and (3) wind speed reduction, which reduces infiltration of outside air, the effectiveness of ventilation, and convective cooling of building surfaces (Nowak et al., 2017; Simpson, 2002). These alterations to local climate generally reduce building energy consumption during the cooling season (Heisler, 1986). However, during the winter season, when heating energy use determines consumption loads in buildings, trees can actually increase energy use (Heisler, 1986). This increase is commonly associated with the shade that trees cast on buildings, particularly those that are located on the south side of buildings in the northern hemisphere (Heisler, 1986; McPherson, 1984). While such effects are greater for evergreen trees, deciduous trees also cast winter shade and may block up to 35% of incoming solar radiation even during their leaf-off season (McPherson, 1984).

While earlier studies suggested that use of trees around buildings to reduce energy consumption is efficient, in order to clarify the cooling effect of urban trees the influence of specific tree characteristics on building energy use in urban environments needs to be quantitatively assessed and understood. The most important characteristics of trees previously identified to affect the energy demands of buildings include: (1) tree height, (2) distance between trees and buildings, (3) tree canopy density, and 4) tree species (Hsieh et al., 2018). Therefore, the extent to which urban forestry can mitigate for UHI and climate change effects depends in large part on the development of better tools to account for these characteristics and quantify the cost-effectiveness of alternative strategies to more clearly demonstrate their potential benefits (Simpson, 2002).

The focus of this paper is the development of an improved modelling framework for estimating the amount and timing of shading from trees and its effects on cooling and heating energy use in residential buildings. The proposed

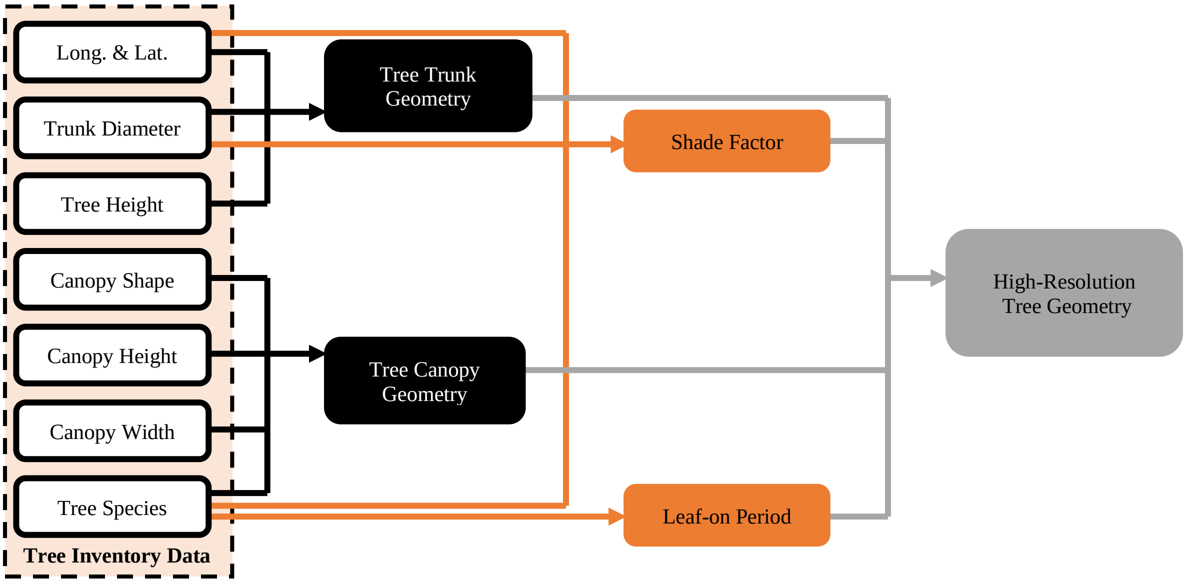

Figure 1: Overview of the framework for creating high-resolution tree geometries for use in urban energy modelling simulations

modelling framework is then applied to a case study, and the sensitivity of the model to different tree geometries is studied in detail. The findings of this study can provide insights to guide better urban designs that include trees to increase resiliency to anticipated climatic challenges.

