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SENSITIVITY AND UNCERTAINTY ANALYSES OF AN URBAN FOREST

STRUCTURE AND FUNCTION MODEL

by

Jian Lin

A thesis submitted in partial fulfillment of the requirements for the Doctor of Philosophy Degree State University of New York College of Environmental Science and Forestry Syracuse, New York April 2020

Department of Environmental Science

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Abstract

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Urban forest models can quantify forest structure and benefits, and are frequently employed in decision-making. This dissertation first reviewed case studies of urban forest modeling practices over the past two-decades, compared the similarities and differences among different models, and summarized the current trends and gaps in the field of urban forest modeling. One gap is the lack of uncertainty assessments for model output. To address this gap, this dissertation performed sensitivity and uncertainty analyses for a popular urban forest model, i-Tree Eco. Based on a case study in New York City, the sensitivity analyses found that the most important input variables are genus for isoprene and monoterpene emissions, DBH for carbon estimators, and leaf area index, temperature, and photosynthetically active radiation for dry deposition estimators. The uncertainty analyses addressed uncertainties associated with the entire i-Tree Eco modeling process, from input data collection, to the characterization of urban tree structure, to the subsequent estimators of the ecosystem services of urban trees. Uncertainty magnitudes were quantified by employing bootstrap and Monte Carlo simulations, and the three sources of uncertainty, input, model, and sampling, were aggregated to derive an estimator of total uncertainty. Through case studies in 16 cities across the United States, the average magnitude of total uncertainty across the 16 cities was 12.4% for leaf area, 12.4% for leaf biomass, 13.5% for carbon storage, 11.1% for carbon sequestration, 40.7% for isoprene emissions, and 25.0% for monoterpene emissions. For leaf and carbon estimators, the total uncertainty is primarily driven by sampling uncertainty, while the magnitudes of sampling, input and model uncertainty are similar across the 16 study cities. In contrast, input, sampling, and model uncertainties all contribute similarly to the total uncertainty for isoprene and monoterpene emission estimators, and there are larger variations in these three sources of uncertainty across the 16 study cities. To reduce overall uncertainty, future studies should develop more accurate urban-, local-, and species-specific allometric relationships, improve the spatial representation of meteorological variables, develop more extensive and accurate local-scale measurements to calibrate and verify models, and improve sampling strategies.

Keywords: urban forestry, i-Tree Eco, ecosystem services, comparative studies, sampling, sensitivity, and uncertainty analyses.

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Chapter 1 Introduction

1 Background and motivation

Urbanization can result in many adverse effects, including increased runoff and nutrient export, increased human exposure to air pollutants, increased temperatures, and increased material consumption and energy use (Arnold & Gibbons, 1996; Shuster et al., 2005; Grimmond, 2007; Duh et al., 2008; Gurjar et al., 2008; Poumanyvong & Kaneko, 2010). Engineered infrastructure (e.g., sewer systems, levees, well-insulated buildings) is often built to alleviate these negative effects and bring benefits to all segments of urban society. However, built infrastructure tends to be expensive in terms of construction and maintenance costs, and there is a lack of flexibility and adaptability when these systems are constructed (Keeler et al., 2019). As a nature-based solution, urban trees are known to provide multiple ecosystem services to benefit human well-being, and these solutions are typically more affordable, flexible and able to provide more diverse benefits than built infrastructure. Many cities have launched large urban tree planting initiatives, and incorporated trees into urban master plans (Morani et al., 2011; McPherson et al., 2011; Pincetl et al., 2013). However, simply increasing tree canopy does not necessarily guarantee alleviating the adverse effects of urbanization or the provision of expected ecosystem services.

To better manage urban forests and increase tree benefits, models have been developed to quantify the structure, function and ecosystem benefits of trees. Both mechanistic and statistical models have been developed. The models use forest structure, locational and environmental parameters as input variables to estimate ecosystem services. Models of the structure, function and services of urban trees can help develop more efficient and effective planting schemes, identify areas where existing forests should be maintained, improve the overall management of urban forests, and better quantify the benefits of these forest resources. These models have been applied in different locations and at varying scales around the world to advocate for the benefits of urban trees. Among these urban forest models, the i-Tree tools (<u>www.itreetools.org</u>), developed by the U.S. Department of Agriculture (USDA) Forest Service, have been used by hundreds of researchers, urban planners, and foresters (Lin et al., 2019). i-Tree Eco consists of five modules which can quantify forest structure, biogenic emissions, carbon storage and sequestration, air pollution removal, and building energy effects of urban forests. This model typically uses field plots, air pollution, and meteorological data as input variables (Nowak & Crane, 2000; Nowak et al., 2008a). The model provides information regarding the structure, function, and benefits of urban forests on ecosystems and their inhabitants. This dissertation focuses generally on urban forest modeling tools, and the i-Tree tools in particular.

i-Tree tools have been extremely beneficial to the planning and management of urban trees, but have their limitations. These tools make assumptions that simplify the function of urban forests and the representation of urban landscapes. While such assumptions are often necessary to model these complex systems, they can increase the uncertainty of model output (Yang et al., 2005), and which may hinder the efficient and effective management of urban forests. The characterization of the uncertainty of output from i-Tree tools should be more fully explored. In the field of environmental modeling, uncertainty analysis is regarded as a necessary component of modeling practices because uncertainty information can facilitate model transparency and clarify the nature of evidence (Bryant et al., 2018). When these models are applied to support decision making, such as in policy analyses, risk assessments, and environmental impact assessments, decision makers may adjust their decision making process when they are made aware of the uncertainty of the information they are incorporating to make these decisions (Walker et al., 2003).

This research first conducts a literature review of urban forest modeling during the past two-decades, and then using i-Tree Eco performs a sensitivity analysis and develops methods to characterize the uncertainty of i-Tree Eco output. The sensitivity analysis maps the relationships between input and output variables to determine which input variables have the greatest impact on output variability, and this information is then used when assessing the uncertainty of model output. This work explores not only the uncertainty of output due to the uncertainty of input variables, but also the uncertainties associated with other aspects of the model and modeling processes (e.g., sampling uncertainty and model uncertainty).

2 Sensitivity and uncertainty analyses

A model is an abstract representation of a system or process (Turner & Gardner, 2015), involving a certain degree of aggregation and exclusion (Christopher Frey & Patil, 2002). For any model, a critically important component is to assess the sensitivity of model output to model inputs, and to develop estimators of the uncertainty of model outputs (Halpern, 2005; Marino et al., 2008). Sensitivity analysis (SA) focuses on the change in model output values that result from changes in model input values (Saltelli et al., 2008).

Saltelli et al. (2004 & 2008) provide a comprehensive review of SA techniques, classification and comparisons, application settings, and case studies. Overall, SA techniques can be roughly divided into global and local methods, and are generally applied using four techniques: factor fixing, factor prioritization, factor mapping, and variance cutting. Local methods typically involve variations of input parameters at one specific location (e.g., at one solution), and do not attempt to fully explore the sample space of the input variables. In contrast, global method allows simultaneous variation of all input variables across the entire input variable space (Saltelli et al., 2008). By fixing non-influential factors, factor fixing is able to identify the subset of input factors which explain most of the variance in the outputs. With this information, one can reduce the dimensionality of the problem. Factor prioritization is then performed to identify the most influential factors from this subset of input factors. Factor mapping explores which factor or combination of factors is mostly responsible for producing realizations of specific outputs. The objective of variance cutting is to reduce the output variance to a specific threshold.

Uncertainty analysis (UA) attempts to describe the entire set of possible outcomes, together with their associated probabilities of occurrence (Loucks et al., 2005). Various methods for UA have been developed. These methods range from classical frequentist analyses (Omlin & Reichert, 1999) to complex Bayesian networks (Bishop, 2006), and can be either subjective (e.g., expert assessment; Uusitalo et al., 2015) or objective (e.g., probability theory; Pearl, 2003). Of all these methods, gradient-based first-order error analyses, resampling methods, and Bayesian techniques are most frequently employed (Clark, 2005). Gradient-based first-order error analyses techniques, which are sometimes referred to as delta methods, are based on a first-order Taylor series approximation to the variance of the output parameters (Loucks et al., 2005). Resampling techniques require multiple model simulations, all of which are generally assumed to be equally likely, and then examining the distribution of the output parameter. For resampling techniques, input parameters are often randomly chosen with a preconceived notion of their probability distribution (Helton et al., 2006). Bayesian techniques require the user to have a prior distribution of the uncertainty of the input, and then for each parameter set, the model is simulated based on the prior distribution. In Bayesian techniques, a posterior distribution of the output is then developed, where each prior simulated output is weighted by the likelihood it occurred (Freer et al., 1996).

Currently only limited efforts have been devoted to assessing the sensitivity of i-Tree Eco outputs to their inputs, and to characterize the uncertainty of model output. Hirabayashi et al. (2011) performed a SA of air pollution removal (i-Tree Eco-D) using Monte Carlo simulations with a Latin hypercube sampling and a Morris one-at-a-time sensitivity test. Nowak et al. (2008b) examined the effects of plot size and number of plots on the variability of urban forest assessments. Based on the criterion of standard error and relative standard error of output, as well as tradeoffs between cost, precision and the length of the typical sampling season, Nowak et al. (2008b) recommended a minimum of 200 plots and plot size of one-tenth of an acre. The application of both SA and UA to i-Tree Eco, one of the i-Tree tools, will be the primary focus of this thesis.

3 Research objectives

This research assesses the sensitivity of i-Tree Eco output to its inputs, and develops and implements a methodology to characterize the uncertainty of i-Tree Eco output. The intellectual merit of this work includes: (1) identifying new emerging topics, and discovering broad trends and insight in the field of urban forest modeling; (2) developing methods and frameworks to explicitly quantify and present model uncertainties to increase the credibility of the modeling process; and (3) providing urban managers more complete information about the structure, function, and value of their forest resources to support effective decisionmaking. In addition, the developed methods and framework can be applied to other urban forest models to advance urban forest modeling practices in general.

This thesis revolves around four research objectives. Below each research objective is presented, along with a related research questions and a testable null hypothesis.

Research Objective 1

The first research objective is to review literature on the modeling of urban forest structure and function during the last two-decades, compare the similarities and differences between modeling techniques and applications, and assess model case studies among different locations, units and scales.

Research Questions

What are the most commonly used models in the field of urban forestry? Can urban forest modeling case studies throughout the world be generalized? What topics or ecosystem services do most urban forest models quantify?

Null Hypothesis

All the urban forest models are equally applied and are used to estimate similar ecosystem services.

Research Objective 2

The second research objective is to assess the sensitivity of output from i-Tree Eco, one of the most commonly employed urban forest models, to changes in input parameters. Specially, we explore how individual inputs or groups of inputs contribute to the variability of i-Tree Eco outputs, and differentiate the relative importance of different input variables.

Research Questions

Which input variables contribute most to the variance of output parameters of interest? What effects (e.g., negligible, linear and additive, non-linear or interaction, threshold effects) do input variables have towards the output of interest?

Null Hypothesis

All input variables contribute equally to the uncertainty of model outputs.

Research Objective 3

The third research objective is to assess the uncertainties associated with input data, field sampling methods and model error throughout on the quantification of urban forest structure and function, and to aggregate these three sources of uncertainty to derive an estimator of total uncertainty.

Research Questions

What are the magnitudes of model output uncertainty, and which uncertainty sources contribute most to the total uncertainty of i-Tree output estimators? For different model

outputs, are the conclusions the same?

Null Hypothesis

All three sources of uncertainty contribute equally to the total uncertainty of i-Tree output estimators.

Research Objective 4

The fourth research objective is to apply the uncertainty framework to 16 cities having different urban characteristics and located in different climatic zones across the US, and to assess whether similar relationships between model, sampling and input uncertainty are consistent across these cities.

Research Questions

What are the range for the magnitudes of the total uncertainty, and how do they change across cities? How do the characteristics of the three sources of uncertainty (e.g., their magnitudes and rankings) vary across cities?

Null Hypothesis

The characteristics of the three sources of uncertainty are consistent across 16 cities.

4 Thesis Outline

This thesis follows a manuscript format, where subsequent chapters are written as stand-alone manuscripts. Chapter 1 contains a brief introduction to the thesis and presents the thesis research objectives and questions. Chapter 2 provides a thorough review of urban forest modeling, and has been published in Urban Forestry & Urban Greening (Lin et al., 2019). Chapter 3 presents a sensitivity analysis of three components of i-Tree Eco: biogenic volatile organic compounds (BVOCs) (isoprene and monoterpenes) emissions, carbon storage and sequestration, and dry deposition of nitrogen dioxide, sulfur dioxide, and ozone. This chapter has been accepted for publication in Arboriculture and Urban Forestry (Lin et al., 2020). Chapter 4 presents an analysis of model, sampling, input uncertainty on output from i-Tree Eco's urban forest characterization, BVOCs, carbon storage and sequestration, and air pollution removal. This chapter uses New York City as a case study. Chapter 5 expands the uncertainty analyses of Chapter 4 to other US cities to see if the results found in New York City are consistent with those found in other cities. Finally, Chapter 6 provides a thesis summary and reflects back on the research objectives and questions presented in Chapter 1.

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Chapter 2 A review of urban forest modeling: implications for management and future research Abstract

Urban forest modeling is becoming increasingly complex, global, and transdisciplinary. Increased modeling of urban forest structure and function presents an urgent need for comparative studies to assess the similarities and differences between modeling techniques and applications. This paper provides a systematic review of 242 journal papers over the past two-decades, and identifies 476 case studies. We assess model case studies among different locations, units and scales, compare the ability and functional capacity of the models and different tools, compare papers published in different disciplines, and identify new emerging topics in the field of urban forest modeling. Conclusions from this analysis include: (1) the spatial distribution of case studies is primarily clustered around the US, Europe, and China, with the most popular units to model being streets and parks; (2) the most commonly used model types are the i-Tree toolset, ENVI-met, computational fluid dynamic models, and the Hedonic price model; (3) uncertainty assessment of urban forest models is limited; (4) spatially explicit models are critically important for estimating of ecosystem services as well as for environment management; (5) most case studies focus on biophysical benefits with few studies estimating economic and social benefits; and (6) linkages between urban forests and their social-psychological and health effects are less common due to subjectivity and uncertainty in expressing and quantifying human cultures, attitudes and behaviors. Based on a comparison of different models and a syntheses of case

studies, we make suggestions for future research connecting urban forestry and urban ecosystems, model development, and ecosystem services. Such knowledge is critical for policy- and decision-makers, and can help improve urban forest planning, design and management.

Key words: urban forestry, comparative studies, multi-scale, ecosystem services, socialecological system

1 Introduction

A term first used in 1965 (Gerhold, 2007), "urban forestry" has become increasingly transdisciplinary in terms of theories (from both physical and social sciences), methods (e.g., Geographic Information Systems, remote sensing, monitoring, and modeling), and participants (e.g., researchers, government officials, citizens, and volunteers). Many definitions of urban forestry have been given, and the definition and terminology harmonization is challenging (Konijnendijk et al., 2006). However, several widely-used definitions, such as those provided by Jorgensen (1986), Society of American Foresters (Helms, 1988), Konijnendijk et al. (2006), and Nowak et al. (2010), all emphasize urban forestry's comprehensive nature, which involves scientific, management, and planning elements. In this article, we look at urban forestry in a general way. Literally, "urban forestry" consists of two parts "urban" and "forestry". An "urban" system is a spatially heterogeneous, complex adaptive social-ecological system (Wu, 2014), which aims for not only environmental functionality, but also social equity and economic viability (BES LTER, 2018). Compared to traditional forestry, "forestry" in the urban context focuses on additional services to advance urban sustainability. As a demographic trend and land transformation process (Pickett et al, 2001), urbanization creates many environmental issues (e.g., Duh et al., 2008; Grimmond, 2007; Poumanyvong & Kaneko, 2010); these issues make the design of sustainable urban forestry (Fazio, 2003) particularly challenging.

The morphological characteristics (e.g., leaf area, stem diameter), functions (e.g., photosynthesis, evapotranspiration), and structure (e.g., species composition, spatial pattern) of trees provide a wide range of ecosystem services (ES) and benefits that can alleviate the adverse effects of urbanization (Nowak & Dwyer, 2007). Many cities have established substantial programs to increase their tree canopy coverage (Morani et al., 2011; McPherson et al., 2011). However, simply increasing tree canopy itself does not guarantee the provision of expected ES. For example, Vos et al. (2013) have shown that it may not be a viable solution to alleviate a local air pollution hotspot by using urban vegetation, and Wu (2014) indicated that urban greening may lead to unintended environmental injustice issues such as 'ecological gentrification'.

To better manage urban forests and maximize tree benefits, several models have been developed and implemented. These models have been applied in case studies on individual locations and provide us with knowledge about urban tree services and benefits. Although there is evidence of a global trend of increased urban landscapes and ecological structural homogenization (Wu, 2014; Turner & Gardner, 2015), each city is still unique, and the ES provided by urban forests change with forest characteristics and environmental conditions. Findings for one city can be quite different compared to those of another city, and the current global distribution of urban forest case studies tends to cluster within specific regions. There are limited comparative studies of urban forest ecosystem models. Of interest here is summarizing and generalizing findings across a wide range of case studies to identify trends and gaps in urban forest modeling. Such knowledge is critical for urban forests research and management. By reviewing urban forest modeling over the past two-decades, the goal of this paper is to facilitate a better understanding of model characteristics and uses, and integrate different model practices and case studies to advance our knowledge of urban forestry and inform future research and management.

2 Key terms and concepts

The urban forest contains all trees, shrubs, lawns, and pervious soils in urban areas (Escobedo et al., 2011; Roy et al., 2012). Our review here focuses on trees and shrubs in different urban areas (e.g., street, park, and residential area), as well as their local site and environmental conditions. Green roofs, green infrastructure, and green space (Rowe, 2011) are all different, but related concepts, and they include various vegetative components. They are also included in this review if their study focuses on the structure and benefits of urban trees and shrubs.

There are many definitions of interdisciplinarity and transdisciplinary. We differentiate them based on participants and final goals. Here interdisciplinary studies refer to the involvement of several academic disciplines under a common research goal to create new knowledge. Alternatively, transdisciplinary studies involve not only academic researchers but also non-academic participants (e.g., the public and policy-makers) for the purpose of solving real-world problems (Tress et al., 2005).

A model is a simplified description of a real system with inputs, key components of the system and their relationships, and outputs constrained within specific spatial boundary (Jones, 2013). A model can be developed based on either mechanistic approaches or empirical relationships, or a hybrid of both. The models considered in this study must be able to describe urban forest structure (e.g., size, species composition, spatial configuration) (Nowak et al., 2008), and function (e.g., various ES) in highly complex systems. They use forest structure, as well as other site and environmental parameters, as input variables to estimate ES as model outputs. We focus on numerical and statistical models since they are used extensively to quantify forest derived ES. To link more directly to management implications and limit the scope of the analyses reviewed, models focusing entirely on forest structure and dynamics (e.g., growth, mortality) are excluded. As input datasets are a necessary part of any model, characteristics of input datasets are also explored from the perspective of data acquisition approaches: bottom-up approaches mainly consist of field surveys and sampling while top-down approaches rely mainly on remotely sensed data.

Since the release of the UN's Millennium Ecosystem Assessment (MEA) (MEA, 2005) and The Economics of Ecosystems and Biodiversity (TEEB) report (TEEB Foundations, 2010), ES have gained broader attention in the literature (Escobedo et al., 2011; Gómez-Baggethun & Barton, 2013). The differentiation between ecosystem function and service has been well-established, with the former emphasizing ecosystem processes (means) while the latter focusing on specific outputs or products (ends) (Escobedo et al., 2011; Roy et al., 2012). In this study, we focus on ES that can be derived from forest structure and function. Following the classification scheme of urban forest ES provided by Nowak and

Dwyer (2007), we expressed them in three value-domains: biophysical, social and economic.

3 Study Methods

Model practices and case studies of urban forests in academic English-language journals were reviewed during the past two-decades (1996-2017). Here we use the term "case study" to refer to one simulation at one location employing either numerical or statistical models. To be comprehensive, objective and accurate, a systematic quantitative literature review was first performed (Petticrew, 2001). Two worldwide scholarly electronic databases, Google Scholar and Scopus, were employed in this study. Keywords or combination of keywords used for the search included: 'urban tree/forest/vegetation/green roof', 'ecosystem services/benefits', and 'model/tool'. For each identified paper, articles of related or similar topics were identified via: (1) references within the paper, (2) 'related articles/documents' function in Google Scholar and Scopus, and (3) articles that cited the paper. Although this step was mainly implemented based on Google Scholar and Scopus, other scholarly electronic databases were involved because search results often led to different links (e.g., Science Direct, Research Gate, Springer Link, and individual journal websites). While our literature search was not exhaustive, we believe we have captured a majority of journal articles on this topic.

After identifying journal articles, the following items were extracted from each paper: (i) year of publication, (ii) case study location, (iii) model(s), (iv) input data, (v) title, (vi) author(s), (vii) journal, (viii) discipline, and (ix) topics and ES. A spatio-temporal analysis was then performed using (i) year of publication and (ii) case study location. For this analysis, each paper was grouped by continent and major climatic zone to determine the distribution and pattern of urban forest studies. Following the work of Roy et al. (2012), the continents included were North America, South America, Europe, Asia, Australia, and Africa; and the climatic zones were tropical, dry, subtropical, temperate, and continental. Other space-based analyses included identifying the scale of each study performed (e.g., city, region, nation), and the unit for each case study (e.g., park, street, neighborhood, community, district, watershed). Next, comparisons among models and among disciplines were conducted using (iii) model(s), (iv) input data, and (viii) discipline. For each model, the total numbers of papers and citations (how many times that particular paper has been cited) were calculated. In addition, as input datasets are part of any model, each paper was also characterized based on the acquisition sources of the input datasets. Each journal was grouped into a specific field, and a comparison among fields was conducted. We grouped journals into fields based on journal description and the topics of the identified papers from journals. Finally, comparisons between ES were investigated using (ix) ES topics.

4 Results

We identified 242 relevant papers and 476 case studies over the time period 1996-2017 (see Supplementary Material for a list of papers), with more than half of the papers published during the past 6 years (2012-2017). There are more case studies than publications because some papers include several case studies. Citation numbers, primarily conducted between the period of November 2017 to January 2018 based on Google scholar, show a relatively exponential-type growth pattern over time (Figure 2.1), reflecting the increasing number of publications, activities and influences of this field.



Figure 2.1 The number of publications and citations yearly from 1996 to 2017 (citation counting was conducted between the period of November 2017 to January 2018 based on Google scholar).

4.1 Place-based, comparative studies

Among the papers examined, a total of 476 model practices and case studies were identified globally (Figure 2.2): North America (66.6%), Europe (14.5%), Asia (11.1%), Australia (3.6%), South America (2.7%), and Africa (1.5%). Another way to express the global distribution of case studies is to classify case studies by climatic zones: tropical (2.8%), dry (7.4%), subtropical (4.9%), temperate (44.9%), and continental (40.0%) (Figure 2.3). The global distribution of case studies was uneven, with a majority of studies focused on urbanizing regions of temperate and continental climatic zones in the US, Europe and China; there were comparatively few studies of urban forest modeling in South America, Australia, and Africa.



Figure 2.2 Global distribution of urban forest case studies With regards to scale, there were 8 papers conducted at a national level, 9 at a regional level, 61 at a city level, 8 at a watershed level, 49 at a local scale level, and 107 at a microscale level (Figure 2.3). Both local and microscale levels are scales smaller than a city level. Local scale includes neighborhoods, communities, districts, planning zones, socioeconomic sub-regions, and other similar units, while microscale includes green roofs, buildings, parks, streets and other similar settings. Most of the studies were conducted at city, local and microscale levels, while some studies have been made at watershed, regional and national levels.



Figure 2.3 Summary statistics (percentage) of 242 original papers in different sub-categories: continents, climatic zones, scale, and input data sources. The percentages for each continent and climatic zone are calculated based on number of case studies, while percentages for each scale and input data source are based on number of papers.

Inside the city, a variety of geographies have been employed in case studies,

depending on the study purpose and discipline. Each discipline may identify a geographical unit or the most salient features associated with the unit differently (Grimm et al., 2000), such as a watershed (hydrology), land use or land cover types (geography), neighborhood or community (social science), and street canyon or building block (energy science). For the local scale, the most studied units were districts/communities with a total of 28 case studies; within the microscale, streets, parks, and green roofs received the most attention, with the numbers of case studies being 58, 22 and 25, respectively.