Methods

Study area

The Capitol East neighbourhood in Des Moines, Iowa (located at 41.6°N latitude and 93.6°W longitude) was chosen for this pilot study because civic officials had expressed a commitment to development of a sustainable, equitable city. This neighbourhood is a resource-vulnerable neighbourhood and is considered representative of many mid-sized US city neighbourhoods that are affected by climate change. The Polk County Health Department (PCHD), with jurisdiction over Des Moines and adjacent suburban/rural communities, has indicated a need for improved knowledge about vulnerability of residents to extreme heat in these areas. The neighbourhood is comprised of predominantly older single- or multi-family residential properties, some occupied by more than one household (Iowa State University Planning Team, 2014).

This setting offers unique, often underestimated challenges related to climate change especially for increased frequency and intensity of heat waves. The area has harsh, cold winters with design temperature of -19.4°C and hot, humid summers with design conditions of 32.4°C dry-bulb / 23.8°C wet-bulb temperatures (ASHRAE, 2009). Extreme heat conditions can be as high as 38°C (ASHRAE, 2020). For a standard house in the urban core, active heating and cooling energy systems are required throughout the year to manage internal comfort (Passe et al., 2020). However, the existing residential building stock in resource-vulnerable neighbourhoods like Capitol East typically have little insulation, older windows and leaky building envelopes with very low R-values. Additionally, up to 50% of homes in the most vulnerable neighbourhoods, and 25% in the case of the Capitol East neighbourhood specifically, do not have functional central air conditioning (AC) systems and thus rely only on natural ventilation in summer possibly enhanced by the use of fans (Polk County Health Department [PCHD], 2015, 2019).

Modelling framework

Tree shade effects on building energy use are attributed to tree configuration, building characteristics, and/or climate. The major characteristics of trees that affect energy demand of buildings are tree height, position relative to the built structure, tree canopy shape and density, tree species, and duration of the leaf-on period.

For this case study, tree data for 1142 neighbourhood trees were collected in an inventory during the summer of 2017 using a Trimble Geo 7X Handheld GNSS receiver. The data collected included tree species, trunk diameter, tree height, canopy shape/height, canopy width in two dimensions, and latitude/longitude coordinates. The framework introduced in this study for developing high-resolution tree models is based on input from this comprehensive tree inventory (Figure 1).

As the first step in this framework, tree trunks were first modelled as simplified cylinders using the base location, trunk radius, and tree height as input to the model. Then, each tree canopy in the inventory was classified under one of the following eight representative tree canopy shapes to facilitate modelling: (1) spheres, (2) ellipsoids, (3) cylinders, (4) cones, (5) horizontal rectangular cuboids, (6) vertical rectangular cuboids, (7) umbrella shapes, and (8) paraboloids. One of these eight tree canopy shapes (Figure) were created for each of the catalogued trees using the two-dimensional canopy parameters as well as canopy height to define canopy shape.

Shade, defined as the percentage of sky covered by foliage and branches within the perimeter of individual tree crowns, is commonly used to model the effects of trees on building energy use (McPherson et al., 2018). To account for shading by trees, the leaf-on period of trees based on their species was determined using tables provided by McPherson (1984) and adjusted for the selected case study's unique climate based on our expert opinion (Appendix A). This was determined for deciduous trees in particular. Then tree species, climate, and diameter at breast height were used to calculate shade factors for both leaf-on and leaf-off seasons (based on McPherson et al., 2018).

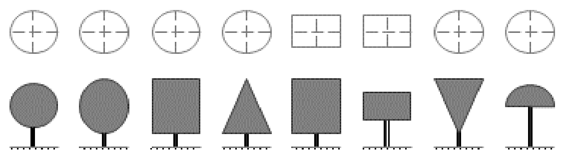

Figure 2: Eight representative tree canopy shapes used for modelling (Adapted from Hashemi, Marmur, Passe, & Thompson, 2018)

These detailed tree inventory data were then converted into a GIS shapefile and integrated with a building data GIS shapefile from the city assessor's database which contained building footprints, elevations and parcel-level data for 340 buildings within the same neighbourhood. The combined tree and building data were then integrated into the urban modelling interface (*umi*) using the GIS

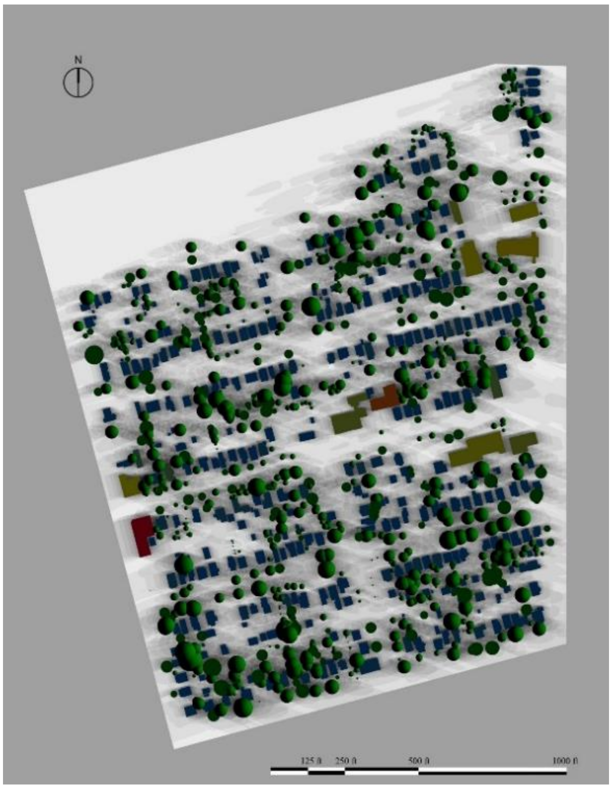

Figure 3: Aerial view of the Capitol East neighborhood as modeled in the umi environment

data-parsing plug-in Meerkat (**Error! Reference source not found.**). The *umi* is a Rhinoceros-based design tool for which the underlying simulation engines are US DOE's flagship EnergyPlus, Radiance/Daysim, as well as a series of Grasshopper and Python scripts (Reinhart et al., 2013). Each month was simulated with a different model to account for differences between leaf-on and leaf-off period and the associated shade factors for all trees modelled.

Results

The model provided input for *umi* to simulate energy performance of each building in the neighbourhood area for three different tree modelling scenarios under five different climate assumptions (Figure 4).

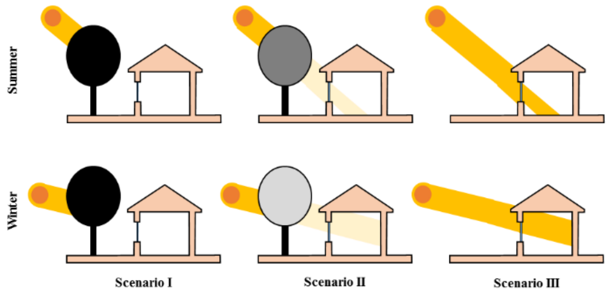

Figure 4: A schematic diagram of the three tree modelling scenarios studied

The tree modelling scenarios considered here include:

(1) A simplified model with tree geometries that did not account for leaf-on periods of trees and with the assumption that all trees had a constant shading factor equal to full shade for the entire year of study;

(2) A detailed model with high-resolution trees that accounted for leaf-on periods and the varying shading factors associated with them; and

(3) A model without any of the trees.