4.2 Field-based analyses

Sixty-nine journals were identified over a wide range of fields (Table 2.1), revealing the transdisciplinary nature of this topic. Three fields interact closely and contribute the largest number of papers on this topic (in parenthesis are the number of papers and percentages, respectively): environment (53, 21.9%), forestry (48, 19.8%), and energy (37, 15.3%). The reason that the environmental field occupied the largest number of papers is due to the contribution from two journals: Environmental Pollution (16, 6.6%) and Atmospheric Environment (12, 5.0%). Thirty-four papers were published in Urban Forestry & Urban Greening, which makes forestry the next most common field. This field was followed by energy, with the largest contributions from Building and Environment (16, 6.6%) and Energy and Buildings (15, 6.2%). Other fields that also contribute to this topic were landscape (28, 11.6%), ecology (14, 5.8%), economics (11, 4.5%), climatology (12, 5.0%), and geography (3, 1.2%) (Table 2.1). This topic attracts attention from not only scientists, but also urban planners and policy makers, leading to papers in urban planning and management journals (e.g., Journal of Environmental Management, Environmental Management).

| Fields | Journal Title | No. of Papers | Field Total |
|--------------------------------|---|---------------|-------------|
| Environment | Environmental Pollution | 16 | 53 |
| | Atmospheric Environment | 12 | |
| | Journal of Environmental Management | 7 | |
| | Science of the Total Environment | 5 | |
| | Environmental Modelling & Software | 2 | |
| | Environmental Science & Technology | 1 | |
| | International Journal of Environment and Pollution | 1 | |
| | Environmental Management | 1 | |
| | Environmental Science and Pollution Research | 1 | |
| | Environment and Behavior | 1 | |
| | Journal of Environmental Planning and Management | 1 | |
| | International Journal of Environmental Science and Development | 1 | |
| | Atmospheric Pollution Research | 1 | |
| | Procedia Environmental Sciences | 1 | |
| | Ambio | 1 | |
| | AIMS Environmental Science | 1 | |
| Forestry and Arboriculture | Urban Forestry & Urban Greening | 34 | 48 |
| | Journal of Arboriculture | 5 | |
| | Arboriculture and Urban Forestry | 3 | |
| | Journal of Forestry | 2 | |
| | iForest-Biogeosciences and Forestry | 1 | |
| | Frontiers of Forestry in China | 1 | |
| | Journal of Sustainable Forestry | 1 | |
| | Forests | 1 | |
| Energy | Building and Environment | 16 | 37 |
| | Energy and Buildings | 15 | |
| | Solar Energy | 3 | |
| | Energy Procedia | 1 | |
| | Applied Energy | 1 | |
| | Building Simulation | 1 | |
| Landscape | Landscape and Urban Planning | 28 | 28 |
| Ecology | Urban Ecosystems | 7 | 14 |
| | Ecological Modelling | 2 | |
| | International Journal of Biodiversity Science, Ecosystem Services & | 2 | |
| | Management | 2 | |
| | Ecological Applications | 1 | |
| | Ecosystem Services | 1 | |
| | Ecosystems | 1 | |
| Meteorology and Climatology | Theoretical and Applied Climatology | 4 | 12 |
| | Meteorologische Zeitschrift | 2 | |
| | Atmosphere | 2 | |

Table 2.1 Distribution of urban forest modeling papers among different fields

| | International journal of climatology | 1 | |
|-----------|---|---|----|
| | Boundary-layer meteorology | 1 | |
| | Advances in Meteorology | 1 | |
| | Journal of Applied Meteorology and Climatology | 1 | |
| Economics | Ecological Economics | 4 | 11 |
| | Journal of Forest Economics | 1 | |
| | Journal of Environmental Economics and Management | 1 | |
| | Land Economics | 1 | |
| | The Appraisal Journal | 1 | |
| | Australian Journal of Agricultural and Resource Economics | 1 | |
| | The Journal of Real Estate Finance and Economics | 1 | |
| | Forest Policy and Economics | 1 | |
| Geography | Urban Geography | 1 | 3 |
| | Moravian Geographical Reports | 1 | |
| | Chinese Geographical Science | 1 | |
| Other | Sustainable Cities and Society | 6 | 36 |
| | Sustainability | 5 | |
| | JAWRA Journal of the American Water Resources Association | 3 | |
| | Cities | 2 | |
| | Journal of Wind Engineering and Industrial Aerodynamics | 2 | |
| | Land Use Policy | 2 | |
| | Advances in Urban Rehabilitation and Sustainability | 1 | |
| | Journal of Sound and Vibration | 1 | |
| | Journal of Contemporary Water Research & Education | 1 | |
| | Agriculture and Agricultural Science Procedia | 1 | |
| | Remote Sensing of Environment | 1 | |
| | Spatial Demography | 1 | |
| | International Journal of Sustainable Development and Planning | 1 | |
| | Transportation Research Part D: Transport and Environment | 1 | |
| | Book Chapter | 4 | |
| | Official publication from USDA, National Recreation and Park | 4 | |
| | Association and ENVI-met | 4 | |

4.3 Urban forest models

Urban forest case studies have been analyzed and simulated using a wide range of models (Table 2.2). In terms of numerical models, they can be roughly divided into two categories: general-purpose models (ENVI-met, computational fluid dynamics (CFD), Green Cluster Thermal Time Constant (Green CTTC), DOE-2 building-energy simulation program
(DOE-2), and Solar and Longwave Environmental Irradiance Geometry (SOLWEIG)), and urban forest-specific models (i-Tree, CITYgreen). The detailed description of these models can be found in the Supplementary Material to this paper.

i-Tree is the most dominant model used in urban forest modeling (Table 2.2). i-Tree and ENVI-met are toolsets, including various sub-tools or modules (Table 2.3). Of the various i-Tree toolsets, Eco (formerly UFORE) was implemented most frequently, although case studies can also be found using Streets (formerly STRATUM), Hydro, Canopy, and Species. The next widely used models are ENVI-met and CFDs. For ENVI-met application, the typical approach is based on a scenario comparison of designed or real landscapes (e.g., with/without trees, tree configuration, tree-building spatial layouts) (e.g., Skelhorn et al., 2014; Salata et al., 2015; Morakinyo & Lam, 2016). CFD is a collection of models that are based on the fundamental laws of fluid mechanics and thermodynamics. Typical applications of CFD include the thermal effects of trees on surrounding buildings and pedestrian environments (e.g., Dimoudi & Nikolopoulou, 2003), and removal and trapping of air pollutants from road traffic due to trees' deposition effects, filtering capacity, and aerodynamic effects (e.g., barrier, ventilation performance) (e.g., Jeanjean et al., 2015; Amorim et al., 2013). Detailed principles, processes and parameterizations of CFDs can be found in Buccolieri et al.'s (2018) review of urban tree CFD modeling. Unlike i-Tree, which emphasizes the impact of different tree aspects, ENVI-met and CFDs also simulate the impacts of street and building characteristics (e.g., sky view factor, road traffic volume, canyon geometry, and ground and building materials) (e.g., Wania et al., 2012; Tan et al., 2016; Salata et al., 2015; Shahidan et al., 2012). As such, ENVI-met and CFDs are also

employed in the areas of landscape architecture, building design, and energy and environmental planning (Ambrosini et al., 2014).

Although not as widely used as the above-mentioned models, CITYgreen, Green CTTC, DOE-2, and SOLWEIG are also frequently employed (Table 2.2). CITY green had many applications from 1996 - 2006, but became less used afterwards due to model limitations (Longcore et al., 2004) and probably the increased use of i-Tree tools. Both DOE-2 and SOLWEIG also have applications in building energy analysis, emphasizing the impacts of building characteristics (e.g., building layouts, constructions, conditioning systems, and shade patterns of walls) on energy usage (Akbari et al., 2001; Lindberg & Grimmond, 2011). While other models were also represented, their contributions were minimal. For example, Shadow Pattern Simulator is found in three case studies examining tree's effect on residential energy use and indirectly carbon reduction (e.g., Simpson & McPherson, 1998; Jo & McPherson, 2001). Only two case studies use the fine resolution atmospheric multi-pollutant exchange atmospheric transport model (e.g., McDonald et al., 2007) and the coupled weather research and forecasting and urban canopy model (Loughner et al., 2012). One case study was found utilizing the vegetated urban canopy model (Lee, 2011), and the CHIMERE air quality model (Alonso et al., 2011).

Regarding statistical models, 45 papers and 60 case studies were identified over the study period. Three characteristics can be summarized. First, statistical models often have a strong economic focus, and consider issues such as an urban forest's impact on property values (Donovan & Butry, 2010), rental rates (Laverne & Winson-Geideman, 2003), and energy savings (Pandit & Laband, 2010). Second, 18 out of 45 papers adopted a spatially

explicit approach. Even for some models adopting a non-spatial approach, they considered spatial effects indirectly by employing location or distance factors as predictor variables (Tyrväinen, 1997; Laverne & Winson-Geideman, 2003; Morancho, 2003). Finally, among the 45 papers focusing on statistical models of urban forests, 32 papers used Hedonic price modeling, a method to estimate the contribution of ecosystem or environmental services to the value of a property (Sander et al., 2010) (Table 2.2).

Two characteristics of models are also investigated: spatial explicitness and uncertainty. A model is spatially explicit when the inputs, outputs or processes vary spatially (Turner & Gardner, 2015). ENVI-met, CFD, SOLWEIG, i-Tree Design and i-Tree Landscape are spatially explicit models, while other models investigated are generally not spatially explicit (Table 2.3). Uncertainty, due to incomplete information or the lack of knowledge of underlying processes, is a fundamental characteristic of any model (Wu et al., 2006). Uncertainty is generally insufficiently evaluated, or overlooked, in current urban forest models (Table 2.3). Uncertainty assessments are usually something added after the model has already been developed. For example, in models such as ENVI-met, Green CTTC, and SOLWEIG, only model output uncertainty (or prediction error) is assessed and expressed as the discrepancy between the model predictions and observations (e.g., Wu & Chen, 2017; Shashua-Bar & Hoffman, 2002; Lindberg & Grimmond, 2011). In addition, only specific kinds of uncertainty are typically assessed. For example, in i-Tree, only sampling error of field plot data is evaluated while other kinds of uncertainties (e.g., model structure and parameter uncertainty) are ignored, resulting in the underestimation of the overall uncertainty (Nowak et al., 2013). None of the papers address uncertainty in communication of model

| Table 2.2 Summary statistics of urban forest models | | | | | | | | |
|---|-----------|---------|--------------|--------------|--|--|--|--|
| | Citations | Country | Case studies | Publications | | | | |
| i-Tree | 8461 | 21 | 264 | 76 | | | | |
| ENVI-met | 2614 | 18 | 50 | 43 | | | | |
| CFD | 2206 | 8 | 35 | 35 | | | | |
| CITYgreen | 305 | 2 | 8 | 6 | | | | |
| Green CTTC | 881 | 3 | 7 | 7 | | | | |
| DOE-2 | 1658 | 2 | 24 | 5 | | | | |
| SOLWEIG | 222 | 3 | 4 | 4 | | | | |
| Hedonic price model | 2996 | 10 | 40 | 32 | | | | |
| Others | 2710 | 10 | 44 | 34 | | | | |

output to the public and decision-makers.

| Models | Initial release & current version | Sub-modules & web references | Free / open source or not | User programming knowledge required (low, medium, high) | Uncertainty assessments (No, limited, developed) | Spatially explicit or not |
|----------------|--|--|------------------------------------|--|---|---------------------------------|
| i-Tree | 1996; Version 6 | Eco, Hydro, Streets, Vue, Species, Canopy, Design, & Landscape: https://www.itreetools.org/ ^a | Yes / No | Low | Limited | Yes for specific modules |
| ENVI-met | 1994; Version 4.3 (As of Nov 2017) | Atmospheric, Vegetation, Soil, and Built environment & Building system: http://www.envi-met.com/ | Yes / No | Low | Limited | Yes |
| CFD | 2004; Version 1712 (As of Dec 2017) | Open Field Operation and Manipulation (OpenFOAM) http://www.openfoam.com | Yes / Yes | High | Limited | Yes |
| | 1996; Version 19.1 (As of May 2018) | ANSYS' Fluent https://www.ansys.com/products/fluids /ansys-fluent | No / No | Medium | Limited | Yes |
| | 1981; Version 2018 | CHAM's PHOENICS http://www.cham.co.uk/ | No / No | Medium | Limited | Yes |
| | 1989; Version 6.3 (As of July 2014) | Lohmeyer's Microscale Flow and Dispersion Model (MISKAM): http://www.lohmeyer.de/en | No / No | Medium | Limited | Yes |
| CITY- green | 1996; Version 5 (As of March 2004) | None | Yes /No | Low | No | No |
| Green CTTC | 2002; None | None | None | None | Limited | No |
| DOE-2 | 1978; Version 2.3 (As of July 2017) | http://doe2.com/ | Yes / No | Medium | Limited | No |
| SOLWEIG | 2008; Version 2016a (as of Sept 2016) | http://www.urban-climate.net/content/ | Yes / Yes | Medium | Limited | Yes |

Table 2.3 Characteristics of the main numerical urban forest models

a The last access of weblink is July 2018;

In terms of acquiring input datasets, 164 papers employed only bottom-up approaches, while 78 papers used the top-down approaches relying on remotely sensed imagery (Figure 2.3), including aerial photographs, AVHRR, Landsat, MODIS, LiDAR, NLCD, TRMM, IKONOS, and QuickBird imagery. Fifty-four of the 78 papers were published after year 2011, indicating the increasing utilization of remotely sensed imagery. A wide range of top-down approaches were employed to derive different model inputs. For example, MODIS has been used to estimate leaf area index (e.g., Nowak et al., 2014), and high resolution digital imagery and Landsat data have been employed to estimate tree canopy and land cover types (e.g., Morani et al., 2011; Yang et al., 2005).

4.4 Ecosystem services estimated with urban forest models

ES found in the papers examined were classified into three categories: biophysical, social and economic (Table 2.4). Biophysical benefits had 432 case studies, which was much higher than economic benefits (80) and social benefits (25), indicating an uneven distribution of case studies. Of the 432 case studies examining biophysical benefits, air pollutant removal was ranked highest with 264 case studies, followed by temperature and microclimatic modifications (98), carbon storage and sequestration (39), and water regulation (28). There were also three case studies analyzing wildlife and biodiversity, and one case study focused on noise effects. Regarding economic benefits, the most dominant topics were building energy cost reduction (e.g., cooling effects, heating effects) (39) and increased property values (36), followed by aesthetic quality (5). Among social benefits, thermal comfort received the most attention with 15 case studies, followed by reduced crime rate (5) and human health and disease (3).

In terms of new emerging topics, there appears to be an evolution in urban forest modeling. While studies of biophysical benefits continue to be most common, studies of fine particulate matter (PM_{2.5}), ultraviolet light, elemental carbon, and water quality appeared only after 2011. Assessing the impacts of urban forests on these issues increases the diversity of

urban forest ES and presents new challenges and opportunities in urban forest modeling. Some topics (e.g., urban heat island, park cool effect, thermal comfort, human health and disease) show an increasing rate of study after year 2011, indicating a potential increasing trend in the future.

| | 1996-2010 | 2011-2017 | 1996-2017 |
|---|-----------|-----------|-----------|
| Ecosystem services | (#/year) | (#/year) | Total # |
| Physical/Biological Benefits | | | |
| Removal of Air Pollutants | | | |
| Remove course particulate matter (PM10) | 1.2 | 5.1 | 54 |
| Remove ozone (O ₃) | 1.2 | 4.8 | 52 |
| Remove nitrogen dioxide (NO ₂) | 0.9 | 4.8 | 47 |
| Remove carbon monoxide (CO) | 0.9 | 3.7 | 40 |
| Remove sulfur dioxide (SO ₂) | 0.7 | 3.6 | 36 |
| Remove fine particulate matter (PM2.5) | 0.0 | 2.4 | 17 |
| Remove volatile organic compounds (VOCs) | 0.5 | 1.0 | 15 |
| Remove elemental carbon (EC) | 0.0 | 0.3 | 2 |
| Remove nitrogen monoxide (NO) | 0.0 | 0.2 | 1 |
| Remove ultraviolet (UV) radiation | 0.0 | 0.2 | 1 |
| Temperature and Microclimatic Modifications | | | |
| Lower air temperature | 1.4 | 3.0 | 42 |
| Provide tree shade | 1.0 | 0.7 | 20 |
| Reduce urban heat island (UHI) | 0.1 | 1.4 | 12 |
| Provide evaporative and transpiration cooling | 0.3 | 0.4 | 8 |
| Provide park cool effect | 0.1 | 0.9 | 8 |
| Regulate wind | 0.1 | 0.9 | 8 |
| Reduce incoming solar radiation | 0.0 | 0.3 | 2 |
| Carbon storage and sequestration | | | |
| Carbon storage and sequestration | 0.9 | 3.5 | 39 |
| Storm water regulation | | | |
| Reduce runoff | 0.9 | 1.9 | 26 |
| Improve water quality | 0.0 | 0.3 | 2 |
| Other | | | |
| Wildlife and biodiversity | 0.1 | 0.2 | 3 |
| Noise effect | 0.0 | 0.2 | 1 |
| Economic Benefits | | | |
| Reduce building energy use (e.g., heating, and cooling) | 1.5 | 2.3 | 39 |
| Increasing property value or rent price | 1.3 | 2.3 | 36 |
| Aesthetic quality | 0.1 | 0.4 | 5 |
| Social Benefits | | | |
| Thermal comfort/heat stress | 0.1 | 2.0 | 15 |
| Crime rate | 0.1 | 0.6 | 5 |
| Human health and disease | 0.1 | 0.3 | 3 |
| Environmental inequality | 0.0 | 0.3 | 2 |

Table 2.4 Number of case studies assessing urban forest ES

5 Discussion

5.1 Place-based, comparative studies

5.1.1 Distribution of case studies

The systematic review presented here assesses and compares urban forest modeling practices among places and across scales. We identified that: (1) the spatial distribution of case studies is clustered around certain locations (e.g., US, Europe and China and mostly in temperate and continental climatic zones); (2) most of the studies were conducted at and below city scales, and only a few studies were made at regional or national scales; and (3) within cities, the most popular units were parks and individual streets. The popularity of specific locations, cities and units could be attributed to several factors. The US and Europe are highly developed areas while China is one of the most rapidly developing countries; all have a large number of cities and associated various kinds of urban environmental issues. As such, cities in those areas provide ideal natural laboratories for urban forests studies. In addition, some models (e.g., ENVI-met, CFD) are designed for microscale simulations, and thus favor units like parks and street canyons. Urban forest studies in these areas are generally more comprehensive, and these studies have the potential to provide information to support future urban forest studies in less-studied regions.

These analyses contribute to our understanding of the structure, function, and benefit of urban forests, and the interactions between social and natural systems. Unfortunately, the uneven and fragmented distribution of case studies may bias our knowledge and understanding of urban forestry. Each place is unique in its own way and findings for one city can be quite different than for another city. For example, Nowak et al. (2006) performed computer modeling of air pollution removal by trees in 55 US cities and their results showed that pollution removal per unit canopy cover varied significantly from place to place, depending on pollution concentrations, length of in-leaf season, amount of precipitation, and other meteorological variables. Overall, management of urban tree canopy cover could be a viable strategy to improve air quality. However, Setälä et al. (2013) studied two Finnish cities and concluded that the ability of urban vegetation to remove air pollutants is minor in northern climates considering the short growing season. Vos et al. (2013) conducted a computer simulation and reached the conclusion that trees can deteriorate air quality at least locally at roadside locations based on summary of 17 scenario simulations of various vegetation settings. Conclusions about air pollution removal effects are clearly location- and scale-specific, and caution is needed when generalizing results. Regarding carbon storage, based on the studies of 28 cities and 6 states in the US, carbon density per unit of tree cover varied among cities based on tree density, tree size distributions, and species composition, with the general pattern of forested regions having greater carbon densities than grassland or desert regions (Nowak et al., 2013a). In terms of carbon sequestration, depending on which models are employed (e.g., i-Tree Streets, allometric equations from Urban Tree Database, or other empirical equations), the differences among the magnitudes of carbon sequestration estimates can be up to a factor of 2 (Boukili et al., 2017). Apart from the magnitude, the direction (e.g., from source to sink) can also vary. Based on two studies in Singapore and Mexico City, Velasco et al. (2016) concluded that carbon sequestration by urban trees are both positive, but when including soil respiration effects, overall carbon sequestration is

negative, i.e. the trees and soil in Singapore act as a carbon source and not a sink. Soil respiration is typically ignored due to large areas of impervious surfaces in cities. Even within one city, the impact of location cannot be neglected. For example, in terms of cooling effects and human thermal comfort, avenue-trees often have the strongest impact, façade greening has some noticeable effect, and roof greening is mostly ineffective (Ng et al., 2012; Gromke et al., 2015). Trees also appear to perform differently depending on their placement within a unit (such as the leeward, windward, central, and end parts of street canyons) (Moonen et al., 2013). The compilation of numerous case studies, while uneven, can give indications of commonalities and ranges of urban forest effects in different cities.

5.1.2 Scale and study unit

Apart from the uneven spatial distribution of case studies, there is also a gap between local research and global generalizations. Local scale research is important and the existing literature illustrates and discusses the need of local forest structure (Escobedo & Nowak, 2009; Nowak et al., 2013a) and local scale tree design (Nowak et al., 2013b). However, due to spatial heterogeneity (Escobedo & Nowak, 2009), urban trees may have opposing effects at different scales (Vos et al., 2013), and there is the need for multi-scale approaches (Jeanjean et al., 2015). Caution is needed to generalize findings among different places and scales, but by understanding the physics, chemistry, biology and social structure of urban forests, generalized principles can be developed to guide urban foresters in designing forest structure to optimize ES.

Another concept that is related to scale is the study unit. Different units provide

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different perspectives, and only through integration of a variety of units can a comprehensive view of urban forestry be achieved. For example, focusing on street canyons, the conclusion that roadside trees negatively affect the local air quality may be obtained under certain conditions (Ries & Eichhorn, 2001; Wania et al., 2012). However, this does not indicate that trees in urban backyards and parks have a similar effect (Vos et al., 2013). More studies are needed to integrate different units and scales. Two challenges exist when considering different study units. First, the increased focus on ecological units and integration of ecological and political units should be pursued in the future. Existing studies focus mostly on political units (e.g., census block groups), while ignoring ecological units such as patches, habitats and ecoregions. Units important to humans are not necessarily relevant for tree species or ecological processes, but help convey information in units important to managers, planners and politicians. The boundaries of different units, such as watersheds and administrative districts, may not coincide. In addition, mismatch between units or scales of ecological processes and the institutions that are responsible for managing them can contribute to decision failures (Cumming et al., 2006). Second, spatially heterogeneous representation of landscapes can be classified as a mosaic, which include patches and corridors with abrupt discontinuities or boundaries, and gradients with gradual differences in concentrations (Forman, 1995). Most studies reviewed in this paper focus on urban mosaics and ignore gradient approaches. This is mainly because the boundaries must be explicitly defined under most modeling frameworks. Due to practical need, boundaries are usually defined where several discontinuities coincide (MEA, 2005). Although gradient areas (e.g., urban-periurban-rural, wildland-urban interface) have been intensively studied in ecology

(Openshaw, 1984), geography (Kwan, 2012), and even urban forestry (Zipperer et al., 1997) using approaches such as landscape metrics, spatial statistics, and transect analyses (Luck & Wu, 2002; Kong & Nakagoshi, 2006), few studies incorporate these ideas or principles in urban forest modeling.

5.2 Field-based analyses

Urban forestry has developed rapidly (Figure 2.1) due to contributions from many fields (Table 2.1). For example, the concept of sustainable urban forestry is largely based on sustainability concepts from the ecology field (Fazio, 2003); the theories about scale and spatial heterogeneity from geography contribute greatly to spatially explicit research of urban forests (Escobedo & Nowak, 2009); the laws of fluid dynamics and thermodynamics from energy science improve our understanding of interactions between surface, vegetation and the atmosphere (Bruse & Fleer, 1998); and landscape ecology principles are used in the design and planning of urban green spaces (Zhou et al., 2011). Urban forestry is interdisciplinary by fusing knowledge from several fields, and transdisciplinary by applying scientific knowledge in policy-relevant ways. Transitioning more urban forestry initiatives and studies from interdisciplinary to transdisciplinary could be of great benefit. For example, with volunteer public participation, the MillionTrees program and 10-year cycle street tree census (2015-2016) in New York City have been implemented more efficiently (NYC Parks, 2018). Discipline-bound approaches conflict with the nature of urban forestry because by definition urban systems are social-ecological, and urban forests provide a wide range of ES which are of common interest to multiple disciplines. Urban forestry not only concerns itself with

scientific research, but also involves in management, planning, education and outreach (Moskell et al., 2010;Rae et al., 2010).