For the climate assumptions, the following five weather datasets (Figure 5) were used in the reported sensitivity analysis:

(1) A typical weather data file in the Typical Meteorological Year (TMY3) format for the Des Moines International Airport that consists of 12 typical meteorological months (January through December), with individual months selected from different years of the period of record (1991-2005) (Rabideau et al., 2012). This dataset was obtained from the official EnergyPlus website (EnergyPlus, n.d.).

(2) An actual weather file for the year 2017 in the selected location (41.53° N, 93.65° W) was obtained from the National Solar Radiation Database (NSRDB) and formatted according to the TMY3 manual (US Energy Information Administration (EIA), n.d.; Wilcox & Marion, 2008). Hereafter this dataset is referred to as "Actual 2017 Meteorological Year" or "ACM."

(3-5) Three future weather files were used for the simulation of energy consumption by residential building stock. These Future Typical Meteorological (FTMY) datasets were prepared by Patton (2013) who combined the projected changes in climate with existing TMY3 data to create FTMY datasets that represent high, medium and low emission scenarios of FTMY for the 2041–2070 period. In this manuscript, these three datasets are referred to as "FTMY-High", "FTMY-Medium", and "FTMY-Low," respectively.

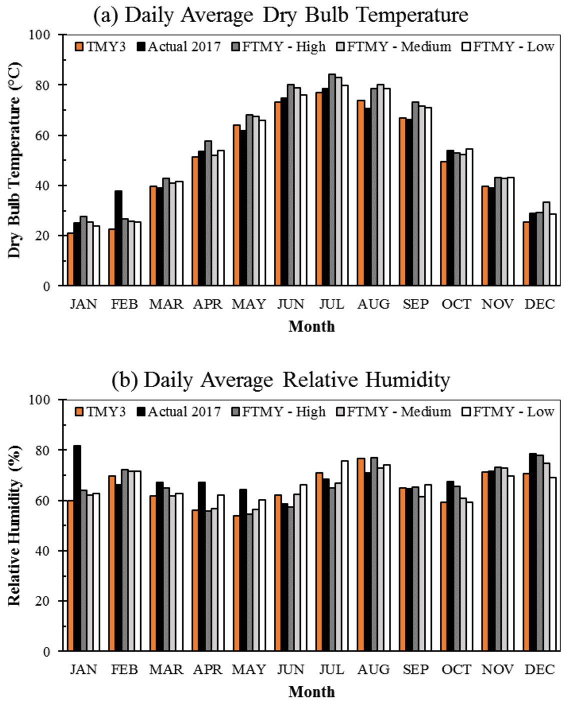

Figure 2: Comparison of different climatic assumptions considered for modelling

In the baseline scenario, all trees were included to provide simplified shading geometry in the model, all buildings were assigned an appropriate template according to the assessor's data, the ASHRAE 90.1 schedule was used for occupancy, and TMY3 data for Des Moines were used as the weather database. As the first step in the analysis, an annual profile of normalised monthly energy consumption was generated for this scenario (Figure). In this model, January had the maximum total monthly operational energy-use intensity (EUI) of all months with an average of 25.3 kWh/ m^2 (8 kBTU/sf) and May had the lowest of all months with an average of only 2.9 kWh/ m^2 (0.9 kBTU/sf). Accordingly, the annual EUI of a typical house in this neighbourhood is predicted to be 120.9 kWh/ m^2 (38.3 kBTU/sf). For a typical house with AC in this scenario, the comparable annual EUI is 134.9 kWh/ m^2 (42.8 kBTU/sf), while the EUI for a typical naturally-ventilated house is predicted to be only 114 kWh/ m^2 (36.1 kBTU/sf). It is important to note that the term 'typical' is used here for a building where the EUI is equal to the average of all residential buildings in the model.

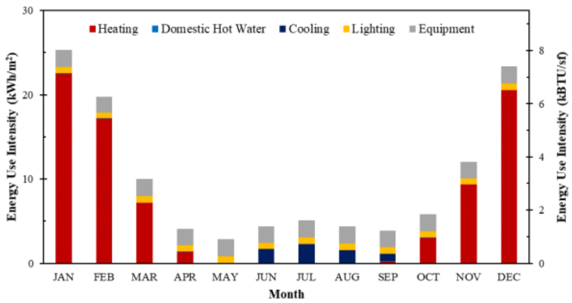

Figure 6: Energy-use intensity (EUI) in the baseline scenario for low-resource neighborhoods in Des Moines, Iowa.

Generally, comparing Scenario 1 under different climatic assumptions, heating loads are expected to decrease in the projection period, while cooling loads are expected to increase. These changes depend on the magnitude of climate change-induced ambient temperature increases over the next five decades. Looking at the simulation results from 2017, the impact of longer periods during which there is greater need for cooling can already be observed in energy consumption of the buildings modelled (Figure). Overall, including trees in the model (Scenarios 2 and 3) results in a general decrease in cooling loads and a general increase in heating loads. This is consistent with findings of previous studies (e.g. Davis et al., 2016; Tabares-Velasco & Srebric, 2012; Ziter et al., 2019) that had linked urban greening with a reduction in building cooling loads due to shade and evapotranspiration effects. In the case of the models with detailed trees (Scenario 2) the reduction is cooling load is lower than that for the simplified model under all five climatic assumptions considered in this study (Figure). The difference between the two models developed under Scenarios 1 and 2 is greatest for the model that uses the actual 2017 meteorological year data for its climatic condition (2.2%). Accordingly, in the Baseline Scenario, the detailed model (Scenario 2) indicates that the cooling loads are expected to be 19.8 kWh/m^2 (6.3 kBTU/sf), while the simplified model (Scenario 1) predicts an annual cooling consumption of only 19.5 kWh/m^2 (6.2 kBTU/sf). These results suggest that an accurate and reliable prediction of cooling loads with simulation tools is not possible without including high-resolution tree geometries. Such geometries need to account for both general geometric properties and shade factors throughout the period of study.

Heating loads are also affected by urban vegetation, as shading could diminish solar heat gains during the winter months. Comparing the model including detailed trees (Scenario 2) to the model with simplified trees (Scenario 1) there was less discrepancy in results (compared to that for cooling loads). This suggests that a simplified model might be sufficient for representing the effect of trees on heating loads in urban energy models.