5.3 Urban forest models

5.3.1 Numerical models

A wide range of urban forest models exist, each suitable for specific applications. i-Tree and ENVI-met are two of the most widely used models (Table 2.2), most likely because they are freely available, do not require user programming experience, and contain various modules for different applications (Table 2.3). One additional reason that i-Tree is the most widely used is that it can be used at new locations or conditions without the re-calibration of model parameters. This is different from approaches adopted by other models (e.g., ENVImet, CFD); when applying models outside their original modeling domains, new site-specific parameter values must be obtained from measured data. i-Tree eliminates the need of parameter calibration by developing i-Tree databases, that contain tree species and location information for many countries to support modeling at new locations (see Supplementary Material). When site-specific parameters are insufficiently calibrated or unavailable, model outputs tend to contain large uncertainties (Walker et al., 2003). CFD models also have many applications for tree temperature effects (e.g., interaction with buildings characteristics), and air pollution removal effects (e.g., interaction with street characteristics and road traffic volume). One limitation of CFDs is that they usually require medium to high user programming experience (Table 2.3). When quantifying trees' thermal and building energy effects is a focus, Green CTTC, SOLWEIG, and DOE-2 are also potential choices.

5.3.2 Statistical models

Statistical models tend to be empirical and subjective due to the selection of predictor variables and functional forms. It is often the case that in one paper, several functional forms are developed, the structures and forms of statistical models often are identified based on the empirical fitting to observational datasets, and comparisons of different fittings are conducted using statistical measurements (e.g., the goodness-of-fit test) and information criteria (e.g., Akaike Information Criterion) (Conway et al., 2010; Sander et al., 2010; Pandit et al., 2013). The resultant best selected model can provide a useful description of the system even without physiological or mechanical knowledge (Jones, 2013). The problems of this approach are that (1) across papers, model forms and explanatory variables can vary widely which makes comparative studies challenging; and (2) the model may only be valid where it is developed and calibrated; caution is needed when generalizing the model to other locations, or when model-based inferences are performed. Future applications of statistical models in urban forestry should emphasize the use of theoretical guidance towards the selection of appropriate model structure and predictor variables.

5.3.3 Spatially explicit modeling

Although spatially explicit modeling can increase model complexity and data burden (Turner & Gardner, 2015), the spatial distribution of trees and their associated ES is essential for designing effective and equitable policy interventions (TEEB Foundations, 2010). The production, flow and use of ES varies spatially, as do the spatial patterns of beneficiaries and policy interventions. In addition, apart from the number of trees, the spatial composition and configuration of trees can also affect the ES they provide (e.g., Li et al., 2012; Zhou et al., 2017). ENVI-met, CFD and SOLWEIG are designed to be spatially explicit; the i-Tree tool suite is also transforming from lumped to spatially explicit modeling, with two new modules, i-Tree Design and Landscape, that can provide location information at local and landscape scales, respectively. Spatially explicit approaches are also often adopted by statistical models directly by using spatial regression or indirectly by employing location or distance factors as predictor variables. Providing equivalent tree cover per capita (or per land area) and accessibility to green space, especially for underrepresented or disadvantaged groups, could be a top priority for future urban forest management programs. Better quantifying the composition and configuration of trees and its influences on ES will also benefit forest management.

5.3.4 Model uncertainties

Although the importance of uncertainty in modeling is well recognized (Walker et al., 2003), few studies of urban forest modeling provide critical information about model uncertainties. For those models that do provide uncertainty information, only specific kinds of uncertainties (e.g., sampling error, prediction error) are typically considered. This may be due to two reasons. First, for existing models that describe complex ecosystem interactions (e.g., i-Tree, ENVI-met), a full and thorough uncertainty assessment (especially quantification and reduction) usually involves significant changes to model architecture (e.g., model assumptions, simplifications, formulations, and parameterizations). The lack of time and funding given other competing priorities of model developments limits current

uncertainty assessments. Second, although uncertainty assessment methods are welldeveloped (Refsgaard et al., 2007), no method is universally applicable and effective for all models. Guidance to select appropriate methods for specific model types and applications is lacking, plus each method has a learning curve (Pappenberger & Beven, 2006), which further limits uncertainty assessment. Given the importance of uncertainty analyses, especially for those models focused on policy- or decision-making, future modeling exercises could focus on improving the assessment and communication of uncertainty. Incorporating uncertainty assessment at the beginning of problem framing and model framework design, and tracking and documenting uncertainty throughout model development could significantly reduce overall efforts to incorporate uncertainty analyses in urban forest models.

5.3.5 Model comparisons

The comparison and integration of numerical models is rare, with only a few studies on model integration (e.g., Tiwary et al., 2009; McPherson & Kotow, 2013; Morakinyo et al., 2016) and model comparison (e.g., Russo et al., 2014; Guidolotti et al., 2016). General comparisons of models and model outputs may not be useful, and sometimes can even be misleading. Different models can estimate similar ES based on different input variables, model assumptions and formulations. For example, when estimating trees' temperature effects, a CFD model is based on the fundamental laws of fluid mechanics and thermodynamics to simulate the effects of vegetation on transpirational cooling and mean air flow and turbulence (e.g., Gromke et al., 2015). Contrary to this, Green CTTC employs an energy balance approach which quantifies anthropogenic heat-release, reduction of the solar gain due to tree canopy, energy consumption for evapotranspiration, and the change in the heat stored based on leaf surface temperature (Shashua-Bar & Hoffman, 2004). In this case, the differences in a tree's temperature effects could be due to different modeling approaches rather than a tree's structure and function. However, this does not mean that model comparisons should be avoided. Modeling experiences from other fields (e.g., public health, agriculture crop yield) have shown that the combined information of several models is superior to that of a single model (Thomson et al., 2006; Cantelaube & Terres, 2005). The way models are compared and integrated is important. Model comparisons and integration can be conducted at the decision-making level; if different models, with dissimilar theoretical foundations, reach similar conclusions about the effects of urban forests, it will increase the confidence of urban forests management decisions based on such similar conclusions, especially when uncertainty analyses are lacking.

5.3.6 Input datasets

Remotely sensed images play an important role in urban forest modeling. This is mainly due to increased availability of free remotely sensed imagery (Patino & Duque, 2013), and many ready-to-use image derived products (e.g., vegetation index, leaf area index, tree canopy cover) (O'Neil-Dunne et al., 2014; Morani et al., 2011; Yang et al., 2005). Although there is a trend of increasing utilization of remotely sensed imagery, this information mainly serves as input variables for urban forest models. A closer connection between remote sensing and urban forest modeling is needed, which will open up additional possibilities for future research and innovation. Two-dimensional images may greatly improve our ability to perform spatially explicit modeling, and long-term archives of time-series images present an opportunity to improve our understanding of the dynamics of urban forests and the impacts of these changes. In addition, remote sensing can sometimes aid in validating models (e.g., biomass, LAI) (Lu et al., 2016; Alonzo et al., 2016), which reduces model uncertainties and increases the credibility of a model and its outputs.

5.4 Ecosystem services estimated with urban forest models

5.4.1 Biophysical, economic and social benefits

Most case studies focus on biophysical benefits while only a few estimate economic and social benefits. This disparity may be due to significant advances we have achieved in linking forest structure to function. For instance, we have a good understanding of how a tree's characteristics (e.g., albedo, surface roughness) and biophysiological processes (e.g., evapotranspiration, storing carbon) affect temperature (Bonan, 2008), and how trees uptake and remove air pollution by dry deposition processes (Hirabayashi et al., 2011). We are able to parameterize these attributes and formulate these processes explicitly in models. However, we have limited capability to simulate economic and social benefits due to a lack of theory and large subjectivity and uncertainty in expressing and quantifying human cultures, values, attitudes and behaviors in models. For example, trees can provide amenity services to increase property values (e.g., Payton et al., 2008; Sander et al., 2010). However, amenity services (e.g., aesthetic enjoyment, recreation, intellectual development, and spiritual fulfillment) are influenced and shaped by human cultures, knowledge systems, religions, and social interactions (MEA, 2005). As such, quantifying those benefits suffers from large uncertainties and biases. In terms of social benefits, for instance, trees can affect human health by reducing air pollutant concentrations, but valuing the effects suffers from subjectivity due to the cost of illness, willingness to pay to avoid illness, and productivity losses associated with health events (Nowak et al., 2014). Different individuals have different behavioral patterns, dietary patterns and physiological characteristics (e.g., breathing rates) (WHO, 2008), which adds additional complexity to model the effects of air pollutant exposure. Although challenging, human behaviors and values are well modeled in other fields (e.g., economic, political ecology) (Anderies, 2000; Peterson, 2000); those advanced experiences should benefit future urban forest modeling. The linkages between forest structure and biophysical benefits is well understood and modeled, and ES delivery in biophysical terms also provides solid ecological underpinnings to economic and social metrics (TEEB Foundations, 2010). Expanding the links to incorporate trees' socialpsychological and health effects, as well as quantifying and valuing those effects, is a priority area where additional work is needed.

5.4.2 Health-related ES

Studies regarding the health-related ES of trees increased after 2011, compared to the period 1996-2010. These include 'thermal comfort/heat stress' and 'human health and disease' from social benefits, as well as various kinds of air pollutant removals (e.g., particulate matter, ozone), which have important health implications (Kinney, 2008). Many ES are public goods, and people usually lack direct incentives to protect and maintain them (TEEB Foundations, 2010). One of the key challenges facing urban forest campaigns is to get

the attention and involvement of different stakeholders (Zhang et al., 2007), and human health is one of the few ES that is relevant to almost everyone. Emphasizing the health effects of trees is an effective strategy to convey the importance of urban forests and gain support from stakeholders.

5.4.3 Ecosystem disservices

Another aspect that is less studied is ecosystem disservices (EDS) of urban forests. Common examples of EDS found in the literature include biogenic volatile organic compound emissions (Calfapietra et al., 2013), increases in potential energy use (Nowak et al., 2017), allergenic effects (Dobbs et al., 2014), air pollution trapping at road sites (Vos et al., 2013), and gentrification (Wolch et al., 2014). Although the adverse effects of urban forests have been mentioned and discussed in several papers (e.g., McDonald et al., 2007; Buccolieri et al., 2009; Morani et al., 2011), there are few studies to simulate and quantify EDS (Vos et al., 2013; Nowak et al. 2013b), let alone integrate EDS in decision-making. Since EDS are often ignored, the overall net benefits of urban forests may be less than initially estimated. The combined effects of ES and disservices and their influence on urban forest management and decision making are rarely investigated.

5.4.4 ES interactions

Regarding individual ES, the majority of papers explore specific types of ES while ignoring the interaction among different ES. These interactions can happen at different levels. For instance, for air pollutant removal, most studies estimate the removal of PM₁₀, O₃, CO, NO₂, and SO₂ in parallel. This makes sense for primary gases (e.g., NO₂, SO₂), but not for secondary gases (e.g., ozone), which can be created through complex chemical reactions and interactions (Pickett et al., 2011; Morani et al., 2011). Ignoring these interactions will lead to inaccurate estimation of net ozone effects (Cabaraban et al., 2013). At a higher level, the change of one ES could also affect other kinds of ES. For example, temperature reductions have implications for energy use, air quality, and human health (Nowak et al., 2014); energy savings can result in reduced emissions of CO₂ and air pollutants (McPherson et al., 2017; Nowak et al., 2017). Those interactions, either positive synergies (multiple services are enhanced simultaneously) (Bennett et al., 2009) or negative tradeoffs (the provision of one service is reduced as a consequence of the increased use of another) (Turner & Gardner, 2015), are commonplace in ecosystems (MEA, 2005). In contrast to the above common definition of tradeoffs, Mouchet et al. (2014) also refers to tradeoffs as various types of compromises, such as management compromises between ES. For instance, are tree species and locations being chosen to maximum or prioritize air pollution removal benefits or energy conservation benefits? Urban forest management decisions should consider these interactions and compromises to better avoid tradeoffs and enhance synergies.

6 Future directions and conclusions

Future directions in urban forest modeling can be organized around three key themes: urban systems, model development, and ES. An urban system is a complex and adaptive socio-ecological system which is characterized by spatial dependence and heterogeneity. However, urban ecosystems are often modeled non-spatially, which can ignore some local or microscale effects and interactions due to spatial arrangements. Future studies of urban forestry could focus on: (1) summarizing and generalizing experiences from well-studied regions (e.g., US, Europe, China) to support urban forest studies in less-studied regions; (2) multi-scale approaches to capture interactions among spatial heterogeneity at the local scale, and interaction among cities, suburbs, and their regional background environments at the regional scale; (3) improving linkages between ecological processes and social organization scales to improve urban forest modeling, planning, management and stewardship. With regards to model development, future research could focus on (1) improving uncertainty analyses, (2) employing spatially explicit expressions of location information, including issues related to environmental justice, (3) comparing and integrating models at a policymaking level, (4) increasing utilization of remote sensing, (5) increasing model capability to incorporate the effects of human cultures, values, attitudes and behaviors, and (6) increasing mechanistic understanding and its integration into statistical models. In addition, more effort could be devoted to model training to engage broader audiences and better utilize existing software, and to better communicate model outputs to stakeholders and decision-makers. In terms of ES, emphasis could be put on: (1) expanding linkages between forest structure and function to incorporate trees' social-psychological and health effects, (2) quantifying and valuing EDS, and (3) investigating ecosystem service synergies and tradeoffs.

With well-developed scientific rationales, models serve as a basis for collaboration and knowledge exchange between academic researchers and non-academic participants, and provide a scientific means to achieve sustainable urban forestry. Urban forest modeling is becoming increasing complex, global, and transdisciplinary, and this trend is likely to continue. As such, there is an urgent need for comparative studies and studies across a wide range of geographic settings. By synthesizing case studies from the perspectives of places, units, scales, disciplines, tools, and topics, this review provides insights and suggestions for future urban forest modeling research. Such knowledge can improve urban forest planning, design and management, and better support critical policy- and decision-making processes.

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8 Supplementary material

8.1 Literature database

| in this study | | | | |
|---------------------------|-------------------------------------|----------------|--|--|
| Author (Year) | Journal | Model | | |
| Abhijith & Gokhale (2015) | Environmental Pollution | CFD | | |
| Akbari (2002) | Environmental pollution | DOE-2 | | |
| Akbari et al. (1997) | Energy and buildings | DOE-2 | | |
| Akbari et al. (2001) | Solar energy | DOE-2 | | |
| Alchapar et al. (2017) | Theoretical and Applied Climatology | ENVI-met model | | |
| Alexandri & Jones (2008) | Building and Environment | Other | | |
| Alonso et al. (2011) | Environmental Pollution | Other | | |
| Alonzo et al. (2016) | Urban Forestry & Urban Greening | i-Tree Eco | | |
| Ambrosini et al. (2014) | Sustainability | ENVI-met model | | |
| | | | | |

Table 2.5 Author(s), year, journal and models employed of the 242 research papers identified in this study

| Amorim et al. (2010) | | |
|------------------------------|--|--|
| Amorim et al. (2013a) | | |
| Amorim et al. (2013b) | | |
| Balczó et al. (2009) | | |
| Baró (2014) | | |
| Baumgardner et al. (2012) | | |
| Berland & Hopton (2014) | | |
| Bodnaruk et al. (2017) | | |
| | | |
| Bottalico et al. (2016) | | |
| Bottalico et al. (2017) | | |
| Boukhab & Alkam (2012) | | |
| Boukili et al. (2017) | | |
| | | |
| Bruns & Fetcher (2008) | | |
| Bruse & Fleer (1998) | | |
| Buccolieri et al. (2009) | | |
| Ca et al. (1998) | | |
| Cabaraban et al. (2013) | | |
| Carver et al. (2004) | | |
| Chen et al. (2015) | | |
| Cho et al. (2008) | | |
| Chow et al. (2011) | | |
| Civerolo et al. (2000) | | |
| | | |
| Conway et al. (2010) | | |
| Currie & Bass (2008) | | |
| Declet-Barreto et al. (2013) | | |
| Del Barrio (1998) | | |
| Dimoudi & Nikolopoulou | | |
| (2003) | | |
| Dombrow et al. (2000) | | |
| Donovan & Butry (2009) | | |
| Donovan & Butry (2010) | | |
| Donovan & Butry (2011) | | |
| Duncan et al. (2014) | | |
| Dwyer & Miller (1999) | | |
| Endreny et al. (2017) | | |
| Escobedo & Nowak (2009) | | |
| Escobedo et al. (2006) | | |
| Escobedo et al. (2008) | | |
| Escobedo et al. (2015) | | |
| Fahmy et al. (2017) | | |

Advances in Urban Rehabilitation and Sustainability Science of the Total Environment Advances in Meteorology Meteorologische Zeitschrift Ambio **Environmental Pollution** Urban Forestry & Urban Greening Landscape and Urban Planning Agriculture and Agricultural Science Procedia Urban Forestry & Urban Greening Energy Procedia Urban Forestry & Urban Greening Journal of Contemporary Water Research & Education Environmental Modelling & Software Science of the Total Environment Building and Environment Environmental pollution Environmental management AIMS Environmental Science **Ecological Economics** Theoretical and Applied Climatology Atmospheric Environment The Journal of Real Estate Finance and Economics Urban Ecosystems Urban Ecosystems Energy and buildings Energy and buildings The Appraisal Journal Energy and Buildings Landscape and Urban Planning Urban Forestry & Urban Greening Spatial Demography Journal of Arboriculture Ecological modelling Landscape and urban planning Urban forestry & urban greening Journal of environmental management

Ecosystem Services

Energy and Buildings

CFD CFD CFD CFD, MISKAM i-Tree Eco i-Tree Eco and WRF-Chem i-Tree Street i-Tree Eco i-Tree Eco Other ENVI-met model i-Tree Street CITYgreen ENVI-met model CFD, FLUENT Green CTTC model i-Tree Eco CITYgreen Other Regression model (Global and local) ENVI-met model Other Spatial regression model (Hedonic & lag model) i-Tree Eco ENVI-met model Other CFD, PHOENICS Regression model (Multiple) Regression model (Linear) Hedonic price model Hedonic price model Spatial regression model CITYgreen

i-Tree Eco i-Tree Eco i-Tree Eco i-Tree Eco Hedonic price model ENVI-met & DesignBuilderV4.2 Fahmy et al. (2010) Greene & Millward (2017) Gromke et al. (2008) Gromke et al. (2015) Guidolotti et al. (2016) He & Jim (2010) Hilde & Paterson (2014) Hirabayashi & Nowak (2016) Hirabayashi et al. (2011) Hirabayashi et al. (2012) Hofman et al. (2016) Holtan et al. (2015) Hong et al. (2017a) Hong et al. (2017b) Hwang et al. (2017) Intasen et al. (2017) Jamei & Rajagopalan (2017) Janssen et al. (2011) Jayasooriya et al. (2017) Jeanjean et al. (2015) Jeanjean et al. (2017) Jeanjean et al. (2016) Jim & Chen (2009) Jim & Chen (2010) Jin et al. (2014) Jin et al. (2017) Jo & McPherson (2001) Jun & Kim (2017) Kadish & Netusil (2012) Kim & Wells (2005) Kim (2016) Kim et al. (2015) Kim et al. (2016) Kirnbauer et al. (2013) Kiss et al. (2015) Kondo et al. (2017) Kong et al. (2007) Kong et al. (2017) Lahme & Bruse (2003) Laverne & Winson-Geideman (2003)

Building and Environment Urban Ecosystems Atmospheric Environment Building and Environment Environmental Science and Pollution Research **Ecological Modelling** Journal of environmental management Environmental pollution Environmental Modelling & Software Environmental pollution Urban Forestry & Urban Greening Environment and Behavior Sustainable Cities and Society Atmosphere Landscape and Urban Planning Journal of Sustainable Forestry Solar Energy Book Chapter Urban Forestry & Urban Greening Atmospheric Environment Urban Forestry & Urban Greening Atmospheric Environment Cities Land Use Policy Atmospheric Environment **Building Simulation** Journal of Environmental Management Cities Landscape and Urban Planning Journal of Forestry Sustainability Urban Forestry & Urban Greening Sustainability Urban forestry & urban greening Moravian Geographical Reports Landscape and Urban Planning Landscape and urban planning Sustainable Cities and Society envi-met.com Journal of Arboriculture

ENVI-met model Spatial regression model (GWR) CFD, FLUENT CFD i-Tree Eco and EMEP MSC-W Other i-Tree Eco i-Tree Eco i-Tree Eco i-Tree Eco ENVI-met Regression model (Multiple) CFD: Reynolds-averaged Navier-Stokes (RANS) model CFD: Reynolds-averaged Navier-Stokes (RANS) model EnergyPlus i-Tree Eco ENVI-met ENVI-met model i-Tree Eco CFD, OpenFOAM CFD, OpenFOAM CFD, OpenFOAM CITYgreen Hedonic price model CFD, MISKAM CFD, FLUENT SPS and MICROPAS Spatial regression model (Hedonic) Spatial regression model (Autoregressive) Hedonic price model i-Tree Eco i-Tree Eco and Canopy i-Tree Eco i-Tree Hydro i-Tree Eco Regression model Hedonic price model SOLWEIG ENVI-met model

Regression model (Multiple)

Other Lazzarin et al. (2005) Energy and Buildings Lee (2011) Boundary-layer meteorology Other ENVI-met model Lee et al. (2016) Landscape and Urban Planning International Journal of Sustainable Lega & Endreny (2016) i-Tree Hydro Development and Planning Lerman et al. (2014) Landscape and urban planning i-Tree wildlife Li et al. (2015) Spatial regression model (Hedonic) Landscape and Urban Planning Journal of Wind Engineering and Industrial Lin et al. (2008) Other Aerodynamics Lindberg & Grimmond Theoretical and applied climatology SOLWEIG (2011a) Lindberg & Grimmond SOLWEIG Urban Ecosystems (2011b) Locke et al. (2017) Landscape and Urban Planning Regression model Longcore et al. (2004) Urban Geography CITYgreen Loret de Mola et al. (2017) Forests Regression model (Multiple) Journal of Applied Meteorology and Loughner et al. (2012) Other Climatology Lu et al. (2017) ENVI-met Sustainable Cities and Society Luck et al. (2009) Ecosystems Time-Lag Models Maco & McPherson (2003) Journal of Arboriculture i-Tree Street Manes et al. (2012) **Ecological Applications** Other Mansfield et al. (2005) Journal of forest economics Hedonic price model International Journal of Biodiversity Martin et al. (2012) Science, Ecosystem Services & i-Tree Eco Management Martin et al. (2013) Arboriculture and Urban Forestry i-Tree Eco Other McDonald et al. (2007) Atmospheric Environment McPherson (2010) Arboriculture & Urban Forestry i-Tree Street McPherson & Kotow (2013) i-Tree Street Urban Forestry & Urban Greening McPherson et al. (1997) Urban Ecosystems i-Tree Eco McPherson & Simpson (2002) Urban Forestry & Urban Greening i-Tree Eco DOE-2 McPherson & Simpson (2003) Urban Forestry & Urban Greening McPherson et al. (2011) Landscape and Urban Planning i-Tree Eco McPherson et al. (2016) Urban Forestry & Urban Greening i-Tree Street i-Tree Street & CUFR Tree Carbon McPherson et al. (2017) Urban Forestry & Urban Greening Calculator (CTCC) McPherson et al. (2005) Journal of Forestry STRATUM Mei et al. (2017) Forest Policy and Economics Hedonic price model Mensink et al. (2011) ENVI-met model Book Chapter Mentens et al. (2006) Landscape and urban planning Regression model (Linear) Middel et al. (2015) Urban Forestry & Urban Greening ENVI-met model Millward & Sabir (2010) Journal of Environmental Management STRATUM Millward & Sabir (2011) Landscape and urban planning STRATUM

| Mochida et al. (2008) | Journal of Wind Engineering and Industrial | CFD | |
|--------------------------|--|-------------------------------------|--|
| Mohamed & Wood (2015) | Book Chapter | CFD | |
| Moonen et al. (2013) | Atmospheric Environment | CED FLUENT | |
| Moradpour et al. (2016) | Atmospheric Pollution Research | CED | |
| Morakinyo et al. (2016a) | Energy and Buildings | ENVI-met model and EnergyPlus | |
| Morakinyo et al. (2017a) | Building and Environment | ENVI-met & RayMan | |
| Morakinyo et al. (2017b) | Energy and Buildings | ENVI-met & EnergyPlus | |
| Morakinyo et al. (2017c) | Urban Forestry & Urban Greening | ENVI-met model | |
| Morakinyo & Lam (2016) | Building and Environment | ENVI-met model | |
| Morakinyo et al. (2016b) | Journal of Environmental Management | ENVI-met model | |
| Morancho (2003) | Landscape and urban planning | Hedonic price model | |
| Morani et al. (2011) | Environmental Pollution | i-Tree Eco | |
| Müller et al. (2014) | Theoretical and applied climatology | FNVL-met model | |
| Multiple et al. (2006) | Remote Sensing of Environment | Regression model (Non-linear) | |
| No et al. (2014) | Urban Ecrostry & Urban Graaning | i Trace Eac and mathematical model | |
| Natural et al. (2014) | Land Economics | Ladonia price model | |
| Netusii et al. (2010) | International journal of anyironment and | neuonic price model | |
| Ng & Chau (2012) | pollution | CFD, FLUENT | |
| Ng et al. (2012) | Building and Environment | ENVI-met model | |
| Ning et al. (2016) | iForest-Biogeosciences and Forestry | i-Tree Eco | |
| Nowak & Crane (2000) | Official publication from USDA | i-Tree Eco | |
| Nowak & Crane (2002) | Environmental Pollution | i-Tree Eco | |
| Nowak & Dwyer (2007) | Book Chapter | i-Tree Eco | |
| Nowak & Heisler (2010) | Official publication | i-Tree Eco | |
| Nowak (2006) | Urban Forestry & Urban Greening | i-Tree Eco and Hydro | |
| Nowak et al. (2017) | Urban Forestry & Urban Greening | i-Tree Eco | |
| Nowak et al. (2000) | Atmospheric environment | i-Tree Eco | |
| Nowak et al. (2004) | Environmental pollution | i-Tree Eco | |
| Nowak et al. (2006) | Urban forestry & urban greening | i-Tree Eco | |
| Nowak et al. (2008) | Aboriculture & Urban Forestry | i-Tree Eco | |
| Nowak et al. (2013a) | Environmental Pollution | i-Tree Eco | |
| Nowak et al. (2013b) | Environmental Pollution | i-Tree Eco | |
| Nowak et al. (2013c) | Official publication from USDA | i-Tree Eco | |
| Nowak et al. (2014) | Environmental Pollution | i-Tree Eco | |
| Nowak et al. (2016b) | Urban Ecosystems | i-Tree Eco | |
| | | Regression model (multiple & Mixed- | |
| Pandit & Laband (2010a) | Ecological Economics | modeling) | |
| Pandit & Laband (2010b) | Journal of Arboriculture | Hedonic price model | |
| Pandit et al. (2013) | Landscape and Urban Planning | Spatial regression model (Hedonic) | |
| Dandit at al. (2014) | Australian Journal of Agricultural and | Spatial regression model (Hederic) | |
| 1 anult 61 al. (2014) | Resource Economics | Spanal regression model (Hedonic) | |
| Paoletti (2009) | Environmental Pollution | i-Tree Eco | |
| Paoletti et al. (2011) | Procedia Environmental Sciences | i-Tree Eco | |

Park et al. (2017) Parmehr et al. (2016) Payton et al. (2008) Peng et al. (2008) Perini et al. (2017) Perini & Magliocco (2014) Pham et al. (2012) Poudyal et al. (2009) Pugh et al. (2012) Reynolds et al. (2017) Ries & Eichhorn (2001) Robitu et al. (2005) Russo et al. (2014) Russo et al. (2015) Sahnoune & Benhassine (2017) Sailor (2008) Salata et al. (2015) Salim et al. (2011) Sander & Haight (2012) Sander et al. (2010) Santiago et al. (2017) Saphores & Li (2012) Selmi et al. (2016) Shahidan et al. (2012) Shashua-Bar & Hoffman (2002)Shashua-Bar & Hoffman (2003)Shashua-Bar & Hoffman (2004)Shashua-Bar et al. (2006) Shashua-Bar et al. (2010a) Shashua-Bar et al. (2010b) Simpson & McPherson (1996) Simpson & McPherson (1998) Skelhorn et al. (2014) Soares et al. (2011)

Urban Forestry & Urban Greening Urban Forestry & Urban Greening Journal of Environmental Planning and Management Frontiers of forestry in China Energy and Buildings Urban Forestry & Urban Greening Landscape and Urban Planning Land Use Policy Environmental science & technology Sustainability Meteorologische Zeitschrift Solar Energy International Journal of Biodiversity Science, Ecosystem Services & Management Urban Forestry & Urban Greening International Journal of Environmental Science and Development Energy and buildings Energy and Buildings Building and Environment Journal of environmental management **Ecological Economics** Atmosphere Landscape and Urban Planning Urban Forestry & Urban Greening Building and Environment International journal of climatology Building and Environment Journal of Arboriculture Atmospheric Environment Landscape and Urban Planning Urban Forestry & Urban Greening

Linear regression i-Tree Canopy and other Spatial regression (Hedonic) CITYgreen ENVI-met and TRNSYS ENVI-met model Spatial regression model (Multivariate & autoregressive) Hedonic price model CFD i-Tree Street & i-Tree Canopy CFD, MISKAM CFD i-Tree Eco and CUFR Tree Carbon Calculator i-Tree Canopy and other ENVI-met EnergyPlus ENVI-met model CFD, FLUENT Hedonic price model Spatial regerssion model (Autoregressive error model) CFD Spatial regerssion model (GWR and Cliff-Ord model with spatial lags) i-Tree Eco ENVI-met model and HTB2 software Green CTTC model SPS and MICROPAS SPS ENVI-met model

i-Tree Street

Srivanit & Hokao (2013) Steffens et al. (2012) Stephan & Endreny (2016) Strunk et al. (2016) Su et al. (2017) Sun & Zhang (2017) Sun et al. (2017) Taha (1996) Tallis et al. (2011) Tan et al. (2016) Tan et al. (2017) Thom et al. (2016) Thompson et al. (2011) Timilsina et al. (2014) Tiwary & Kumar (2014) Tiwary et al. (2009) Tong et al. (2016) Troy & Grove (2008) Troy et al. (2012) Tsilini et al. (2015) Tyrväinen & Miettinen (2000) Tyrväinen (1997) Van Renterghem et al. (2012) Vidrih & Medved (2013) Vos et al. (2013) Votsis (2017) Vranckx et al. (2015) Wang et al. (2008) Wania et al. (2012) Wolfe & Mennis (2012) Wong et al. (2003) Wu & Chen (2017) Xiao & McPherson (2002) Xue & Li (2017) Yang et al. (2017) Yang et al. (2005) Yang et al. (2011)

Building and Environment Atmospheric Environment JAWRA Journal of the American Water Resources Association Urban Forestry & Urban Greening Sustainability Transportation Research Part D: Transport and Environment Building and Environment Atmospheric Environment Landscape and Urban Planning Energy and Buildings Building and Environment Urban Forestry & Urban Greening Landscape and Urban Planning Landscape and Urban Planning Science of the Total Environment Environmental pollution Science of the Total Environment Landscape and urban planning Landscape and Urban Planning Sustainable Cities and Society Journal of Environmental Economics and Management Landscape and Urban planning Journal of Sound and Vibration Urban forestry & urban greening Environmental pollution Ecological Economics Science of The Total Environment JAWRA Journal of the American Water Resources Association Journal of environmental management Landscape and Urban Planning Energy and buildings Landscape and Urban Planning Urban ecosystems Sustainable Cities and Society Applied Energy Urban Forestry & Urban Greening JAWRA Journal of the American Water Resources Association

ENVI-met model CFD, CTAG i-Tree Hydro i-Tree Eco ENVI-met model CFD: FLUENT ENVI-met & RayMan Other i-Tree Eco ENVI-met model ENVI-met model SOLWEIG i-Tree Eco i-Tree Eco (UFORE equations) ENVI-met model i-Tree Eco and ADMS-Urban CFD, CTAG Spatial regression model (adjusted regression & Hedonic price model) Spatial regression model ENVI-met model Hedonic price model Hedonic price model Other CFD, FLUENT ENVI-met model Spatial regression (Hedonic) CFD, OpenFOAM i-Tree Hydro ENVI-met model Spatial econometric regression DOE-2 ENVI-met model Other CFD: Reynolds-averaged Navier-Stokes (RANS) model CFD: ANSYS Fluent i-Tree Eco i-Tree Hydro

| Yang et al. (2015) | Urban Forestry & Urban Greening | i-Tree Hydro |
|----------------------------|---------------------------------|------------------------|
| Yli-Pelkonen et al. (2017) | Atmospheric Environment | Regression model |
| Yu & Hien (2006) | Energy and Buildings | ENVI-met model and TAS |
| Yuan et al. (2017) | Sustainable Cities and Society | ENVI-met model |
| Zhang et al. (2017) | Landscape and Urban Planning | ENVI-met model |
| Zheng et al. (2016) | Urban Forestry & Urban Greening | CFD |
| Zhou et al. (2011) | Chinese Geographical Science | CFD |

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8.2 Model description

i-Tree (<u>https://www.itreetools.org/</u>) is a suite of freely available software tools which quantify a wide range of ES (e.g., biophysical, economic, and social) at various scales based on either mechanical processes (e.g., dry deposition) or empirical relationships (e.g., allometric equations) using field plots, air pollution, and meteorological data (Nowak et al., 2008a). To achieve satisfactory accuracies of outputs, approximately 200 plots of one-tenth acre are needed (Nowak et al., 2008b), and inside the plot, eight input variables (e.g., actual land use, total tree height, height to live top, height to crown space, crown width, percent crown missing, crown health, and crown light exposure) are recommended, in addition to two required input variables: species and diameter at breast height. Some outputs, such as building energy conservation due to trees, require additional input variables (e.g., tree-building spatial relationships) (Nowak et al., 2017).

i-Tree Database contains the database for species and location. The species database includes data for more than 6,500 tree and shrub species and their corresponding attributes. The location database includes site-specific parameters for many countries (e.g., leaf on & off dates, pollution, climate region, ozone state, cost of electricity and fuels). Users can contribute to the development of i-Tree Database by uploading their local site-specific data, but need to be validated by i-Tree team.

ENVI-met (http://www.envi-met.com/) is a holistic microclimate model designed to simulate the surface-plant-air interactions in urban environments, with focus on the impacts of vegetation on the local microclimate and pollutant dispersion (e.g., Ng et al., 2012, Wania et al., 2012). Two main input files are required by ENVI-met: a configuration file which contains information for initial meteorological conditions and thermo-physical properties of land covers, and an area file which contains the layout of buildings and vegetation (Skelhorn et al., 2014; Wu & Chen, 2017). Although ENVI-met is also based on CFD principles, it is regarded as an individual category because it has its own well-developed platform and framework.

CFD is a collection of models that are based on the fundamental laws of fluid mechanics and thermodynamics, including Open Field Operation and Manipulation (OpenFOAM), ANSYS' Fluent, CHAM's PHOENICS, and Lohmeyer's Microscale Flow and Dispersion Model (MISKAM). Detailed description of each CFD model can be found at website links provided in Table 2.3.

CITYgreen is currently an extension to the Environmental Systems Research Institute's ArcGIS software, which can map, measure, and analyze storm water, summer energy savings, carbon storage and sequestration, air quality, and wildlife of urban ecosystems. It was originally created by the AMERICAN FORESTS

(http://www.americanforests.org) in 1996.

Green CTTC is a thermal model that quantifies vegetation's temperature effects and subsequently reductions in building energy use based on an energy balance approach which combines the processes of solar radiation, anthropogenic heat-release, heat transfer and evapotranspiration (Ca et al., 1998; Shashua-Bar & Hoffman, 2002).

DOE-2 (http://doe2.com/) calculates buildings energy use, energy savings and CO₂ emission reductions (Akbari, 2002). Although DOE-2 is widely used in the area of building energy use and cost analysis (Zhu et al., 2013), its application in urban forestry is limited, with most applications examining the effects of shade trees (Akbari et al., 1997; Akbari et al., 2001; Akbari, 2002; Wong et al., 2003).

SOLWEIG (<u>http://www.urban-climate.net/content/</u>) simulates the influence of vegetation on radiant temperature based on six longwave and shortwave radiation fluxes (upward, downward and from the four cardinal points) (Lindberg & Grimmond, 2011).

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Chapter 3 Ecosystem service-based sensitivity analyses of i-Tree Eco

Abstract

Trees are known to provide various ecosystem services and disservices (ESD) to urban communities. These ESD can be quantified using models based on field and environmental data, but it is often uncertain how tree structure and environmental variables impact model output. Here we perform a sensitivity analysis (SA) of i-Tree Eco, a common urban forest model, to analyze the relative impact of different model inputs on three model outputs: biogenic volatile organic compounds (BVOCs) (isoprene and monoterpenes) emissions, carbon storage and sequestration, and dry deposition of nitrogen dioxide, sulfur dioxide, and ozone. The SA methods included novel applications of Morris one-at-a-time method and a variance-based decomposition method which integrates Monte Carlo simulation with Latin hypercube sampling and Iman Conover analysis. A case study was performed in New York City with field plot data collected in 2013. Genus has the largest influence on BVOC emissions by determining base emission rates and its high interactions with other input factors. BVOC emissions are sensitive to leaf biomass in a concave manner and temperature in a convex manner, while *isoprene* emissions show a strong linear relationship with photosynthetically active radiation (PAR). Diameter at breast height plays the most important role for both carbon storage and sequestration estimators; crown light exposure and tree condition are also important for carbon sequestration. Dry deposition velocity is sensitive to leaf area index and relative humidity in a nearly linear way while sensitive to temperature and PAR in a concave manner. These results provide guidance to facilitate future field plot campaigns and model development. The knowledge revealed by the SA is also beneficial for model uncertainty reduction, which in turn facilitates more effective urban forest management and decision-making.

Key words: Air pollutant; Carbon storage and sequestration; Monte Carlo; Urban forests; Volatile organic compounds.

1 Introduction

As a demographic trend and land transformation process, urbanization creates many environmental problems (e.g., increased runoff and nutrient export, increased temperatures, and increased material consumption and energy use) (e.g., Duh et al., 2008; Poumanyvong & Kaneko, 2010). One way to alleviate these impacts is through urban greening, and many cities have launched large urban tree planting initiatives (McPherson et al., 2011). Models of urban tree impacts on the environment can help develop more efficient and effective planting schemes (Morani et al., 2011), identify areas where existing forests should be maintained (Locke et al., 2011), improve the overall management of urban forests, and better quantify the benefits of these forest resources (Nowak et al., 2008a). One popular model is i-Tree Eco (https://www.itreetools.org/), which can quantify the structure, function and ecosystem benefits trees provide (Nowak & Crane, 2000), and has been used by thousands of researchers, urban planners, and others around the world to advocate for the benefits of urban trees (Lin et al., 2019).

While this tool has been extremely beneficial to the planning and management of urban

trees, this model makes assumptions that simplify the relationships between structure and function of urban forests and the representation of urban landscapes (Nowak & Crane, 2000). While such assumptions are often necessary to model these complex systems, they can increase the uncertainty of model output, and hinder the efficient and effective management of urban forests. Several studies point out that the uncertainty regarding various aspects of urban forest models (e.g., mortality rates of trees, transpiration rates, and meteorological conditions) should be better addressed (Yang et al., 2005; Morani et al., 2011; Selmi et al., 2016). Current uncertainty estimation within i-Tree Eco is limited to the standard error of the total number of trees within the study area (Nowak et al., 2008b), and its impact on selected model outputs (e.g., carbon storage) (Nowak et al., 2013). In addition, those standard errors usually come from sampling error instead of error of estimation (e.g., allometric equations), and therefore tend to underestimate the overall uncertainty (Nowak et al., 2013). This study focuses on developing an advanced sensitivity analyses (SA) of i-Tree Eco, including assessing how changes in model outputs can be apportioned to different model inputs, differentiating the relative importance of different model inputs, and identifying specific input-output relationships.

SA can be used in different settings (e.g., variance cutting, factors prioritization and fixing; Saltelli et al., 2004), and serves a variety of purposes (e.g., model development, scenario analyses, and comparative studies; Saltelli et al., 2004; Hirabayashi et al., 2011; Steffens et al., 2012). A wide range of SA techniques have been developed, ranging from classical frequentist analyses to complex Bayesian inference, and from local (e.g., Morris one-at-a-time) to global (e.g., variance-based methods) methods (Marino et al., 2008; Saltelli

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et al., 2008). Different SA methods can also be integrated together to achieve a more complete understanding of the relationship between input and output variables (Van Griensven et al., 2006).

This study employs a Morris one-at-a-time method (MOAT), and a variance-based decomposition method (VD) which integrates Monte Carlo simulation with Latin hypercube sampling (LHS-MC) and the Iman Conover method to address the correlation structure of the input variables (Iman & Conover, 1982). The novel applications of SA are illustrated with a case study in New York City (NYC) for 2013. The specific goals of this analysis are to: (1) determine the relative importance of input variables on i-Tree Eco outputs; (2) improve the understanding of the input-output variable relationships in i-Tree Eco (e.g., linear and additive effects, non-linear and interaction effects, and threshold effects); and (3) explore the implications of the results for future research and urban forests management (e.g., areas where additional data collection and analyses may be needed).

2 Methods

2.1 Model description

i-Tree Eco consists of modules which can quantify urban forest structure, function and value using field plots, air pollution, and meteorological data as input variables (Nowak & Crane, 2000; Nowak et al., 2008a) (Figure 3.1). The input module, Eco-A, characterizes urban forest "Anatomy", or the structure and composition based on data from field plots. Other modules examined here include one ecosystem disservice and two ecosystem services of urban trees. The Eco-B module estimates biogenic volatile organic compounds (BVOCs)

from trees based on tree species, leaf biomass, air temperature and other environmental factors. Trees emit hundreds of species of BVOCs, but the two major BVOCs are isoprene and monoterpenes (Bonan, 2015). The Eco-C module estimates total carbon storage and annual carbon sequestration based on allometric equations, tree growth, mortality and decomposition rates. The Eco-D module estimates the hourly air pollution removal by urban forests based on dry deposition processes (Nowak et al., 2006). The interactions between input variables and these modules are outlined in Figure 3.1, and the outputs from i-Tree Eco that will be examined in this study are listed in Table 3.1.



Eco procedures

Figure 3.1 Input variables, procedures in each module, and output variables from i-Tree Eco.

| Module | Output variable | Unit | Description |
|--------|----------------------------|--------|--|
| Eco-B | Isoprene | µgC/hr | Isoprene emission |
| Eco-B | Monoterpenes | µgC/hr | Monoterpenes emission |
| Eco-C | Carbon storage | kg | Carbon storage |
| Eco-C | Carbon gross sequestration | kg/yr | Annual gross carbon sequestration |
| Eco-D | $V_d of NO_2$ | cm/s | Dry deposition velocity of nitrogen dioxide (NO2) |
| Eco-D | $V_d of SO_2$ | cm/s | Dry deposition velocity of sulfur dioxide (SO ₂) |
| Eco-D | V_d of O_3 | cm/s | Dry deposition velocity of ozone (O ₃) |

Table 3.1 A list of output variables used in this experiment.

Eco-B estimates BVOC emissions (E) as:

$$E = B_E * B * \gamma \tag{1}$$

where B_E is the base genus emission rate, which is defined as the emission level standardized to T = 30 C and PAR = 1000 μ mol m⁻²*s⁻¹ (Nowak et al., 2008a), B is species leaf dry weight biomass, and γ is the temperature and light correction factor. The i-Tree species database contains data for more than 6,500 tree and shrub species and their corresponding attributes; among these attributes, B_E are compiled from the literature (Nowak et al., 2002). Users can also upload local site-specific B_E values to the i-Tree database (this needs to be validated by the i-Tree team). For isoprene, γ is estimated as:

$$\gamma = \frac{\exp\left(\frac{c_{T1}*(T-T_S)}{R*T_S*T}\right)}{0.961 + \exp\left(\frac{c_{T2}*(T-T_M)}{R*T_S*T}\right)} * \frac{\alpha * c_{L1} * PAR}{\sqrt{1 + \alpha^2 * PAR^2}}$$
(2)

while for monoterpenes it is:

$$\gamma = \exp\left(\beta * (T - T_s)\right) \qquad (3)$$

where c_{T1} = 95000 J*mol⁻¹, c_{T2} = 230000 J*mol⁻¹, T_M = 314 K, α = 0.0027 µmol⁻¹*m²*s, c_{L1} =1.066 (dimensionless), β =0.09 K⁻¹ (empirical coefficient), R is the ideal gas constant (8.314 J*K⁻¹*mol⁻¹), T_s is a standard temperature (303 K), and T is leaf temperature (K), which is assumed to be equal to air temperature (Guenther et al., 1995; Guenther, 1997).

Eco-C estimates forest biomass (Bio) using allometric equations from the literature (Nowak et al., 2013). The two most commonly used equations have the forms:

$$Bio = exp(A + B * LN(X))$$
 and $Bio = A * (X^B)$ (4)

where A and B are coefficients whose values vary based on species information. Species also determine the selection of equation forms. X is the predictor variable. Two forms of X employed in Eco-C are:

$$X = DBH and X = (DBH2) * HEIGHT$$
 (5)

For Eco-D, detailed equations used to calculate aerodynamic resistance, boundary layer resistance, canopy resistance, and dry deposition velocity can be found in Hirabayashi et al., (2011).

2.2 Study area and data employed

A sensitivity analysis case study of three i-Tree Eco modules was performed for NYC. Tree species, diameter at breast height (DBH), tree height, crown height and width, tree condition, crown light exposure (CLE), percent crown missing and land use type associated with 1075 trees were obtained from 296 field plots measured in 2013, which is more than the 200 plots used by many i-Tree studies (Nowak et al., 2008b). Although, some rare species are likely omitted by random sampling, random sampling produce statistically accurate estimates, with known bounds of error of urban forest structure (e.g., number of trees, and tree sizes). Tree condition is estimated as the percent of the crown that is composed of dead branches (to nearest 5%), which has a total of seven categories ranging from dead to excellent; CLE is the number of sides (four cardinal directions and one top side) of the tree receiving sunlight from above (ranging from 0 to 5), which is employed to estimate light environment and consequently growth rates (Nowak et al., 2008a). Eight land use types were identified across the field plots; land use affects carbon storage and gross carbon sequestration, which is addressed by assigning land use biomass adjustment factors (Nowak et al., 2008a). Leaf area index (LAI) statistics for this study area were taken from Breuer et al. (2003) (Table 3.2), which summarize LAI for 26 temperate regions. Model meteorological inputs (e.g., temperature, relative humidity (RH), wind speed, air pressure, and photosynthetically active radiation (PAR)) were obtained or derived from data from the nearest airport (NCDC, 2018). PAR, which is the visible part (400-700 nm) of the solar spectrum, is calculated as 46 percent of total solar irradiance (Hirabayashi et al., 2011). The summary statistics for each input parameter are presented in Table 3.2.

| Module | Parameter | Туре | Mean | Standard Deviation | Minimum | Maximum | Distribution | p-value for Kolmogorov– Smirnov Test |
|--------|-----------------------|-------------|------|-----------------------|---------|---------|--------------|--|
| Eco-B | Genus | Categorical | | | | | Uniform | |
| | Leaf biomass (kg) | Continuous | 8.18 | 18.5 | 0 | 267 | Lognormal | 0.19 |
| | PAR (W/m2) | Continuous | 84.3 | 122 | 0 | 483 | Gamma | 0.08 |
| | Temperature (C) | Continuous | 13.3 | 10.1 | -10 | 37.2 | Gumbel | 0.09 |
| Eco-C | Species | Categorical | | | | | Uniform | |
| | DBH (cm) | Continuous | 16.3 | 18.3 | 2.5 | 122 | Lognormal | 0.12 |
| | Height (m) | Continuous | 7 | 4.98 | 1.2 | 30.5 | Lognormal | 0.1 |
| | Land use | Categorical | | | 1 | 8 | Uniform | |
| | Tree condition | Categorical | | | 0 | 6 | Uniform | |
| | CLE* | Categorical | | | 0 | 5 | Uniform | |
| Eco-D | LAI | Continuous | 5.8 | 1.7 | 2 | 10 | Uniform | |
| | Pressure (Mbar) | Continuous | 1010 | 7.79 | 978 | 1030 | Lognormal | 0.05 |
| | PAR (W/m2) | Continuous | 84.3 | 122 | 0 | 483 | Gamma | 0.08 |
| | Relative humidity (%) | Continuous | 61 | 19 | 8 | 100 | Beta | 0.04 |
| | Temperature (C) | Continuous | 13.3 | 10.1 | -10 | 37.2 | Gumbel | 0.09 |
| | Wind speed (m/s) | Continuous | 5.27 | 2.83 | 0 | 20.6 | Weibull | 0.09 |

Table 3.2 Summary statistics of input variables (each integer represents one category for categorical variables).

* CLE affects the calculation of leaf biomass, and therefore is also employed as an input parameter for Eco-B.