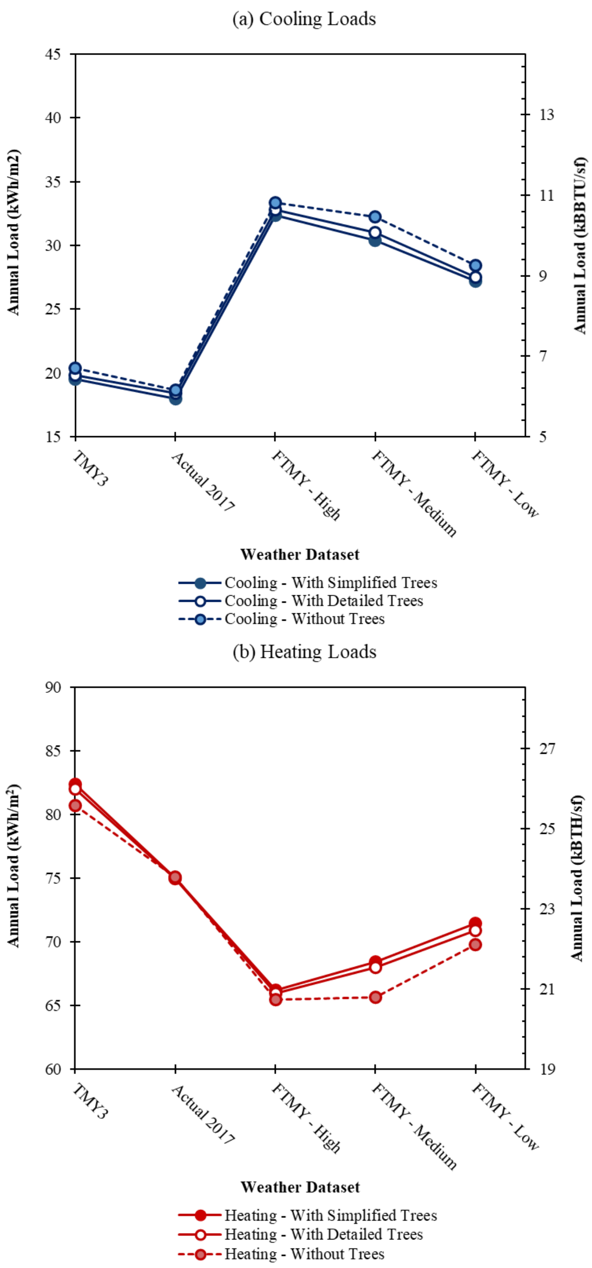

Figure 7: Comparison of current and future projected climate scenarios on annual energy consumption. Note: TMY = typical meteorological year; and FTMY = future typical meteorological year.

Average annual household utility costs were also determined for the baseline scenario for a typical building with a total living area of 110 m^2 (Figure). A typical household in this neighbourhood spends an average of US$710.7 on energy expenditures (US$442 electricity, US$268 natural gas) per year. Considering that the majority of households in this neighbourhood are categorised as low income (annual income levels of under US$30,000, less than 80% of Des Moines residents' median income), energy use accounts for at least 2.4%, and in many cases a much larger proportion, of residents' annual income before taxes (Drehobl & Ross, 2016; U.S. Census Bureau, n.d.). This is consistent with previous studies which indicated that an American family with less than US$30,000 annual income would spend approximately 7% of before-tax income (or 23% of after-tax income) on energy costs (Drehobl & Ross, 2016; Kontokosta et al., 2020; U.S. Government Publishing Office, 2015). Such residents are thus the most vulnerable to energy price increases, as well as potential costs associated with increases in energy consumption due to extreme climatic conditions (Kontokosta et al., 2020; U.S. Government Publishing Office, 2015).

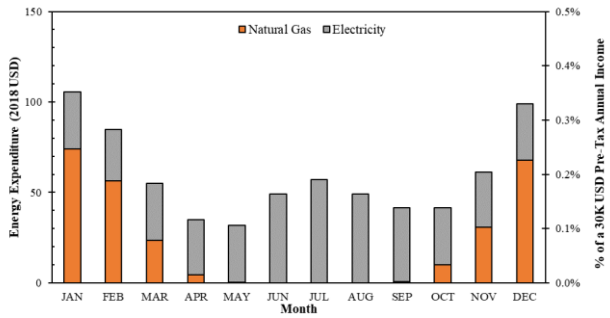

Figure 8: Energy burden costs in the baseline scenario for low-resource neighborhoods in Des Moines, Iowa.

Based on these data, the annual energy expenditure for a typical house with AC in this neighbourhood is US$860, which represents at least 2.9% of their annual pre-tax income. Households with naturally-ventilated homes, on the other hand, are expected to spend about US$637, or at least 2.1% of their annual pre-tax income, on energy expenditures in the baseline scenario. While the relative increase in energy consumption is higher comparing these two scenarios, the effect of detailed tree data for modelling annual energy expenditure were less noticeable. This is because heating loads are dominant in the studied climate, and an increase in cooling loads does not affect annual energy expenditure as much.

Conclusion

The challenges encountered for developing a high-resolution urban energy model with tree geometries that accurately represent the actual setting were significant. Our preliminary results indicate a relatively modest effect of trees on potential cooling savings, but the model and simulation does not yet include evapotranspiration, which is likely to increase the effect of trees on building energy dynamics, as suggested by other researchers (Hsieh et al., 2018; Wang & Akbari, 2016). Moreover, the main goal for developing high-resolution tree geometries for trees was related to increasing the fidelity between predicted and actual energy consumption of buildings in urban energy models. Accordingly, our results indicate a significant step toward meeting this goal compared to performance gaps previously outlined by other researchers (e.g., Fedoruk et al., 2015; Zou et al., 2018).