2.3 Sensitivity analyses

2.3.1 Morris one-at-a-time analysis

Two SA methods were employed in this study: MOAT and a variance-based decomposition (VD) method. MOAT and VD, along with regression analyses to support the SA, were conducted using the R statistical software package. MOAT is a local sensitivity method which is computationally inexpensive and can differentiate input variables as negligible, linear/nonlinear, or having interaction effects (Saltelli et al., 2004 & 2008). The method starts by random sampling k parameters, $X_1...,X_i$,..., X_k , from predefined levels of all input variables and calculating the subsequent model output $Y(X_1...,X_i,...,X_k)$. For different

Eco modules, the number of model parameters (k) varies (k = 3 for isoprene, 2 for

monoterpenes, 3 for carbon storage, 5 for carbon sequestration, and 6 for dry deposition. In the second run, only one parameter, X_i , is increased by step size Δ with all other parameters remaining at their starting values and model output is again calculated $Y(X_1...,X_i+\Delta,...X_k)$. From this, the elementary effect, EE, (Saltelli et al., 2008; Van Griensven et al., 2006), of the ith input variable is estimated as:

$$EE_{i} = \frac{\frac{Y(X1...,Xi + \Delta,...Xk) - Y(X1,...,Xi,...Xk)}{Y(X1...,Xi,...Xk)}}{\frac{\Delta}{X_{i}}}$$
(6)

which is the percent change of the output divided by the percent change of the input. For each random sample of parameters, every parameter is subsequently increased with all other parameters back at their starting values, and the EE for that parameter is calculated. The levels of the parameters are usually identified by the midpoint of four, six or eight divisions of the parameter range, with each division of equal probability (Saltelli et al., 2004). In this study, eight divisions were used (so $\Delta = 1/8 *$ parameter range), and the above procedure was repeated 20 times, which leads to a total of 20(1+k) runs. The mean (μ) and standard deviation (σ) of the EE for each parameter across all runs is then calculated and plotted. μ measures the overall influence individual parameters have on the output while σ indicates whether the interaction between input and output are linear across the parameter space (low σ) or if nonlinear or interaction effects are present (high σ) (Saltelli et al., 2008). When positive and negative values of EE_i cancel each other out, a low μ may be obtained for parameters which have a large impact on the output. Campolongo et al. (2007) proposed to instead calculate the mean of the absolute value of the $EE_i(\mu^*)$ to avoid this problem; this approach is implemented in this study.

When applying MOAT to Eco-B and C, three things should be noted. First, we dropped the cases when the original model output $Y(X_1...,X_i,...X_k) = 0$, because it will lead to an error (division by zero) when calculating EE_i. For example, when a tree is dead, the annual carbon sequestration is equal to zero; this also occurs when the BVOC emissions are estimated as zero for some species. Second, for the categorical input variables 'land use', 'tree condition' and 'CLE', which have limited categories and can be effectively represented using levels (each category is one level), $\frac{\Delta}{X_i}$ was always set as 1 when changing individual input parameters from one level to the next in the EE_i calculation. Third, the unordered categorical input variables 'species' was not examined because its levels cannot be effectively determined and chosen from hundreds of species in the study site; species were randomly chosen and fixed for each simulation.

2.3.2 Variance-based decomposition (VD) analysis

A flowchart to perform VD by integrating Monte Carlo simulation with Latin hypercube sampling (LHS) and Iman Conover is presented in Figure 3.2. Stage 1 is to determine appropriate probability distribution functions (PDFs) to describe input variables, and then to perform LHS on the PDFs. Stage 2 is a Monte Carlo simulation where model outputs are estimated using input variables obtained from the LHS in Stage 1. Stage 3 is a variance decomposition analysis, which decomposes the variance of the output into different fractions that can be attributed to different inputs, as well as a quantile regression analysis to explore the general input-output relationships. Each of these stages is briefly described below.



Figure 3.2 Flowchart to perform sensitivity analyses.

Stage 1 has two components. First, probability distributions were fit to input variables. Specific probability distributions were identified based on either empirical datasets from the study site or literature recommendations (Table 3.2). The use of the Weibull distribution for wind speed and the beta distribution for relative humidity were suggested from the literature (Celik et al., 2010; Yao, 1974), and the PDFs of other identified input variables were empirically identified and estimated based on observational datasets from the study site. The assessment of PDF fit was performed by employing a Kolmogorov-Smirnov goodness-of-fit test and quantile-quantile plots (Wasserman, 2013). For LAI, a uniform distribution was assumed with the minimum and maximum values taken from Breuer et al. (2003). Ordered categorical input variables were assumed to follow a uniform distribution with an equal probability of being within each category. Table 3.2 contains the distribution used for each input variable and the p-values for the Kolmogorow-Smirnov tests, which were all less than

0.2 and generally less than 0.1.

Second, LHS, which combines the advantages of random sampling and stratified sampling (Helton & Davis, 2003), was employed to sample probability distributions from Stage 1. In LHS, the parameter space of each input variable is divided into N (N=1500 in this study) intervals of equal marginal probability, 1/N, and one sample of each variable is made randomly within each interval. Thus, N non-overlapping values for each input parameter are generated (Hirabayashi et al., 2011). The LHS method typically assumes that the sampling is performed independently for each parameter (Marino et al., 2008), though many of the input variables are correlated. To avoid this assumption, the Iman Conover method is used to enforce a dependence structure on input variables (Iman & Conover, 1982). The Iman Conover method is based on rearranging the values of the parameters so that a desired correlation structure, which is derived from Spearman's rank correlation coefficients of empirical datasets (Table 3.3), is imposed on the k parameters. This technique has advantages of being distribution free and can be used with any type of sampling scheme (Helton & Davis, 2003). At Stage 2, i-Tree Eco-B, C and D were batch run using input variables from Stage 1 to generate model outputs.

| _ | Height | Pressure | PAR | Relative humidity | Temperature |
|-------------------|--------|----------|-------|-------------------|-------------|
| DBH | 0.66 | | | | |
| Pressure | | 1.00 | | | |
| PAR | | 0.14 | 1.00 | | |
| Relative humidity | | -0.24 | -0.28 | 1.00 | |
| Temperature | | 0.04 | 0.58 | -0.10 | 1.00 |

 Table 3.3 Spearman's rank correlation coefficient structure among input variables.

 Height Pressure PAR Relative humidity Temperature

Stage 3 has two components. First, VD was employed to characterize and quantify the relative importance of input variables, and then for those input variables which were

identified as important, quantile regression models were fit to binned data to capture specific input-output relationships.

VD is a global SA which can decompose the variance of model output into fractions attributed to each model input and to input interactions (Saltelli et al., 2004 & 2008). The effects of VD are commonly measured by two sensitivity indices: a first order index and a total effect index. Model output, Y, is a function of a vector of k model inputs, $X_1,...,X_k$. The variance decomposition of Y can be expressed as

$$\operatorname{Var}(\mathbf{Y}) = \sum_{i=1}^{k} V_{i} + \sum_{i=1}^{k-1} \sum_{j=i+1}^{k} V_{ij} + \cdots + V_{1,\dots,k}$$
(7)

where $V_i = Var[E(Y|X_i)]$ is the contribution of X_i to the variance of Y, and $V_{ij} = Var(E(Y|X_i, X_j))$ - $V_i - V_j$ is a part of the total variance caused by the interaction between X_i and all other X_j , namely the joint impact of X_i and all X_j on the variance of the output minus their first-order effects (Saltelli et al., 2008). The first-order index (S_i) of X_i on Y is:

$$S_i = \frac{V_i}{Var(Y)} \tag{8}$$

and represents the percentage of the total variance accounted by the first-order effect of X_i . The total effect index (S_{Ti}) is:

$$\mathbf{S}_{\mathrm{Ti}} = 1 - \frac{V_{\sim i}}{Var(Y)} \tag{9}$$

where $V_{\sim i}$ is the total contribution of all parameters except for X_i . S_{Ti} accounts for the total contribution of X_i to the variance of model output (e.g., its first-order effect plus all higherorder effects due to interactions) (Saltelli et al., 2008). By definition, $S_i \leq S_{Ti}$, $\sum S_i \leq 1$ and $\sum S_{Ti} \geq 1$.

Following Saltelli et al. (2010), two base matrices (A and B) with dimension (N, k) were generated by LHS, where N is the number of simulation (N=1500) and k is the number

of input variables. S_i and S_{Ti} are calculated as

$$f_{o} = \frac{1}{N} \sum_{j=1}^{N} f(A)_{j}$$
(10)

$$S_{i} = \frac{1}{N} \sum_{j=1}^{N} \frac{f(B)_{j}(f(A_{B}^{(i)})_{j} - f(A)_{j})}{\frac{1}{N} \sum_{j=1}^{N} (f(A)_{j})^{2} - f_{0}^{2}}$$
(11)

$$S_{\text{Ti}} = \frac{1}{2N} \sum_{j=1}^{N} \frac{(f(A)_j - f(A_B^{(J)})_j)^2}{\frac{1}{N} \sum_{j=1}^{N} (f(A)_j)^2 - f_0^2}$$
(12)

where $A_B^{(i)}$ represents all columns from A except the ith column which is from B, f() is a function to estimate a corresponding ecosystem service, and f(A)_j (or f(B)_j) is the estimate an ecosystem service using the jth row of base matrix A (or B) as input variables. f_o represents the expected value of the ecosystem service across all parameter simulations represented in A, while the denominator of Eqns. (11) and (12) represents the total variance of the ecosystem service across all parameters in A. The main disadvantage of VD is the computational cost (here N(k+2) simulations).

General input-output variable relationships were explored and identified using a binned quantile regression approach (Jucker et al., 2017). We divided the scatterplot points into ten bins with an equal number of points by calculating corresponding quantile points (10%, 20%,, 90%) and using these quantile points to separate scatterplot points; we then estimated the median values of output and input for each bin, and performed a regression exploring both linear and nonlinear relationships (Figure 3.3). Three possible forms of quantile regression for the medians (e.g., linear (c=0), convex (c>0), concave (c<0)) were employed to differentiate different input-output relationships using:

$$Y = a + bX + cX^2 \tag{13}$$

The best form for each input-output relationship was selected based on the Akaike

information criterion (Wasserman, 2013), with the constraint that all the parameters should also be statistically significant. To compare the degree of concavity or convexity among different input-output relationships, regression models were built by standardizing the response and explanatory variables by subtracting the mean from each value and dividing by the standard deviation. A larger |c| value indicates greater concavity or convexity. This approach does more than simply explore the input-output relationships from the equations within i-Tree Eco, but allows us to discover links between correlated variables and model output. An example of the binned regression for the deposition velocity of NO₂ as a function of PAR is shown in Figure 3.3.



Figure 3.3 Bin and quantile regression process: (a) scatterplot of PAR vs V_d of NO₂; (b) scatterplot divided into 10 bins, and each bin represented as a boxplot with median values shown as a red star; and (c) regression curve fit to the median values to express a specific input-output relationship.

3 Results

3.1 MOAT analysis

The MOAT analysis produced a mean absolute value (μ^*) and standard deviation (σ) of

the output elementary effect for each input variable across the 20 simulations. For isoprene (Figure 3.4a), leaf biomass had greatest μ^* , indicating its large impact on model output; temperature and PAR had around the same magnitude of μ^* , indicating their moderate effects on model output. Of the three variables, leaf biomass had a higher σ value indicating that either the values of the elementary effect varied across the sample space or were strongly affected by the choice of other factors' values (i.e. nonlinear effects). For monoterpenes (Figure 3.4b), leaf biomass ($\mu^*=6.74$) was slightly more important than temperature ($\mu^*=4.09$), and both had high values of σ .

Among the three input variables examined for carbon storage (Figure 3.4c), the effect of DBH on the outputs (high μ^* and σ) was much larger than height and land use. The high σ for DBH indicated nonlinear effects of this input variable on carbon storage. For carbon sequestration (Figure 3.4d), two additional input variables related to tree health (condition) and site condition (CLE), were also examined. The five input variables can be grouped into three categories according to μ^* and σ : most important (DBH), moderate importance (condition, height, CLE), and negligible importance (land use).

Eco-D calculates dry deposition of air pollution to trees based on the dry deposition velocity and the air pollutant concentration, and assumes that the pollutants do not damage plant functions. For dry deposition velocity (V_d) of NO₂, temperature and LAI were the most important, as indicated by a high μ^* . While they had similar μ^* , temperature had a higher σ than LAI, indicating that its relationship to V_d of NO₂ was much less linear than for LAI. RH, wind speed, and PAR all had smaller μ^* than temperature and LAI, indicating their more moderate and similar effects on V_d of NO₂; these variables all had a higher σ than LAI,

indicating a less linear relationship to V_d of NO₂. Pressure had a negligible effect, as indicated by low μ^* and σ . For V_d of SO₂ and O₃, a similar pattern of ranking based on μ^* was displayed: temperature > RH > LAI > wind speed > PAR > pressure. Among these, temperature had the greatest μ^* and σ , indicating its large impact on model output and a highly non-linear relationship with output; RH, LAI, wind speed and PAR clustered in the middle of the (μ^* , σ) plane, while pressure had negligible effect.



Figure 3.4 Output from MOAT analysis showing standard deviation of elementary effect (σ) versus the mean of the absolute value of the elementary effect (μ*) for Eco-B (a) isoprene and (b) monoterpenes, Eco-C (c) carbon storage and (d) sequestration, and Eco-D dry deposition velocity (Vd) for (e) NO2, (f) SO2, (g) and O3.

3.2 Variance-based decomposition (VD) analysis

While MOAT is computationally cheap, it cannot fully explore the input space, has difficulty with categorical input variables, and assumes input variables are uncorrelated. To overcome these disadvantages, VD was employed in the study. In addition to four direct input variables (genus, leaf biomass, temperature, and PAR), the sensitivity of one indirect input variable (CLE) was also examined because previous studies have demonstrated that altering CLE values could greatly affect BVOC emissions (Pace et al., 2018). For isoprene (Figure 3.5a), the order of importance measured by S_{Ti} was genus > leaf biomass > temperature > CLE > PAR. Genus played a dominant role since base emission rates were assumed to be based on genera. The differences between S_i and S_{Ti} for all five input variables were large, indicating significant interaction effects between input variables. For monoterpenes (Figure 3.5b), the order of importance measured by S_{Ti} was genus > leaf biomass > temperature > CLE; large interaction effects also existed for all input variables as indicated by the large differences between S_i and S_{Ti} .

Among the four input variables that determine carbon storage (Figure 3.5c), DBH played the dominant role, species had a smaller role, while height and land use had negligible effects. For carbon storage, the model interaction effects were small, as indicated by the small difference between S_i and S_{Ti} . For carbon sequestration (Figure 3.5d), DBH again had the largest effect, while condition and CLE had moderate effects; the other three input variables (species, height, and land use) all had negligible effects. The differences between S_i and S_{Ti} for DBH, condition, and CLE indicated the existence of important interaction effects between these variables and carbon sequestration. For V_d of NO_2 (Figure 3.5e), LAI and PAR had the most dominant effect, while RH, temperature and wind speed had smaller effects, and pressure had a negligible effect. The small differences between S_i and S_{Ti} for these variables indicated minimal interaction effects between these input variables and the output. For V_d of SO_2 and O_3 , the pattern of rankings of importance were similar: PAR had the largest effect, followed by RH, LAI, temperature, and wind speed with moderate effects, and pressure with a negligible effect. For PAR and RH, interaction effects were detected by the differences in S_i and S_{Ti} .



Figure 3.5 Sensitivity measures (Si and STi) of (a) isoprene and (b) monoterpenes emissions, (c) carbon storage and (d) sequestration, and dry deposition velocity (Vd) for (e) NO₂, (f) SO₂, (g) and O₃.

3.3 Bin regression analysis

While VD can quantify the effects of individual input variables and their interaction

impacts on output variability, it does not identify general input-output relationships. For those input variables identified as important (unordered categorical input variables were excluded) in VD, a bin quantile regression analysis was employed, and the general input-output relationships at the aggregated level were described using regression form, regression coefficients and the adjusted R^2 (Table 3.4).

Leaf biomass showed a concave relationship with both emissions of isoprene and monoterpenes (Eco-B outputs), as indicated by a significant negative parameter on X^2 (a significant positive parameter would be convex). With an increase in leaf biomass, the emissions increased at a faster rate initially, then at a slower rate, and finally became relatively insensitive to the change in leaf biomass. The concavity of the monoterpenes vs leaf biomass relationship was greater than that of the isoprene vs leaf biomass relationship. Although leaf biomass of an individual genus at a specific temperature affected BVOC emissions in a linear manner (equation (1)), with different base rates from different genus and the nonlinear relationship between temperature and the monoterpene temperature correction factor (equation (3)), the combined effect across all genera and temperature in the simulation produced a concave relationship. CLE showed a linear relationship with both isoprene and monoterpenes emissions, and their adjusted R² values were lower than that of leaf biomass, indicating a weaker relationship with BVOC emissions when compared with the leaf biomass and BVOC relationship. By contrast, temperature showed a convex relationship with both BVOC emissions, indicating that the output responded relatively insensitively at low and moderate values of temperature, but then increased strongly as the temperature increases; the degrees of convexity, measured by |c|, were 0.49 and 0.39 for isoprene and monoterpenes,

respectively, as a function of temperature. This result makes sense since emission increases are nearly logarithmic with high temperatures. Unlike leaf biomass and temperature, PAR showed a strong linear relationship with *isoprene* emissions. The relationships between binned median inputs and median Eco-B output variables were generally strong, with adjusted R² values ranging from 0.87 to 1.00.

DBH showed a convex relationship with carbon storage while it had linear relationship with gross carbon sequestration; these relationships had a high adjusted R². By contrast, the linear form used to describe the relationships between tree condition and CLE to gross carbon sequestration had a relatively low adjusted R², indicating either a weaker input-output relationship or the model we proposed to represent the binned quantile regression (equation (8)) was inadequate to capture this relationship.

PAR showed concave relationships with V_d of NO_2 , SO_2 , and O_3 , with the degree of concavity of $NO_2 > O_3 > SO_2$; V_d of all three gases also showed concave relationships with temperature with similar degrees of concavity. For all other input variables, linear relationships were detected. LAI showed the strongest linear relationship with V_d (high adjusted R^2), while RH showed the weakest linear relationship (low adjusted R^2). This may indicate V_d responds to RH, and interacts with other input variables in more complex ways. The dry deposition processes of all three gases showed similar regression patterns with input variables.

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| Module | Output variable Y | Input variable X | Regression equation | Regression form | Adjusted R ² |
|--------|----------------------------|-------------------|-----------------------------------|-----------------|-------------------------|
| Eco-B | Isoprene | Leaf biomass | Y=0.16+1.32X-0.18X ² | Concave | 0.99 |
| Eco-B | Isoprene | Temperature | $Y = -0.45 + 0.82X + 0.49X^2$ | Convex | 0.96 |
| Eco-B | Isoprene | PAR | Y=0.94X | Linear | 0.87 |
| Eco-B | Isoprene | CLE | Y=0.95X | Linear | 0.87 |
| Eco-B | Monoterpenes | Leaf biomass | Y=0.34+1.66X-0.38X ² | Concave | 1.00 |
| Eco-B | Monoterpenes | Temperature | $Y = -0.35 + 0.89X + 0.39X^2$ | Convex | 0.99 |
| Eco-B | Monoterpenes | CLE | Y=0.89X | Linear | 0.74 |
| Eco-C | Carbon storage | DBH | Y=-0.18+0.65X+0.2X ² | Convex | 0.99 |
| Eco-C | Carbon gross sequestration | DBH | y=0.99X | Linear | 0.98 |
| Eco-C | Carbon gross sequestration | Condition | y=0.91X | Linear | 0.78 |
| Eco-C | Carbon gross sequestration | CLE | y=0.82X | Linear | 0.59 |
| Eco-D | Vd,NO2 | PAR | y=0.42+1.148X-0.467X ² | Concave | 0.94 |
| Eco-D | Vd,NO2 | Relative humidity | y=0.77X | Linear | 0.55 |
| Eco-D | Vd,NO2 | LAI | y=0.99X | Linear | 0.98 |
| Eco-D | Vd,NO2 | Temperature | y=0.2+0.97X-0.22X ² | Concave | 0.96 |
| Eco-D | Vd,SO2 | PAR | Y=0.35+1.15X-0.39X ² | Concave | 0.99 |
| Eco-D | Vd,SO2 | Relative humidity | Y=0.86X | Linear | 0.71 |
| Eco-D | Vd,SO2 | Temperature | y=0.15+0.98X-0.16X ² | Concave | 0.98 |
| Eco-D | Vd,SO2 | LAI | Y=0.975X | Linear | 0.95 |
| Eco-D | Vd,O3 | PAR | Y=0.37+1.16X-0.41X ² | Concave | 0.98 |
| Eco-D | Vd,O3 | Relative humidity | Y=0.85X | Linear | 0.69 |
| Eco-D | Vd,O3 | LAI | Y=0.9775X | Linear | 0.95 |
| Eco-D | Vd,O3 | Temperature | y=0.15+0.98X-0.17X ² | Concave | 0.98 |

Table 3.4 Bin quantile regression analysis of i-Tree Eco-B, C, and D outputs for most important input variables.

4 Discussion

4.1 The emissions of isoprene and monoterpenes

The amount of BVOCs emitted was affected by tree physiology (e.g., genus, leaf biomass) and environmental factors (e.g., temperature). The VD analysis indicated that genus had the largest influence on the emissions of isoprene and monoterpenes, and there were strong interaction effects among input variables, as indicated by the large differences between S_i and S_{Ti} and the high σ in the MOAT analysis. In Eco-B, each genus has specific B_E values, varying from 0 (e.g., *Pyrus*) to 70 (e.g., *Liquidambar*) ug g⁻¹ hr⁻¹ for isoprene emissions, and from 0 (e.g., *Pyrus*) to 7.9 (e.g., *Pistacia*) ug g⁻¹ hr⁻¹ for monoterpenes emissions.

Misidentifications of tree species may or may not result to large changes in BVOC emissions; however, misidentifications of tree genera could produce large deviations in emissions, as demonstrated in one study in Munich, Germany that shows isoprene emissions decrease and monoterpene emissions increase primarily due to misclassifications of tree species (Pace et al., 2018). Genus-level BVOC emission rates are used. If species-specific emissions are demonstrated to provide more accurate estimates, the model can be updated to uses speciesspecies BVOC emission rates. Note that in the MOAT analysis, μ^* for both Eco-B outputs were much larger in magnitude than for Eco-C and Eco-D outputs. This difference may be because a strong interaction existed among these input variables (high σ). High VOCemitting genera can increase the magnitude of EE.

All the other factors (e.g., leaf biomass, temperature, PAR, and CLE) played roles highly affected by the selection of a specific genus. As expected, the effects of CLE were smaller than leaf biomass because CLE's role is mainly through its effect on leaf biomass. Eco-A calculates leaf biomass using different approaches when CLE changes between classes (e.g., 0~1, 2~3, and 4~5). The same environmental factors may have a small influence if lowemitting genera are selected, and a larger influence when high-emitting genera are selected. Leaf biomass affected BVOC emissions in a concave manner (Table 3.4), which contradicts the linear relationship expressed in Eqn (1). This is probably because in the SA, we resampled across the range of values of genus, leaf biomass, PAR and temperature across the entire parameter space and therefore these other parameters, in addition to leaf biomass, also varied across different simulations. The concave relationships may be due to the simultaneous changes of all the variables and the interactions between the variables across the sample space. The effect of tree physiology (e.g., genus and leaf biomass) is greater than that of environmental factors (e.g., temperature, sunlight), which indicates planting of a low-emitting genus is a good strategy to help prevent BVOC emissions (Nowak & Crane, 2000). Temperature showed a convex relationship with both BVOC emissions, and extreme temperature can strongly increase BVOC emissions (Calfapietra et al., 2013; Sharkey et al., 1991). This may be due to the physiological functions of plants to protect against heat stress (Bonan, 2016). Therefore, cooler environments can also reduce BVOC emissions. While genus and temperature both impact BVOC emissions, an urban planner generally has limited control over temperature; thus, maximizing the use of low VOC-emitting trees is an efficient strategy to prevent and reduce BVOC emissions.

4.2 Carbon storage and sequestration

DBH played a dominant role for both carbon storage and sequestration (high μ^* and S_{Ti}) while land use and tree height had negligible effects (low μ^* and S_{Ti}). These findings indicate that in terms of data collection, increasing the accuracy of DBH measurements is an effective way to reduce model output uncertainty. DBH is important because allometric equations typically have a nonlinear relationship (e.g., exponential or log-log) between DBH and carbon storage, which means that even small errors in DBH measurements can lead to inaccurate carbon estimators (Jucker et al., 2017). These results suggest large trees play a more important role in carbon estimates than small trees; large trees (DBH > 77 cm) store

approximately 1,000 time more carbon than small trees (DBH < 7 cm) (Nowak, 1994). Sustaining the health of large trees, and accurately measuring the DBH of large trees is critical for carbon management and estimation.

Given the high correlation between DBH and height, it is counter-intuitive that height had a small influence on carbon estimation (low μ^* and S_{Ti}). This difference is likely because some allometric equations do not use height as an explanatory variable (Eqn.5). To compete for sunlight, trees often initially allocate resources to maximize tree height growth and approach their maximum height rapidly, and then invest resources in diameter growth (Jucker et al., 2017). This makes carbon estimation based on height alone problematic, because trees of similar height can have very different woody biomass. In addition, urban trees are more open-grown than trees in forested stands. However, McPherson et al. (2016) state that allometric equations using both DBH and height as predicator variables typically have higher accuracy than corresponding allometric equations employing only DBH. Although not as large as previously thought, species also affected the estimations of carbon storage $(S_{Ti}=5.4\%)$ and sequestration $(S_{Ti}=6.5\%)$ mainly through the selection of allometric equations of different forms and coefficients, which reflects differences among wood density and the water content of species (McPherson et al, 2013). This finding indicates that employing species-specific allometric equations can improve the accuracy of carbon estimations. Some studies also indicate that developing urban-specific allometric relationships is necessary (McHale et al., 2009). However, urban-specific allometric equations are scarce and locationspecific, and the very few that exist are usually developed based on street trees (McPherson et al., 2016). Generalizing those equations to be used with other urban trees may be

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problematic. The current approach adopted in Eco-C, namely to use forest-based allometric equations and apply a biomass correction factor if it is an open-grown environment (Nowak et al., 2013), is popular in urban forestry, although some studies criticize that this simple correction results in conservative estimates of biomass (Aguaron & McPherson, 2012). Future studies to develop urban-specific allometric equations, and to perform uncertainty analyses of the biomass correction factor are needed.

For carbon sequestration, two additional input factors (CLE and condition) were examined. CLE indicates site characteristics that impact sunlight to the tree crown, while condition is a measure of tree health. These two factors affect carbon estimates by adjusting tree growth rates. Both MOAT and VD showed that CLE and condition played moderate roles in model output (Figures 3.4 and 3.5), and the bin quantile regression analysis showed that carbon sequestration tended to increase linearly with the increase of CLE and condition (Table 3.4). These linear relationships may inadequately capture input-output relationships, as indicated by the low values of adjusted R² (0.59 and 0.78). Consistent with the results from bin quantile regression, VD also showed that the effects of CLE and condition may depend on the selection of other input factors, as indicated by the large difference between S_i and S_{Ti}. This difference may be due to the responses of different species, which may have different tolerances to abiotic and biotic stressors. This finding suggests that adaptive management approaches are needed to enhance and sustain forest health to maximize carbon sequestration and storage.

4.3 Air pollution removal by dry deposition processes

Both MOAT and VD analyses revealed that LAI was the most important factor for V_d of NO₂, and an important factor for V_d of SO₂ and O₃ (Figures 3.4 and 3.5). Bin quantile regression analysis showed that dry deposition of all three gases tended to respond linearly to LAI, which is consistent with the analysis performed by Hirabayashi et al. (2011). However, this linear relationship is unlikely to be maintained with an increase of LAI. As LAI increases, there is more chance of overlay among the leaf distribution, as well as resource (e.g., nutrients) and microenvironment (e.g., light) limitations (Chapin et al., 2011). Although trees adapt to these limitations, the leaves tend to behave at a lower efficiency as LAI increases and thus are unlikely to maintain a linear relationship with V_d (Van der Zande et al., 2009).

RH was an important factor for V_d of NO₂, SO₂, and O₃ (Figures 3.4 and 3.5). Eco calculates stomatal conductance by employing the Ball-Berry model, which is based on empirical relationships between stomatal conduction and photosynthesis from numerous leaf gas exchange measurements (Medlyn et al., 2011). During the process, Eco assumes RH is equivalent to the relative humidity at the leaf surface (Hirabayashi et al., 2011). Therefore, RH affects the stomatal conduction directly as an input to the Ball-Berry model, as well as indirectly through the influence of net leaf photosynthesis. Dry depositions of all three gases showed linear behavior with the change of RH (Table 3.4), which is consistent with the result obtained by Hirabayashi et al. (2011). However, a linear model may be inadequate to fully capture the response of V_d to RH, as indicated by relatively low adjusted R² values (Table 3.4). Bonan (2015) shows that stomatal conductance responds to vapor pressure deficit

linearly but at different rates with changing temperature, which indicates the linear model is not completely justified to represent the response of V_d to RH. The large differences between S_i and S_{Ti} also indicates that the response of V_d to RH may be depend on other factors. Our conclusion regarding the relationship between RH and V_d is based on applying SA to the Ball-Berry model. However, the model has been criticized for employing leaf surface RH as a direct input because stomata sense and respond directly to transpiration water fluxes (Medlyn et al., 2011). Therefore, it is the leaf-to-air vapor pressure deficit rather than RH that actually drives this process. Future model development should directly incorporate vapor pressure deficit into the calculation of the stomatal conductance.

Wind speed and pressure were among the least important factors for dry deposition (Figures 3.4 and 3.5). Wind speed is important for aerodynamic and quasi-laminar boundary layer resistances because it reduces the thickness of the boundary layer of still air around each leaf and produces steeper gradients for the exchange of elements (e.g., water vapor, carbon dioxide) between the leaf surface and the atmosphere (Chapin et al., 2011). However, canopy resistance, which is the main driver of dry deposition, does not appear to be affected by wind speed (Hirabayashi et al., 2011); as a result, wind speed plays a minor role in determining dry deposition. Pressure appeared to have a limited relationship with V_d (Figures 3.4 and 3.5). Pressure affects stomatal conduction indirectly through the computation of the direct and diffuse PAR (Hirabayashi et al., 2011).

Temperature and PAR affected the opening and closing of stomata during photosynthesis and transpiration (Bonan, 2015). For the photosynthetic process, PAR mainly affects light-harvesting reactions while temperature mainly influences carbon-fixing reactions through the control of enzymes (Bernacchi et al., 2013). For transpiration processes, water is taken up by the tree's roots, transported vertically by the xylem, and evaporates from the leaf surface to the ambient atmosphere through a water potential gradient. The entire process is driven by vapor pressure deficit, which is closely correlated to temperature and light intensity (Will et al., 2013). The MOAT and VD analyses give different conclusions about the V_d response to temperature and PAR. MOAT indicated that temperature is the most important factor while VD indicated that PAR has the largest effect. The differences may be due to the different approaches of two methods, as well as the non-linear response curves of V_d to temperature and PAR. MOAT is a local method based on changing one factor at a time across its entire range while fixing all other factors at certain values, and therefore cannot fully explore the parameter space (a 6-dimensional space in this case). VD is a global method based on the simultaneous change of all input factors among their PDFs. The typical response curve of stomatal conduction to PAR for many species is that conduction increases with increasing PAR up to about 300-400 W/m², and is relatively insensitive to further increases in PAR (Jones, 2013). When the randomly selected levels used to calculate EE lie outside the range of 300-400 W/m², a conclusion that conduction is insensitive to PAR may be obtained. The response curve of V_d to PAR was concave in the bin quantile regression analysis (Table 3.4). V_d also responds to temperature in a concave way but with less concavity than with PAR (Table 3.4). Bonan (2015) shows that there exists an optimal temperature for the response of stomatal conductance, with the values being 15-25 C for most C3 plants (plants that don't have photosynthetic adaptations to reduce photorespiration). The different response mechanisms of V_d to PAR and temperature indicate potential model inadequacies to
differentiate these response curves. More systematic modeling practices, which can capture different V_d response mechanisms (e.g., threshold and optimal points), are needed in the future.

PAR, LAI, RH and temperature all play important roles in dry deposition processes. Note that the VD analysis shows that PAR and RH are the most sensitive variables for V_d of SO_2 and O_3 , while they are less sensitive for V_d of NO_2 (Figure 3.5). This may be because there are greater changes in V_d for SO₂ and O₃ than for NO₂ when input variables are altered similarly. For example, when increasing PAR from 50 to 600 W*m⁻², V_d of SO₂ and O₃ increase by 0.31 and 0.33 cm*s⁻¹, respectively, which is larger than that of NO₂ (0.18 cm*s⁻¹). The variations of V_d against PAR for these three gases are detailed in Figure 3.6. Hirabayashi et al. (2011) also observed similar patterns in their sensitivity analysis of Eco-D in Baltimore. These different degrees of sensitivity may be due to different parametrization schemes for the calculation of the quasi-laminar boundary layer and canopy resistances, where NO₂ show higher values for mesophyll and cuticular resistances compared with SO₂ and O₃ (Hirabayashi et al., 2015). For PAR and LAI, i-Tree Eco employs one of the best available processes in the literature to scale up from the leaf to canopy, and the interaction between PAR and LAI is fully captured by different components of PAR (e.g., direct, diffuse) and LAI (e.g., sunlit, shaded) (Hirabayashi et al., 2011). For RH and temperature, single values, instead of vertical profiles around canopy height, are employed in i-Tree Eco, which may constrain the model performance. In addition, the model assumes that leaf temperature is equal to air temperature, while leaf traits (e.g., hair) and properties (e.g., latent heat exchange) may make leaf temperature differ from air temperature (Yu et al., 2015). Future

model development may focus on the improved representative of RH and leaf temperature to reduce the uncertainties of model outputs.



Figure 3.6 Relationships between V_d and PAR.

5 Conclusions

In this study, sensitivity analyses (SA) are performed to investigate how the characteristics of the i-Tree Eco inputs impact the ecosystem services and disservices of urban trees predicted by this model. Here the focus is on the inputs to three i-Tree Eco modules: BVOC emissions (Eco-B), carbon storage and sequestration (Eco-C), and dry deposition velocity of air pollutants (Eco-D). Two SA with different theoretical foundations are employed. Morris one-at-a-time (MOAT) is based on changing one factor at a time across its entire range to see what effect it has on the output, while variance decomposition (VD) is based on decomposing the variance of the output into different fractions which can be

attributed to different inputs or their interactions. The results provide useful information for future urban Forest Inventory and Analysis (FIA) data collections (https://www.nrs.fs.fed.us/fia/urban/), model uncertainty analyses, and urban forest management.

Genus has the largest influence on BVOC emissions by determining base emission rates and its large interactions with other input factors. Temperature shows a convex relationship with both BVOC emissions, indicating that BVOCs increase at a greater rate with temperature as temperature increases (Sharkey et al., 1991). High temperatures can strongly increase BVOC emissions. Leaf biomass has a concave relationship with BVOCs, indicating that the emissions increase at a faster rate initially, then at a slower rate, and finally become relatively insensitive to the change in leaf biomass; knowing the inflection points from sensitive to insensitive is important to control BVOC emissions while maximizing other leaf related ecosystem services. PAR has a linear relationship with *isoprene* emissions. These findings indicate that maximizing the use of low VOC-emitting trees is an efficient strategy to prevent and reduce BVOC emissions, and maintaining cooler environments (e.g., through tree transpiration) can also help to reduce BVOC emissions.

DBH has the greatest influence on carbon storage and sequestration provided by urban trees, and carbon storage tends to increase in a convex manner as DBH increases. Unlike relationships among input variables and BVOC emissions which show strong interactions, the combined interactions between DBH and the other input variables and their influence on carbon storage and sequestration appears minimal. These results indicate that increasing the accuracy of DBH measurements, especially for larger trees, is critical for accurate carbon

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estimates. Employing species-specific allometric equations can also improve the accuracy of carbon estimates. Effort should be spent in improving current or developing new biomass equation in urban environments whenever possible. By contrast, tree height and land use appear to play minimal roles in carbon storage and sequestration. For carbon sequestration, tree condition and CLE are also important. Maintaining a good site environment and tree health are critical to maximizing carbon storage and sequestration provided by trees.

For the dry deposition processes, PAR, LAI, RH and temperature all play important roles, with PAR and LAI generally having the largest influence. Dry deposition velocity is sensitive to LAI and RH in a nearly linear way while it is sensitive to temperature and PAR in a concave manner. Air pressure has almost no influence on dry deposition, while wind speed has a minimal influence. The interaction between the input variables and their influence on dry deposition velocity is also minimal. There exists an optimal temperature for maximum dry deposition velocity while PAR affects dry deposition velocity up to certain threshold value. Representation of RH and temperature around the entire canopy space as a single value may constrain model performance. Future model development should focus on the improved representative of RH and leaf temperature.

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Chapter 4 An Uncertainty Framework for i-Tree Eco Abstract

Uncertainty information associated with urban forest models are beneficial for model transparency, model development, effective communication of model output, and decisionmaking. However, compared with the extensive studies based on the applications of urban forest models, little attention has been paid to the uncertainty of the output from urban forest models. In this study, bootstrap and Monte Carlo simulation were employed to explore the uncertainty of i-Tree Eco. We assess the uncertainties associated with input data, sampling methods and models throughout the processes of urban forest structure and function quantification, and we propagate and aggregate the three sources of uncertainty to derive an estimator of total uncertainty. The uncertainty magnitude is expressed as the coefficient of variation, the ratio of the standard error of the estimator to the mean of the estimator. Through a case study in New York City in 2013, we find that for leaf area, carbon storage and carbon sequestration estimators, the magnitude of total uncertainty is estimated as 11.3%, 12.8%, and 10.1%, respectively. The sampling uncertainty is largest, followed by model and then input uncertainties. The magnitude of total uncertainty is 36.0% for isoprene and 25.2% for monoterpenes emission, and the three sources of uncertainty all play important roles. For air pollution removal, the magnitude of total uncertainty is 71.3% for nitrogen dioxide removal, 80.5% for sulfur dioxide removal, and 58.5% for ozone removal. Both input and model uncertainties play important roles while sampling uncertainty has a moderate influence. To reduce overall uncertainty, future studies should develop more urban-, local-, and speciesspecific allometric relationships, improve the spatial representation of meteorological weather and air pollutant concentration monitors, develop more extensive and accurate local-scale measurements to calibrate and verify the modules, and improve sampling strategies. **Key words**: urban forestry, ecosystem services, model uncertainty, bootstrap, Monte Carlo.

1 Introduction

Modeling techniques have become increasingly popular in urban forestry, and a fundamental yet often overlooked characteristic of a model is its uncertainty (Wu et al., 2006). Uncertainty typically exists in every component of a model such as input data, model parameters, and model structure (Beck, 1987; Beven & Binley, 1992; Draper, 1995). The model building and calibration process (e.g., modeling assumptions, calibrating to datasets, communicating outputs, making decisions) could also introduce additional sources of uncertainty (Ascough et al., 2008; Beven et al., 2015; Hallegatte, 2009; Helton et al., 2006). In addition, applying models to real world applications typically increases the magnitude of output uncertainty. Urban systems are highly complex, and spatial heterogeneity requires the calibration of models to local conditions that may differ from those on which the models are based and developed (Hill, 2000). In addition, scale effects require re-verification of model structure and re-estimation of initial and boundary conditions and coefficient thresholds (Narasimhan et al., 2005), because there are not necessarily reasons why relationships valid at one scale would be valid at another scale (Rindfuss et al., 2004). Given these issues, uncertainty analysis (UA) should be regarded as important as model output, and the assessment of model output uncertainty should be formally integrated in modelling practices

(Pappenberger & Beven, 2006; Gallagher & Doherty, 2007). In the fields of decision support such as policy analysis, risk analysis, and environmental impact assessment, decision-makers may alter their management decisions with an understanding of uncertainty information associated with model output (Bryant et al., 2018; Walker et al., 2003).

While various methods of UA have been developed to identify and quantify different sources of uncertainties in many fields of environmental sciences (Clark, 2003; Held, 2005; Mishra, 2009), uncertainty in urban forest modeling has been limited (Lin et al., 2019). UA is usually something added after a model has already been developed. For example, in models such as ENVI-met and the Green Cluster Thermal Time Constant, only model output uncertainty (or prediction error) is assessed and expressed as the discrepancy between the model predictions and observations (Shashua-Bar & Hoffman, 2002; Wu & Chen, 2017). In addition, only specific kinds of uncertainties are typically assessed. For example, in i-Tree Eco, only sampling error of field plot data is evaluated while other kinds of uncertainties (e.g., model structure, parameter uncertainty) are ignored, resulting in an underestimation of overall uncertainty (Nowak et al., 2013).

Many models of urban forests have been developed to quantify the structure, function and ecosystem benefits that trees provide. i-Tree Eco (here after referred to as "Eco") (https://www.itreetools.org/), is a model that has been widely employed in urban forest decision making such as developing priority planting schemes (McPherson et al., 2011) and urban forest master plans (Leff, 2016), informing environmental regulatory issues (Nowak et al., 2014), and assessing the tradeoffs among different kinds of ecosystem services (Bodnaruk et al., 2017). Considering these wide applications and the currently limited UA in urban forest models, it is necessary to more fully assess and characterize uncertainty to both increase the credibility of the modeling process and to facilitate the effective use of model outputs in urban forest decision-making.

This study focuses on an UA of Eco. Despite efforts devoted to reducing output uncertainty of Eco, the model only produces uncertainty estimates based on the impact of sampling uncertainty (Nowak et al., 2008a). To overcome the gaps and promote a better use of this tool, here we assess the uncertainties associated with the entire modeling process, from urban forest characterization and the subsequent estimators of urban forest function, to estimators of the services and benefits of urban trees. This includes assessing input, sampling and model structure uncertainties (Regan et al., 2002; Refsgaard et al., 2007; Yanai et al., 2018). These three sources of uncertainty are estimated and compared to assess their relative magnitudes and identify the largest sources of uncertainty, are aggregated to derive an estimator of total uncertainty, and this estimator is then compared to the sampling uncertainty to ascertain whether the current model uncertainty estimator (based on sampling uncertainty alone) underestimates total uncertainty. Forest structure and function considered in this study include leaf area and biomass, biogenic volatile organic compound (BVOC) (isoprene and monoterpenes) emissions, carbon storage and sequestration, and air pollution removal (nitrogen dioxide (NO₂), sulfur dioxide (SO₂), and ozone (O₃)). The detailed processes to estimate those outputs can be found in the supplementary material (Eqns S1-S10). A case study is performed in New York City (NYC) for 2013, and the implications of the results on future urban forest plot inventory assessments, model development, and better use of the model output to support decision-making are discussed.

2 Methods

2.1 Field plot data

A total of 296 plots were selected by simple random sampling and inventoried in NYC in 2013. The plots are one-tenth acre in size and have a circular shape. The collected tree variables included tree species, diameter at breast height (DBH), tree height, crown height and width, tree condition, crown light exposure (CLE), and percent crown missing. Trees are defined as having a DBH greater than or equal to 2.54 cm (1 in), and therefore the minimum DBH size is 1 inch. CLE is the number of sides (four cardinal directions and one top side) of the tree receiving sunlight from above (ranging from 0 to 5) (Nowak et al., 2008a). There were a total of 1075 trees across all the plots, with the tree numbers in individual plots ranging from 0 to 71.

2.2 Uncertainty analysis

Three kinds of uncertainties (e.g., input, sampling and model uncertainty) were evaluated in this study. Assuming the independence of these three sources of uncertainty, we also aggregate them to derive an estimator of total uncertainty. Since the most pressing social-ecological problems and the associated decision-making (e.g., policy formulation and urban forest master plans) are typically addressed at the landscape scale, the uncertainty of Eco outputs is assessed based on the total estimate per unit land area (e.g., carbon storage (Mg)/hectare, leaf area (m^2)/ hectare) rather than based on individual trees. To cancel out unit effects and facilitate the comparisons among different Eco outputs, the magnitudes of uncertainty are presented as the coefficient of variation (CV), the standard error of an estimator divided by the estimate (e.g., mean value) from the estimator. The UA is demonstrated through application to a case study of NYC.

2.2.1 Input uncertainty

Sensitivity analyses were previously performed to investigate the relationships between input and output variables in Eco and to identify the most important parameters for estimating urban forest structure and function (Lin et al, 2020; Pace et al., 2018). For leaf area (LA) and leaf biomass (LB) estimators, sensitivity analyses from Chapter 3 identified crown height and width to be the most important variables; for BVOC emission estimators, leaf biomass, temperature, and photosynthetically active radiation (PAR) were most important; and for carbon storage and sequestration estimators, DBH was most important. We represented input uncertainty of tree attributes (e.g., DBH, crown height and width) and meteorological data (e.g., temperature and PAR) in different ways. For tree attributes, input uncertainty was represented as measurement error. Here the criteria of the USDA Forest Service's Forest Inventory and Analysis (FIA) national core field guide were adopted (https://www.fia.fs.fed.us/library/field-guides-methods-proc/). The core guide employs two criteria to indicate measurement quality: measurement tolerance (MT) that is the range of measurement that is acceptable, and measurement quality objective (MQO) that is the percentage of time that collected data are required to be within MT. Here we assumed that these FIA criteria are indicative of the measurement error of tree attributes. The FIA core guide states that the MT for tree height and compacted crown ratio (defined as the portion of

the tree supporting live foliage) should be within +/- 10% of the true length, and the MQO should be at least 90% (meaning that crews are expected to be within the measurement tolerance at least 90% of the time). We assumed that measurement errors of crown heights follow a normal distribution. Based on the MT (within +/- 10% of crown height) and MQO (at least 90% of repeated times) criteria, the probability distribution of measurement error of crown height was represented as:

$$P(\mu - 0.1\mu \leq \varepsilon \leq \mu + 0.1\mu) = 0.9$$
(1)

where ε denotes the measurement error of crown height and μ is the mean of ε . From Eqn (11), we calculated the CV for ε as 0.0608. Using this methodology, ε is a function of tree size, where larger trees have larger measurement errors. For the measurement error of crown width, the FIA core guide doesn't provide specific guidance. Here we assumed crown width measurement error follows a normal distribution with a specific CV that is similar in magnitude to the CV for crown height. To evaluate the sensitivity of the effects of measurement errors of crown width to CV magnitudes, CV values of 0.05, 0.075, and 0.01 were tested.

For DBH, the FIA core guide states that MT should be within +/- 0.1 inch per 20.0 inch increments of measured DBH, and MQO should be at least 95%. Since DBH in the NYC plot data ranges from 1- 47.9 inches, we have three MT values, +/- 0.1, +/- 0.2, and +/- 0.3, for DBH varying from 1-20, 20-40, and 40-47.9, respectively. Following similar procedure as those used to obtain measurement errors for crown height, we calculated measurement errors for the three DBH size groups with a standard deviation (SD) equal to 0.051, 0.102, and 0.153 inches, respectively. With this methodology, larger trees again tend to have larger

measurement errors than smaller trees.

Eco uses a single monitoring station closest to the study area's geographic center for meteorological data, and for air pollutant concentration data it uses the average across all monitoring stations within the study area. For meteorological and air pollutant concentration data, spatial variability, as opposed to the variability of individual measurements, most likely dominates input uncertainty. We represented input uncertainty for meteorological variables as the spatial variability among the meteorological monitoring data downloaded from the National Solar Radiation Database (NSRDB) (https://nsrdb.nrel.gov/). For air pollutant data, we obtained data from the Environmental Protection Agency for three monitoring sites for NO2, three for SO2, and five for O3

(<u>https://aqs.epa.gov/aqsweb/airdata/download_files.html#Raw</u>). Similar to the studies of Hanna et al. (2005), Situ et al. (2014) and Zheng et al. (2010), we assumed temperature (T) and PAR have normal distributions. The mean of T was derived by:

$$\mu_{i,j} = \frac{\sum_{k=1}^{3} T_{i,j,k}}{3} \qquad (2)$$

where i is the number of dates in July (one of the hottest months), j is the hours of the day, and k is the station. The overall SD of T (σ) was estimated as a function of the SD for a specific hour of the day ($\sigma_{i,j}$) where:

$$\sigma_{i,j} = \sqrt{\frac{\sum_{k=1}^{3} (T_{i,j,k} - \mu_{i,j})^2}{3-1}} \qquad (3)$$

and

$$\sigma = \sqrt{\frac{\sum_{i=1}^{31} \sum_{j=1}^{24} \sigma_{i,j}^2}{31*24}} \qquad (4)$$

We obtained the SD for input uncertainty of temperature by adjusting σ with the hourly temperature autocorrelation structure using an autoregressive model of order one (Salas,

1980):

$$\varepsilon_I = \emptyset_1 * \varepsilon_{I-1} + \varepsilon_{\varepsilon_I} \tag{5}$$

where ε_I is the input uncertainty of temperature at time T, ϕ_1 is the lag-lautoregressive parameter between two continuous time periods T and T-1 which is derived from the hourly temperature data from all available monitoring stations, and $\varepsilon_{\varepsilon_I}$ is a random error term of the input uncertainty of temperature which is assumed to be normally distributed with a mean of 0 and a standard deviation of σ . A thousand sequences of ε_I were then simulated through our model for the month of July, and the standard deviation and CV of model outputs across all one thousand simulations were then calculated. The mean and SD values for input uncertainty of PAR, relative humidity (RH), and air pollutant concentrations were estimated in a similar manner as temperature.