A potential drawback of this framework is the amount of effort required to build a comprehensive tree inventory dataset. Although many municipalities have some data for street trees, there are relatively few comprehensive urban forest inventories that include so much information on canopy dimensions, the degree to which the canopy is filled with leavers, and fewer still include such data for trees on private properties. It may be that the development of specific empirically-based models will allow calibration of models using other available data (such as LiDAR imagery with detail for tree canopy shape and size) in the future. Further cross-variable simulations are planned to explore and refine these preliminary outcomes.

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Appendix A

Table 1: Estimates for Leaf-on Duration for Tree Species Present in the Capitol East Neighborhood, Des Moines, IA

SPECIES	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
American Basswood					■	■	■	■	■	■		
American Elm					■	■	■	■	■	■		
American Sycamore					■	■	■	■	■	■		
Amur Cork Tree					■	■	■	■	■	■		
Bitternut Hickory					■	■	■	■	■	■		
Black Locust					■	■	■	■	■	■		
Black Maple					■	■	■	■	■	■		
Black Oak					■	■	■	■	■	■		
Black Walnut						■	■	■	■			
Black Willow				■	■	■	■	■	■	■		
Blue Spruce	■	■	■	■	■	■	■	■	■	■	■	■
Boxelder					■	■	■	■	■	■		
Bur Oak					■	■	■	■	■	■		
Callery Pear					■	■	■	■	■	■		
Cherry spp					■	■	■	■	■	■		
Common Hackberry					■	■	■	■	■	■		
Cottonwood				■	■	■	■	■	■			
Crabapple spp					■	■	■	■	■	■		
Eastern Red Cedar	■	■	■	■	■	■	■	■	■	■	■	■
Eastern Redbud						■	■	■	■			
Eastern White Pine	■	■	■	■	■	■	■	■	■	■	■	■
Elm Hybrid					■	■	■	■	■	■		
Green Ash					■	■	■	■	■	■		
Hackberry					■	■	■	■	■	■		
Honey Locust						■	■	■	■	■		
Japanese Lilac					■	■	■	■	■	■		
KY Ceetree						■	■	■	■	■		
Littleleaf Linden					■	■	■	■	■	■		
Maple spp					■	■	■	■	■	■		
Mulberry spp					■	■	■	■	■	■		
Northern Catalpa					■	■	■	■	■	■		
Northern Hackberry					■	■	■	■	■	■		
Northern Red Oak					■	■	■	■	■	■		
Northern White-cedar	■	■	■	■	■	■	■	■	■	■	■	■
Norway Maple					■	■	■	■	■	■		
Norway Spruce	■	■	■	■	■	■	■	■	■	■	■	■
Oak spp					■	■	■	■	■	■		
Ohio Buckeye						■	■	■	■	■		
Paper Birch					■	■	■	■	■	■		
Pear spp					■	■	■	■	■	■		
Plum spp					■	■	■	■	■	■		
Red Maple					■	■	■	■	■	■		
Saucer Magnolia				■	■	■	■	■	■			
Siberian Elm					■	■	■	■	■	■		
Silver Maple				■	■	■	■	■	■	■		
Slippery Elm					■	■	■	■	■	■		
Sugar Maple					■	■	■	■	■	■		
Swamp White Oak					■	■	■	■	■	■		
Sycamore					■	■	■	■	■	■		
Tree of Heaven					■	■	■	■	■			
Tulip Tree (Y. Pop)					■	■	■	■	■	■		
White Ash					■	■	■	■	■	■		
White Mulberry					■	■	■	■	■	■		
White Oak					■	■	■	■	■	■		