2.2.2 Sampling uncertainty

We also evaluated the effects of sampling uncertainty, based on the number and distribution of plot data, on model output estimators using a bootstrap simulation, a resampling technique (Efron, 1982). We resampled 296 plots from the original 296 plot data set with replacement for 1000 iterations, calculating model output for each iteration. Using the results for all 1000 iterations, the standard error for each Eco output estimator can be estimated (Efron, 1982), from which the CV for model outputs can be estimated.

2.2.3 Model uncertainty

The Eco estimators of LA and LB, and carbon storage and sequestration are based on

empirical allometric regression models. We represented model uncertainty using the reported mean square error (MSE) of these regression models. Note that model selection uncertainty is not addressed in this analysis. The uncertainty (variance) of mean predictions from a regression model can be estimated as:

$$\hat{\sigma}_{M}^{2} = MSE_{s} * \left(\frac{1}{n} + \frac{(X_{0} - \bar{X})^{2}}{\sum(X_{i} - \bar{X})^{2}}\right)$$
 (6)

where n is the sample size used to develop the regression model, X_0 is the value of the explanatory variable for which the prediction is to be made, and \overline{X} is the mean of the explanatory variables, X_i , used to develop the regression model. While we can obtain the reported MSE for each regression model, n, X_i , and \overline{X} are not provided. Here we assumed that n, X_i , and \overline{X} of the samples used to develop regression equations are equivalent to the values from the tree plot data in our study area. The model uncertainty was then quantified using MC simulation. We first randomly sampled an error term, ε_S , from a normal distribution with mean equal to zero and variance equal to the original MSE_S value for that allometric equation. We then replaced MSE_S by ε_S in Eqn (6), and calculated a value for the error term, ε_M , using this equation, added this value back to the original allometric equations, and then applied these equations to all trees using that specific allometric equation. We repeated the iteration 1000 times to calculate the CV for each output estimator.

BVOC emissions in Eco are estimated based on the procedures shown in Eqns (S3)-(S6) in the supplementary material, an approach which was also adopted by the Biogenics Emission Inventory System (BEIS) from the US Environmental Protection Agency (Hanna et al., 2005). Previous studies based on other models of BVOC emission estimators, such as previous versions of BEIS (Hanna et al., 2005), the Model of Emissions of Gases and Aerosols from Nature (Situ et al., 2014), and the Global Biosphere Emissions and Interactions System (Zheng et al., 2010), demonstrate that model parameters are key sources of uncertainty for BVOC emission estimators (Situ et al., 2014; Zheng et al., 2010). The uncertainty information (e.g., distribution, mean, and standard deviation (SD)) of the main parameters (e.g., c_{T1} , c_{T2} , T_M , c_{L1} , α , and β) in the Eco processes were obtained from the literature (Hanna et al., 2005). The meanings of the parameters and how they are employed to estimate BVOC emissions can be found in the supplementary material to this paper. Their statistical information and default values employed in Eco are summarized in Table 4.1. We then used MC to randomly sample parameter values, and then estimated BVOC emissions with these parameter values. The CVs were then calculated using the output from the 1000 iterations.

| Parameter | Original value in Eco | Unit | Distribution | Mean | SD |
|-----------|-----------------------|---------------|--------------|--------|--------|
| cT1 | 95000 | J*mol-1 | Lognormal | 95000 | 20000 |
| cT2 | 230000 | J*mol-1 | Lognormal | 230000 | 150000 |
| TM | 314 | Κ | Normal | 314 | 3 |
| cL1 | 1.066 | dimensionless | Normal | 1.06 | 0.2 |
| α | 0.0027 | µmol-1*m2*s | Lognormal | 0.0027 | 0.0015 |
| β | 0.09 | K-1 | Lognormal | 0.09 | 0.02 |

Table 4.1 Statistical information of main model parameters to estimate BVOC emissions

Air pollutant removals in Eco are estimated based on dry deposition processes. The detailed methodology employed in Eco can be found in Hirabayashi et al. (2011) and Nowak et al. (2006). Estimating the model uncertainty of air pollutant removal by trees via dry deposition is challenging due to the limited availability of data to assess model performance. The one study we identified is by Morani et al. (2014) who compared O₃ flux estimators from Eco with measurements from an Eddy Covariance tower in Rome, Italy. Morani et al. presented the sum of squared deviations between the Eco O₃ flux estimators and the Eddy

Covariance flux measurements, as well as the cumulative flux from Eddy Covariance measurements. Using this information and the number of observations, we were able to estimate the model uncertainty for the average Eco O₃ flux measurement as 40.3%. This is most likely an overestimate of model uncertainty. The output produced by Morani et al. (2014) included two simulation periods: one for dry conditions and one for wet conditions. One would expect in urban areas, where trees are often watered, these dry conditions may not occur, and thus this data, which is the only data we have available to us, may overestimate model error. As we have no other data to support our analysis, here we assume the model uncertainty for the Eco NO_2 and SO_2 removal estimators to also be 40.3%.

2.2.4 Total Uncertainty

In addition to estimating the input, model and sampling uncertainties for each Eco output estimator, we also calculated the total uncertainty. Assuming the input, model and sampling uncertainty is independent, we estimate the CV of total uncertainty as:

$$CV_{Total} = \frac{\sqrt{(CV_{Input} * Estimate)^{2} + (CV_{Model} * Estimate)^{2} + (CV_{Sampling} * Estimate)^{2}}}{Estimate}$$
(7)

3 Results

Figures 4.1 contained boxplots of LA and LB estimators from the simulations of input, model and sampling uncertainties, and the calculated CV across all simulations. The CV values indicated the uncertainty magnitudes. Since LA and LB displayed almost identical results, the following description focused on LA. By combining the estimators of input, model and sampling uncertainties, and assuming independence amongst these uncertainty

sources, the total uncertainty for LA was estimated as 11.3%. The input uncertainty is for crown height (CH), crown width (CW) under different magnitudes of measurement errors, and both of these parameters together (CH & CW) assuming they are independent. The magnitudes of different forms of uncertainty for LA deceased from sampling to model and then to input. The largest uncertainty source came from sampling uncertainty, which is around 11% for LA. Nowak et al. (2008b) suggest a selection of 200 plots by balancing estimating precision and time costs. The sampling uncertainty for 200 plots was 13.9% for LA (results in Figure 4.1 are from resampling of 296 plots). Both model uncertainty (represented as confidence intervals in prediction of the mean) and input uncertainty (represented as measurement errors of crown height and width) had negligible effects on output variability. We performed a sensitivity analysis for measurement errors of crown width by increasing CV values from 0.05 to 0.1, and the overall conclusions were the same. The solid red line in Figure 4.1 showed the Eco outputs for LA from running the original 296 plots, while the dashed red lines were the 25th and 75th quantiles for LA estimated using the reported standard error from Eco and assuming a normal distribution. All simulations were centered around the solid line, as expected; the sampling uncertainty from our simulation produced similar 25th and 75th quantiles as those produced by Eco.



Figure 4.1 Uncertainty estimates for LA and LB, where CH and CW represent crown height and crown width respectively. The input uncertainty is due to the measurement errors from both CH and CW. The solid red lines represent the Eco outputs from running the entire plot data set, and the dash red lines represent the Eco outputs at 25% and 75% quantiles, respectively.

Figure 4.2 contained similar output as Figure 4.1, but for carbon storage and gross carbon sequestration estimators. The total uncertainty magnitude was 12.8% for carbon storage, and 10.1% for carbon sequestration. The ranking of uncertainty magnitude was again sampling > model > input. Sampling uncertainty had the greatest CV values, indicating it had the greatest impact on the uncertainty of model outputs; model uncertainty had smaller CV values than sampling uncertainty, indicating its relatively minor impact, while input uncertainty had negligible effects. For the sampling uncertainty, reducing plot number from 296 to 200 resulted in the change of CV values from 12.64% to 15.1% for carbon storage, and 10.01% to 12.23% for carbon sequestration. Again the sampling uncertainty results matched those produced by Eco.



Figure 4.2 Uncertainty magnitudes estimates for carbon storage and sequestration. The solid red lines represent the Eco outputs from running the entire plot data set, and the dash red lines represent the Eco outputs at 25% and 75% quantiles, respectively.

Sampling

Total

Model

400

Input

Figure 4.3 contained the uncertainty results for isoprene and monoterpenes emissions. For isoprene emissions, the total uncertainty was 36.0% and the order of output uncertainty magnitudes measured by CV was model > sampling > input. The output from Eco using the 296 plots was provided (solid red line), but Eco did not currently estimate the standard error of isoprene estimators so no 25th and 75th percentiles were provided. Among the five model parameters that determine isoprene emissions (Figure 4.3a), c_{L1} and c_{T1} played dominant roles, followed by α and c_{T2} , while T_M had a negligible effect. Among the input uncertainty, the largest contributions came from temperature, while PAR and leaf biomass

had a much smaller effect on isoprene emissions. Note that when reducing plot numbers to 200 (recommended minimum in Eco), sampling uncertainty increased from 18.3% to 22.1%.

For monoterpenes emissions (Figure 4.3b), the total uncertainty was 25.2%, and the sampling uncertainty had the largest magnitude while the input and model uncertainties had around the same level of magnitude. The magnitude of sampling uncertainty was similar to that for isoprene emissions. However, compared with isoprene emissions, model uncertainty had a much smaller effect on monoterpenes emissions. This is probably because only one model parameter involved in the process of calculating the environmental correction factor. Among the input uncertainty, temperature had a large influence while leaf biomass had a negligible effect. Sampling uncertainty for monoterpenes using 200 plots increased from 19.0% to 22.8%.



Figure 4.3 Uncertainty magnitudes estimates for isoprene and monoterpenes emissions, and the red lines represent the Eco outputs from running the entire plot data set. LB is leaf biomass, Temp is temperature, Alpha, CL1, CT1, CT2, and Tm are model parameters (see Table 4.1).

Figure 4.4 contained the uncertainty results for the air pollution removals. Trees can remove air pollutants through dry deposition processes. We calculated the estimators for the changes in air pollutant concentration due to the process. The magnitudes of input and sampling uncertainties were calculated based on Monte Carlo simulation and bootstrap simulation, respectively while the magnitude of model uncertainty was obtained based on one existing study in Rome, Italy that compared O₃ flux estimators from Eco with measurements from an Eddy Covariance tower. Therefore, there were no boxplots provided for model uncertainty in Figure 4.4. The magnitudes of total uncertainty were 71.3% for NO₂, 80.5% for SO₂, and 58.5% for O₃, respectively. For all three gases, input and model uncertainties contributed the largest amount to the magnitude of total uncertainty, while sampling uncertainty played a moderate role. Among the input uncertainty, the air pollutant concentration had the largest influence, followed by the PAR; all other input variables had negligible effects. The magnitudes of total, input, and model uncertainties in the dry deposition output were larger than the corresponding values for other Eco estimators, while the magnitudes of sampling uncertainty were lower than for other Eco estimators.



Figure 4.4 Uncertainty magnitudes estimates for NO₂, SO₂ and O₃, and the red lines represent the Eco outputs from running the entire plot data set. Temp is temperature, and Air represents ambient air pollutant concentration.

4 Discussion

4.1 Leaf area and leaf biomass estimators

For LA and LB estimators, the CV values for model, input and sampling uncertainties were very similar. This is probably due to the fact that LB is calculated by multiplying LA and a species-specific constant value (gram of dry weight per square meter of leaf area). Regression equations for LB estimators have also been developed (Nowak, 1996). However, they are not employed directly in Eco because the ranges of tree parameters (e.g., the minimum and maximum values of crown width) are typically out of the application ranges of these equations. The discussion below, which is specific to LA, also applies to LB due to their similar estimation processes.

Sampling uncertainty's impact on LA dominated the other two sources of uncertainty, which resulted in the sampling uncertainty being approximately equal to the total uncertainty. The effect of sampling uncertainty was mainly due to the spatial unevenness of the tree population distribution. There were 296 plots across NYC, which had LA densities range from 0 to 7375 m²/ha. Such a large variability resulted in a high sampling uncertainty of 11.0%. An increase in sampling uncertainty from about 11% to 13% was observed when the plot numbers were reduced from 296 to 200. The reduced magnitude is likely a function of sampling intensity and study site heterogeneity. The sampling effects of LA are rarely evaluated, and the literature typically focuses on the influence of sampling on tree populations and tree's ecosystem services (Martin et al., 2013; Nowak et al, 2008b).

Model uncertainty for LA estimator played a minor role (CV = 1.74%). This may be due to model uncertainty being represented using a regression model prediction approach (Eqn 6) rather than using the MSE of the regression, which is integrated across all sites used to develop the regression model (Yanai et al., 2010). Adding MSEs directly to Eqns (S1) and (S7)-(S10) would inflate model uncertainty, as values of independent variables will be affected equally. When applying the approach in Eqn (6), the magnitudes of model uncertainty are also adjusted by the magnitude of independent variable (X_0), with the values close to the mean having smaller effects than values in the tails. Note that here we assume the sample from plots in NYC is the same as the sample used to develop the original regression equation.

Apart from model fitting uncertainty, model selection can also be an important source

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of uncertainty (Yanai et al., 2018). The effects of model choices, such as comparisons among species-specific and multi-species models, and selecting extant foreign models or developing local models, are often evaluated in non-urban sites (Van Breugel et al., 2011). The current method adopted by Eco for the LA estimator is based on a crown-based allometric equation developed from park tree data in Chicago (Nowak, 1996). Other approaches to estimate LA have also been developed, including species-specific equations (McPherson et al., 2016) and DBH-based equations (Timilsina et al., 2017). Comparisons among these methods are available in the literature. For example, by comparing four methods at a site located at northern California, Peper and McPherson (2003) reported that Nowak's (1996) method tends to slightly overestimate LA. Another study, based on 74 urban trees and 5 species collected in Stevens Point, Wisconsin, concluded that locally developed LA models have higher accuracies than the default models employed by i-Tree Eco (Narasimhan et a., 2017). However, these comparisons are typically constrained to limited species and single study sites. Future studies based on more representative datasets and systematic comparisons are needed. Locally developed allometric relationships are generally superior only if they are developed using a sufficiently intensive and representative data set (Breugel et al., 2011). Due to other factors not considered in this study, such as environmental condition differences between application regions, the region of origin of leaf area equations, and management practices (e.g., pruning for aesthetic or safety purposes), the model uncertainty estimated for leaf area most likely is conservative.

Output uncertainty due to measurement errors of crown width and height is negligible when compared with sampling uncertainty. Measurement errors are likely to be large at

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individual tree levels, especially for large trees, due to the exponential relationship in the allometric equation (Eqn S1). However, measurement errors are negligible at a landscape level because we randomly sampled measurement errors for crown parameters, and those errors are equally likely to be positive and negative, and therefore cancel each other out when aggregating at a landscape level. We adopted the FIA core criteria of measurement tolerance and measurement quality objectives, which are most appropriate for experienced professionals. Urban forest programs often employ citizen science to collect tree attribute data (Roman et al., 2017), which may have higher measurement errors and input uncertainty than the results reported in this study.

4.2 Carbon storage and sequestration estimators

The largest uncertainty source for carbon storage and sequestration came from the sampling process, which had a CV of 12.64% and 10.01%, respectively. The total uncertainty was approximately equal to the sampling uncertainty due to the dominating influence of sampling uncertainty. This sampling uncertainty had similar magnitudes as those found for LA, which is probably because they are influenced by the similar spatial heterogeneity of the tree population. The plot densities for carbon storage and sequestration varied from 0 to 6893 kg C/ha and 0 to 274 kg C/yr/ha, respectively, which results in large variations in the MC simulation. There are only limited efforts in the literature that evaluate the effects of sampling intensity on ecosystem service outputs in urban sites. Nowak et al. (2008b) reported that 200 plots are needed to yield a 12% relative standard error on the total number of trees based on a study in Syracuse, NY. Martin et al. (2013) found that in order to achieve a +-10% error, 258,

870, and 483 plots are needed for the estimators of tree number, carbon storage and sequestration, respectively. McPherson et al. (2013) reported that standard errors for carbon storage and sequestration estimators are typically within 5 to 15% based on studies in Los Angeles and Sacramento, CA. Our estimated magnitudes of sampling uncertainty are comparable to these values from the literature. However, to achieve a comprehensive understanding of sampling uncertainty, it is necessary to incorporate the effects of other aspects of sampling strategy (e.g., sampling method), and to perform cross-site comparative studies to evaluate how city characteristics (e.g., city size and heterogeneity) influence sampling uncertainty.

Model uncertainties for carbon storage and sequestration estimators had a CV of 1.61%and 1.18%, respectively, which were smaller than the corresponding sampling uncertainties. Both carbon and LA are estimated based on the regression equations. However, the equations have different MSE values (0.054 and 0.232) for carbon and LA. This disparity has little effect on the resulting magnitude of model uncertainty for carbon (CV=1.61% for carbon storage and 1.18% for carbon sequestration) and LA (CV=1.74%). Similar to the LA model, the magnitude of model uncertainty in the carbon model is also likely to be conservative due to the simplifying assumptions we made for Eqn (6).

Several models have been developed to calculate carbon storage and sequestration, including those employed by Eco, i-Tree Streets, the CUFR Tree Carbon Calculator, and the Urban Tree Database biomass allometries, and substantial variability is reported when the models are compared (Aguaron & McPherson, 2012; Boukili et al., 2017). However, this variability typically results from different models employed (McHale et al., 2009) (i.e. applying different models to the same tree results in different estimates), which makes model selection an important uncertainty source. In the urban forestry field, model selection is further complicated by employing either urban-specific allometric equations, which are relatively scarce, or forest-derived equations with a correction factor for urban open-grown trees. As suggested by Davies et al. (2013) and McHale et al. (2009), standardizing the models and methods used to estimate carbon storage and sequestration may reduce the variability and facilitate improved inter-city comparisons of these estimators. Other aspects of model uncertainty not considered in this study include species composition and species assignment of inappropriate allometric equation. Depending on the species composition of a site, different proportions of the trees may be non-matching (i.e. there is not species-specific equation available), which necessitates the use of the average of results from models of the same genus (Nowak et al., 2008a). A higher proportion of non-matching sample site trees may increase the magnitude of uncertainty.

For input uncertainty, although DBH is identified as the most important variable for carbon storage and sequestration estimators of individual trees (Lin et al., 2020), its effect on model output variability at the landscape scale is negligible. This is probably because we adopted the FIA core guide criteria. The assumed magnitudes of input uncertainty due to the measurement errors are relatively small, which results in a small impact to the output uncertainty.

4.3 Isoprene and monoterpenes emission estimators

BVOC emissions are typically calculated by multiplying genus-based standardized emission rates by LB volumes, and then correcting for environmental effects (Eqn S3). Commonly employed models for estimating BVOC emissions include Eco, BEIS, GloBEIS, and MEGAN (Wang et al., 2016). In Eco, a complete genus base emission rate database has been developed (Nowak et al., 2002), and two environmental correction processes have been built for isoprene (temperature- and light-dependent (Eqns S4-S5)) and monoterpenes (only temperature-dependent (Eqn S6)) emission estimators.

For both isoprene and monoterpenes emissions (Figures 4.3a and 4.3b), the total uncertainty is larger than that of the LA and carbon models. This is because the total uncertainty of isoprene and monoterpenes emissions more affected by all three sources of uncertainty, while the total uncertainty of the LA and carbon models is dominated by sampling uncertainty, with the other two sources having negligible effects. Uncertainty associated with input variables also play an important role, which is mainly due to the contribution from temperature. This finding is consistent with uncertainty assessments based on other BVOC emission models (Hanna et al., 2005; Situ et al., 2014). Apart from temperature and PAR, in other models additional environmental variables (e.g., humidity and wind speed) are also incorporated in BVOC emission estimators (Situ et al., 2014; Wang et al., 2016). It is not clear how these additional variables and associated processes affect the accuracy of BVOC emission estimators. The reduction of the uncertainty magnitude is not guaranteed unless the added processes are well-understood, well-represented and supported by good data (Turner & Gardner, 2015). Inter-model comparisons across different kinds of landscapes are beneficial to improve mechanistic understanding of BVOC processes, and to reduce input and model impacts on output uncertainty.

Compared with the effects of temperature, the uncertainty due to tree structure (e.g., leaf biomass) is negligible. However, this doesn't mean that BVOC emission estimators are totally driven by environmental variables while tree attributes play minor roles. Through a sensitivity analysis, genus and leaf biomass were identified as the two most important input variables for estimating BVOC emissions (Lin et al., 2020; Pace et al., 2018). Input errors impacting LB estimators are likely due to small measurement errors of crown width and height, which limits the impact on output uncertainty. Treating all uncertainties probabilistically is impractical, and some uncertainty sources, such as nominal variables (e.g., genus), are not amenable to quantification (WHO, 2008). For low and high VOC-emitting genera, the differences of base emission rates can be up to a factor of 70 for isoprene, and 8 for monoterpenes (Nowak et al., 2002). The misidentifications of genera could be a large potential source of uncertainty. The i-Tree Database also provides a mechanism for users to upload and employ local-specific species and location information. Advancements in science may not guarantee the reduction of some sources of uncertainty, such as those due to genera misidentifications. An effective approach is to develop a comprehensive local database which captures the diversity of the urban landscape.

Sampling uncertainty for both isoprene and monoterpenes emissions are larger than that for LA or carbon. This is probably because BVOC emissions are affected by not only the spatial heterogeneity of tree population, but also the spatial distribution of tree species. High and low VOC-emitting species may be unevenly spaced, such as when some plots are

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dominated by high-emitting species while others are dominated by low-emitting species. This results in large BVOC emission ranges across the sample plots and more sampling uncertainty.

4.4 The estimators for the changes in air pollutant concentration

For the estimators of changes in air pollutant concentration, two sources of uncertainty derived from input variables and the modeling procedure make the magnitudes of total uncertainty greatly larger than the corresponding values for all other Eco estimators. We calculated the magnitude of model uncertainty based on the reported results in one existing study in Rome, Italy (Morani et al., 2014). To our knowledge, this is the only study that compares the Eco air pollutant flux estimators with observations obtained from an Eddy Covariance tower in an urban location. We believe the calculated model uncertainty of 40.3% is likely an overestimate of model uncertainty. The magnitude of model uncertainty is based on a study from Rome, Italy, which has a Mediterranean climate, and the simulation period from which this uncertainty was derived contained a long dry period. In contrast, the dry deposition velocity in Eco is calculated based on a parameterization of the Ball-Berry model that is a general appropriation for well-watered soils (Bonan, 2015). Most urban areas are not in drought conditions, as even during droughts these systems are often watered. Therefore, using data from the Morani et al. (2014)'s study, which was the only data available to us, most likely results in an overestimate of model uncertainty.

Other limitations of this existing study include (1) the study examined only three model parameters involved in the dry deposition process (e.g., the slope coefficient in the Ball-Berry

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formula, light-saturated rate of electron transport, and maximum carboxylation rate); (2) the study only examined O₃ estimators, and we assumed these results were transferrable to NO₂ and SO₂; and (3) the analysis was only for one site in one city, and may not be transferrable to other urban locations. Future studies to systematically examine all necessary model parameters are needed. The lack of direct measurements of air pollutant flux, especially for NO₂ and SO₂, is one of the main obstacles to perform model uncertainty assessment. Future efforts to establish urban flux towers to obtain spatially distributed local observations are critical to verify model output and increase the credibility of the modeling process.

Input uncertainty has the largest magnitude for SO₂ and O₃, while is the second largest for NO₂. This is mainly due to the uncertainty of the air pollutant concentrations; all other meteorological and tree variables play smaller roles. Assuming the dry deposition velocity stays constant, the amount of air pollutant being removed from trees is linearly related to the air pollutant concentration (see equation 1 in Hirabayashi et al., 2011). In Eco, the current practice is to assign one air pollutant monitor to one study area, and if there is more than one monitor, air pollution removal is estimated for each monitor and the averaged result is reported (Nowak et al., 2014). There are few studies to incorporate multiple monitors to examine the spatial heterogeneity of air pollution removal and to spatially aggregate estimators to estimate total pollutant removal. This approach requires greater data support, and for most cities only a single air quality monitoring site exists. Escobedo and Nowak (2009) divided the Santiago, Chile into three subregions to examine the spatial heterogeneity of air pollution removal. To perform the experiment, they need to prepare three sets of input variables (e.g., tree structure, meteorological variables, and air pollutant measurements) for three subregions, and then run Eco three times. Such a modeling approach may not be realistic for all users due to limited resources (e.g., time, budgets) and the available monitoring sites.

Among the three sources of uncertainty for pollutant removal, sampling uncertainty has the smallest magnitude. The magnitudes of sampling uncertainty are close to the corresponding values for the leaf area estimators. This is probably because for the air pollutant removal, the input variables related to tree structure are the leaf area index and the tree canopy cover.

5 Conclusions

In this study, uncertainty analyses are performed to investigate the magnitudes of input, sampling and model uncertainties on output uncertainty of i-Tree Eco leaf area and biomass, carbon storage and sequestration, biogenic volatile organic compounds (BVOCs) emission (isoprene and monoterpenes) estimators, and the estimators for the air pollutant concentration changes for NO₂, SO₂, and O₃. Bootstrap (for sampling uncertainty) and Monte Carlo (MC) simulation (for input and model uncertainty) are employed to quantify uncertainty magnitudes and identify key sources of uncertainty.

By combining three sources of uncertainty, the total uncertainty is estimated as 11.3% for leaf area, 12.8% for carbon storage, 10.1% for carbon sequestration, 35.6% for isoprene emission, 25.2% for monoterpene emission, 71.3% for NO₂ removal, 80.5% for SO₂ removal, and 58.5% for O₃ removal. For the leaf and carbon estimators, the rank of uncertainty magnitudes is similar, namely sampling > model > input, with the sampling uncertainty

playing a dominant role and model and input uncertainties having negligible effects. By bootstrap sampling the plot data, we found the sampling uncertainty associated with leaf and carbon outputs had similar magnitudes. Conversely, input, model and sampling uncertainties all play important roles in isoprene and monoterpenes emissions. The input uncertainty is important mainly due to the contribution from temperature. For isoprene estimators, five model parameters associated with two environmental correction factors make model uncertainty greater than sampling uncertainty, while the opposite is true for monoterpenes estimators. Relative sampling uncertainty associated with isoprene and monoterpenes estimators is greater than that of leaf and carbon outputs because the latter is affected by only the spatial heterogeneity of tree population, while the former is also impacted by the species distribution. For the air pollutant removal, input and model uncertainties play bigger roles than sampling uncertainty, and input uncertainty is mostly due to the spatial variability for the air pollutant concentrations.

Uncertainty analysis should become a formal practice and necessary component of modelling exercises, especially for models which aim to support decision-making and policy-formation. Although various sources of uncertainty throughout the process, from urban forest characterization to the subsequent ecosystem functions of those urban forests, are assessed, uncertainty magnitudes reported in this study are still believed to be conservative due to the omission of other factors that could increase output uncertainty. To reduce overall uncertainty, future studies should (1) develop urban- and species-specific allometric relationships when they are not available, (2) improve the spatial representation of meteorological weather and air pollutant monitors, (3) break the study domain into subareas when multiple monitors are

available to improve local meteorological and pollutant concentration estimates, and (4) improve sampling strategies which balance sampling intensities and data collection costs. Inter-comparisons among models are also beneficial assuming model mechanisms are well-understood, and the comparisons are based on large sample data and city networks. In addition, there is a lack of experiments which provide data to fully assess the uncertainty of urban forest model output. Regardless, this analysis provides a framework for assessing the uncertainty of urban forest models, allows us to better quantify the uncertainty of model output, and should help us improve urban forest planning and management by providing information on how to reduce uncertainty.

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7 Supplementary material

i-Tree Eco (here after referred to as "Eco") estimates urban forest structure (e.g., leaf area and biomass) and function (e.g., carbon storage and sequestration, and BVOC emissions) using field plots and meteorological data (Nowak et al., 2008), as well as the support of species- and location-specific information from the i-Tree Database. In this section, the methodology employed in Eco to estimate urban forest structure and function is described.

Eco quantifies leaf area (LA) based on species, crown width and crown height from field plots, as well as species-specific shading coefficients from the i-Tree Database using the methodology from Nowak (1996) and Nowak et al. (2008). When crown light exposure (CLE) = 4-5, LA is estimated as:

LA = exp $(-4.3309 + 0.2942 * H + 0.7312 * W + 5.7217 * S - 0.0148 * C + \frac{\sigma^2}{2})$ (S1)

where H is the crown height, equal to the height difference between live top of the tree and crown base; W is the crown width, which is the average of the widths of the crown in the north-south and east-west directions; S is the species-specific shading coefficient (percent light intensity intercepted by foliated tree crowns); C is the crown's outer surface area which is calculated as π W(H+W)/2; and σ^2 is the variance of the model errors, which is assumed to be the mean squared error of regression model used to develop Eqn (1). The model is fitted on the logarithmic scale, and $\frac{\sigma^2}{2}$ is a bias correction term when back-transforming prediction on logarithmic scale to prediction on original scale. When CLE = 0-1, LA is estimated as

$$LA = \left[\frac{\ln (1-S)}{-k}\right] * \pi W^2 \qquad (S2)$$

where again S is the shading coefficient and W is the crown width, and k is the light extinction coefficient. When CLE = 2-3, LA is calculated as the average of the leaf area from

the above two approaches. The final estimates of LA from these methods are adjusted downward based on a constant percentage of crown leaf dieback, which is determined by the user. Leaf biomass (LB) is calculated by converting LA estimates using species-specific measurements of the leaf dry weight per m² of leaf area from the i-Tree Database.

BVOC emissions (E) are calculated based on the methodology from Guenther et al. (1995) and Guenther (1997) as:

$$E = B_E * B * \gamma \tag{S3}$$

where B_E is the base genus emission rate from the i-Tree Database, B is the species leaf dry weight biomass, and γ is an environmental correction factor. For isoprene, γ is estimated as the product of the temperature (γ_{temp}) and light (γ_{PAR}) correction factors, where γ_{temp} is calculated as:

$$\gamma_{\text{temp}} = \frac{\exp\left(\frac{c_{T1}*(T-T_s)}{R*T_s*T}\right)}{0.961 + \exp\left(\frac{c_{T2}*(T-T_M)}{R*T_s*T}\right)}$$
(S4)

while γ_{PAR} is calculated as:

$$\gamma_{\text{PAR}} = \frac{\alpha * c_{L1} * PAR}{\sqrt{1 + \alpha^2 * PAR^2}}$$
(S5)

For monoterpenes, γ is only affected by temperature, and is estimated as:

$$\gamma = \exp\left(\beta * (T - T_s)\right) \qquad (S6)$$

where c_{T1} , c_{T2} , T_M , α , c_{L1} , and β are empirical constants (see Table 4.1), R is the ideal gas constant (8.314 J*K⁻¹*mol⁻¹), T_s is the standard temperature (303 K), T is the leaf temperature (K) which is assumed to be equal to the air temperature, and PAR is the photosynthetically active radiation (μ mol*m⁻²*s⁻¹) (Guenther et al., 1995; Guenther, 1997).

Tree biomass (Bio) is calculated using allometric equations from the literature (Nowak et al., 2013). The allometric regression equations for Bio in Eco have the forms:

$$Bio = exp(A + B * LN(DBH) + \frac{\sigma^2}{2})$$
(S7)

$$Bio = exp(A + B * LN(DBH^2 * HEIGHT) + \frac{\sigma^2}{2})$$
(S8)

$$Bio = A * (DBH^B)$$
(S9)

$$Bio = A * ((DBH^2 * HEIGHT)^B)$$
(S10)

where A and B are species-specific coefficients, DBH is the diameter at breast height, HEIGHT is the tree total height, and σ^2 is the variance of model errors. $\frac{\sigma^2}{2}$ in Eqns S7 and S8 is a bias correction term when back-transforming prediction on logarithmic scale to prediction on original scale. The choices of coefficient values (e.g., A and B) and equation forms (e.g., Eqns (S7) – (S10)) depend on the species matching process. For non-matching species, the average result from equations of the same genus is used (Nowak et al., 2008). The estimates of tree biomass are multiplied by a factor of 0.8 if they are in open-grown environments (e.g., street trees, trees in residential and institutional lands) (Nowak, 1994). Carbon storage is estimated as half of the forest biomass, and carbon sequestration is calculated based on the temporal differences between carbon storage estimates, which are influenced by the length of the growing season, site competition, tree condition, and speciesspecific allometric equations (Nowak et al., 2013).

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Chapter 5 Uncertainty analyses of i-Tree Eco: A comparative study of 16 cities across the United States

Abstract

Urban forest models are increasingly employed to provide estimators of ecosystem services. Often the uncertainty associated with these estimators is ignored or underestimated. To reveal the characteristics of model uncertainty and how it varies across cities with diverse social and ecological settings, we perform an uncertainty analysis of i-Tree Eco, a popular urban forest model, in 16 cities across the United States. We develop an uncertainty framework that consists of input, sampling and model uncertainty, and apply it to the i-Tree Eco modeling process. We employ Monte Carlo simulation to estimate input and model uncertainty, bootstrap simulation to quantify sampling uncertainty, and aggregate all three sources of uncertainty to derive an estimator of total output uncertainty. We express uncertainty magnitude as the coefficient of variation, the ratio of the standard error of the estimator to the mean of the estimator. By applying the uncertainty framework to a network of 16 cities across the United States, we find that the average magnitude of total uncertainty across 16 cities is 12.4% for leaf area, 13.5% for carbon storage, 11.1% for carbon sequestration, 40.7% for isoprene emissions, and 25.0% for monoterpene emissions. For leaf and carbon estimators, the total uncertainty is primarily driven by sampling uncertainty while input and model uncertainties have much smaller effects; the magnitudes of all three sources of uncertainty are comparable across 16 cities. In contrast, all input, sampling, and model

uncertainties contribute to the total uncertainty for isoprene and monoterpene emission estimators, and there are large variations in these three sources of uncertainty across the 16 cities. The commonalities and variabilities across the cities are discussed to reveal factors that may drive the uncertainty magnitudes in particular cities. Such knowledge is important to extrapolate and generalize the findings to support future model development and decisionmaking.

Key words: urban forestry, forest structure, ecosystem services, model uncertainty, bootstrap, Monte Carlo.

1 Introduction

Urban forests provide numerous ecosystem services to mitigate environmental degradation associated with rapid urbanization, including urban stream degradation, increased human exposure to air pollutants, increased temperatures, and increased material consumption and energy use (Roy et al., 2012). As a green infrastructure, urban forestry has been incorporated into many urban plans to complement existing engineered infrastructure to deliver affordable and effective benefits to human beings (Keeler et al., 2019). Many cities have launched large urban tree planting initiatives (Pincetl et al., 2013), and many models of urban trees have been developed to quantify urban forest structure and ecosystem service magnitudes (Lin et al., 2019). These models include mechanistic models (e.g., i-Tree, ENVI-met, and Computational Fluid Dynamics (CFD) models), and empirical models (e.g., hedonic pricing models and contingency valuation). Since many tree-derived ecosystem services cannot easily be directly measured, these models provide valuable ways to estimate and

quantify the ecosystem services and benefits of these systems. The biophysical metrics (e.g., the amount of carbon stored and air pollutants removed) and economic measures (e.g., dollar values saved due to improved air quality) provided by models are increasingly incorporated into trade-off analyses and decision making.

Although urban forest models have become increasingly available and case studies have been implemented in many locations worldwide, the estimated value of ecosystem services and benefits provided by urban forests remain highly uncertain. For example, by applying an uncertainty analysis to the i-Tree Eco model in New York City, Lin and Kroll (2020) estimated the uncertainty of i-Tree model outputs as 12.8% for carbon storage, 10.1% for carbon sequestration, 36.0% for isoprene emissions, and 25.2% for monoterpenes emissions. When quantifying the cooling potential of urban greenery using ENVI-met, Tsoka et al. (2018) estimated the uncertainty of model output, as indicated by the root mean square error derived by comparing modeled results and measured data, as 0.52-4.3°C for air temperature, and 2.7-13.9 °C for mean radiant temperature. When employing CFD modelling of the aerodynamic effect of trees on urban air pollution dispersion, Amorim et al. (2013) found the normalized mean squared error varied from 0.04 to 0.14, depending on model settings.

Overall, the uncertainty assessments of the outputs from urban forest models have been limited, and most scientific studies focus on examining output uncertainty from either a single case study and/or a single source of uncertainty (Nowak et al., 2008b). A comparative study, especially across diverse social, ecological and climatic contexts, is needed to more rigorously assess commonalities and ranges of output uncertainty and to systematically examine how these contextual factors affect the magnitudes of output uncertainty. The extent to which the magnitudes of uncertainty are dependent on factors such as city size, landscape heterogeneity, and diversity of environmental conditions requires a thorough synthesis of case studies across different urban settings. Another limitation of the existing studies is that they typically perform uncertainty assessments at the last stage of the modeling effort by comparing simulated results with measured data (when such data is available), and therefore it is challenging to disaggregate the derived magnitudes of output uncertainty due to different sources of uncertainty, or to extrapolate these results to other cities without such data. Users and decision-makers have limited information about the sources of uncertainty and their magnitudes, such as whether total uncertainty is driven by input measurements, sampling processes, or model structure. Such knowledge is important to provide guidance for future field plot data collection and model development.

To overcome these gaps and promote a better use of these tools, we perform an uncertainty assessment of the output from a popular urban forest model, i-Tree Eco, in 16 cities across the United States (US). Following a similar methodology as presented in Chapter 4, we examine the entire i-Tree Eco modeling process from input data collection, to the characterization of urban tree structure, to the subsequent estimates of the ecosystem services and benefits of urban trees. In this process, we develop and apply an uncertainty framework to quantify the magnitudes of input, sampling and model uncertainty, and based on that, derive an estimator of total output uncertainty. The objectives of this study are to: (1) estimate the total magnitude of uncertainty of i-Tree Eco output; (2) compare the magnitudes of different uncertainty sources to assess their relative importance; and (3) generalize these

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results to see if there are consistent and predictable relationships between uncertainty sources across different cities. Urban tree structure considered in this study includes leaf area and leaf biomass, and ecosystem services include biogenic volatile organic compound emissions (BVOC) (isoprene and monoterpenes), and carbon storage and sequestration. Such a comparative study, based on a network of US cities, can help facilitate generalized findings and develop improved estimators of output uncertainty. The provided knowledge can improve our ability to assess urban forest model outputs and help decision makers and urban forest scientists better incorporate model uncertainty into urban forest planning and management.

2 Study sites and data employed

2.1 Study sites

This study examined a network of 16 cities located in 15 states that have urban forest inventory field plot data available (Figure 5.1). The study sites are spread across the US and cover diverse social and ecological settings. The cities have a range of size and climatic conditions, and arid, boreal and temperate systems are represented. Table 5.1 provides a summary of the study sites, including the average annual precipitation and temperature, and city size.



Figure 5.1 The distribution of 16 cities examined in this study

2.2 Field data

Field data were sampled and collected based on the i-Tree Eco protocols developed by the USDA Forest Service (i-Tree Eco Field Guide, 2019). In each city, circular one-tenth acre plots were established using simple random sampling, and within plots, tree variables include species, diameter at breast height (DBH), tree height, crown height and width, tree condition, crown light exposure (CLE), and percent leaf dieback were measured (Nowak et al., 2008a). The number of field plots varied by city, ranging from 39 plots in Pittsburgh, PA to 745 plots in Chicago, IL. Inside each plot, the inventoried tree numbers also show a large variability, varying from 0 to 71 trees. The summarized information for plots and trees is also provided in Table 5.1, including the year the field plots were sampled, the number of field plots and total number of trees in the field plots, the species richness across plots, and the range of diameter at breast height (DBH) for the sampled trees.

| | Average annual | Average annual | City size | V | No. sampled | No. sampled | Species | |
|-----------------|--------------------|-----------------|-----------|---------|-------------|-------------|----------|----------------|
| City, State | precipitation (cm) | temperature (C) | (ha) | Year | plots | trees | richness | DBH range (cm) |
| Atlanta, GA | 119.6 | 16.3 | 34139 | 1997 | 205 | 2506 | 93 | 2.5-130 |
| Austin, TX | 87.1 | 20.8 | 158013 | 2015 | 207 | 2553 | 62 | 2.5-185 |
| Boston, MA | 112.3 | 9.8 | 14279 | 1996 | 217 | 955 | 82 | 2.5-144 |
| Casper, WY | 31.8 | 7.4 | 5466 | 2006 | 234 | 235 | 47 | 2.5-116 |
| Chicago, IL | 84.3 | 9.8 | 59805 | 2007 | 745 | 1795 | 102 | 2.0-116 |
| Gainesville, FL | 120.4 | 20.4 | 12174 | 2007 | 93 | 1414 | 84 | 5.1-241 |
| Golden, CO | 62.2 | 4.1 | 2447 | 2007 | 115 | 196 | 60 | 2.5-80 |
| Houston, TX | 115.1 | 20.6 | 173270 | 2004 | 332 | 2001 | 68 | 12.7-128 |
| Los Angeles, CA | 47.5 | 17.7 | 121774 | 2007/08 | 348 | 685 | 139 | 2.5-114 |
| Milwaukee, WI | 87.4 | 8.7 | 25057 | 2008 | 216 | 1169 | 82 | 2.5-114 |
| Minneapolis, MN | 77.2 | 9.4 | 15112 | 2004 | 110 | 282 | 41 | 2.5-117 |
| New York, NY | 117.3 | 13.3 | 78647 | 2013 | 296 | 1075 | 139 | 2.5-122 |
| Omaha, NE | 77.7 | 10.6 | 29873 | 2008/09 | 189 | 1005 | 26 | 2.5-145 |
| Phoenix, AZ | 20.4 | 23.9 | 134701 | 2013 | 204 | 270 | 65 | 2.5-89 |
| Pittsburgh, PA | 88.4 | 11.1 | 609 | 2010 | 39 | 501 | 62 | 2.5-114 |
| Washington, DC | 119.6 | 13.2 | 15915 | 2004 | 201 | 1002 | 106 | 2.2-180 |

Table 5.1 The sampled plot and tree information for 16 cities

2.3 Environment data

We obtained weather variables from the National Solar Radiation Database (NSRDB) (https://nsrdb.nrel.gov/). The weather variables considered in this study included temperature and solar radiation. The NSRDB consists of several serially complete collections of hourly and ½ hour values of meteorological data, including the Physical Solar Model (PSM) and the Meteorological Statistical Model 3 (MTS3). Although the MTS3 has a total of 1454 stations across the US, it still provides limited coverage for our study sites. To fully capture the spatial variability of meteorological data, we employed the PSM. The PSM covers the United States from 1998 to 2018, and has a temporal resolution of ½ hour and spatial resolution of 4 km by 4 km. The dataset is developed using a physical model, satellite products, and meteorological station data, and is updated over time as better technologies and new data sets become available (Habte et al., 2017; Sengupta et al., 2018). We downloaded the weather variables inside the city administrative boundary for the same year when the field data were collected for each city, and converted the ½ hour data to hourly data by averaging. We ran our simulation at an hourly time step using weather data for July of that year, which is typically the hottest month of the year in the US. For Atlanta, GA and Boston, MA, the plot data were collected in 1997 and 1996, respectively. We used the PSM data in 1998, the earliest available dataset, in these two cities. In each city, these data sets were assumed to be applicable to all plots in city.

3 Methods

3.1 Uncertainty analysis

Following the methodology of Lin and Kroll (2020), we used an uncertainty framework to quantify input, sampling, and model uncertainties, and an estimator of total uncertainty. Input uncertainty is mainly due to measurement errors of tree structure, and the spatial variability of weather variables. Sampling uncertainty comes from using the field plot data to assess the characteristics of the entire study area. Model uncertainty is due to the uncertainty of the employed model equations and parameters. To facilitate a comparison across different estimators of model outputs, the uncertainty magnitude is expressed as the coefficient of variation (CV), the ratio of the standard error of the estimator to the mean of the estimator. Similar to Lin and Kroll (2020), we employed Monte Carlo (MC) simulation to quantify input and model uncertainties, and bootstrap resampling to quantify sampling uncertainty. For both Monte Carlo and bootstrap simulations, we repeated the experiment 1000 times to calculate the CV.

3.1.1 Input uncertainty

A sensitivity analysis of i-Tree Eco modeling processes performed by Lin et al. (2020) identified the primary drivers of i-Tree Eco model output. Based on that analysis, we examined the impact of the variability of tree crown height, crown width, and DBH, as well as the spatial variability of temperature and photosynthetically active radiation (PAR). The measurement errors of tree structure were derived from the USDA Forest Service's Forest Inventory and Analysis (FIA) national core field guide using the method explained in Lin and Kroll (2020). Specifically, for crown height and crown width, the CVs of the measurement error were 0.0608 and 0.05, respectively; for DBH, the standard deviations (SDs) of the measurement error were 0.051 inches, 0.102 inches, and 0.153 inches for DBH varying from 1- 20 inches, 20-40 inches, and 40-60 inches, respectively. These estimators of measurement errors.

For weather variables, spatial variability across the entire city, rather than the errors in actual measurements, generally dominates input uncertainty. By employing all available NSRDB data within the city and assuming a serially correlated normal distribution for the errors in temperature and PAR (Situ et al., 2014; Zheng et al., 2010), we derived input uncertainty of weather variables by the following process. First, the mean of each weather variable at a specific hour on a specific day was calculated as:

$$\mu_{i,j} = \frac{\sum_{k=1}^{n} T_{i,j,k}}{n}$$
(1)

where $T_{i,j,k}$ is the weather variable (either temperature or PAR) on day i and hour j at the kth station, and n is the total number of stations. Second, the overall SD of the weather variable (σ) was estimated as a function of the SD for a specific hour of the day ($\sigma_{i,j}$) where:

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$$\sigma_{i,j} = \sqrt{\frac{\sum_{k=1}^{n} (T_{i,j,k} - \mu_{i,j})^2}{n-1}} \qquad (2)$$

and

$$\sigma = \sqrt{\frac{\sum_{i=1}^{31} \sum_{j=1}^{24} \sigma_{i,j}^2}{31*24}} \qquad (3)$$

As we ran our simulation on an hourly time step for the month of July at each study area, the denominator in Eqn (3) is 31 (days) * 24 (hours). Third, we obtained the residual error term for the weather variable by accounting for an hourly autocorrelation structure using an autoregressive model of order one (Salas, 1980):

$$\varepsilon_I = \emptyset_1 * \varepsilon_{I-1} + \varepsilon_{\varepsilon_I} \tag{4}$$

where ε_I is the input uncertainty of the weather variable at time t, ϕ_1 is the lag-1 autocorrelation derived from the hourly data from all available NSRDB, and $\varepsilon_{\varepsilon_I}$ is a random error term of the input uncertainty of a weather variable which is assumed to be normally distributed with a mean of 0 and a standard deviation of σ . A thousand sequences of ε_I were then simulated through our model for the month of July, and the standard deviation and CV of model outputs across all one thousand simulations were then calculated.

3.1.2 Sampling uncertainty

For sampling uncertainty, we employed a bootstrap simulation to quantify the uncertainty magnitude. Specifically, we resampled the entire number of plots in each city with replacement for 1000 iterations, and then calculated model output for each iteration. Using the results for all 1000 iterations, the standard error for each i-Tree Eco output estimator can be estimated (Efron, 1982), from which the CV for model outputs can be estimated.

3.1.3 Model uncertainty

Model uncertainty is represented as either errors or variability associated with the employed model equations and the model parameters. Specifically, i-Tree Eco estimates leafand carbon-related outputs using empirical allometric regression models. There are varying degrees of fitting errors when developing these equations, and prediction errors when applying these equations in new locations. We employed the mean square error (MSE_s) associated with these regression equations to represent the fitting errors. In addition, to capture the mean prediction errors, we incorporated the MSE_s to estimate model uncertainty $(\hat{\sigma}_M^2)$

$$\hat{\sigma}_{M}^{2} = MSE_{s} * (\frac{1}{n} + \frac{(X_{0} - \bar{X})^{2}}{\Sigma(X_{i} - \bar{X})^{2}})$$
 (5)

where n is the sample size used to develop the regression model, X_0 is the value of the explanatory variable for which the prediction is to be made, and \overline{X} is the mean of the explanatory variables, X_i , used to develop the regression model. In Eqn (5), we only have access to the MSE values associated with the original regression equations, and therefore we assumed that the data used to develop the equation had the same properties as the sampled field plot data (thus deriving X_i and \overline{X} from the field plot data). The model uncertainty was then quantified by applying Monte Carlo simulation to Eqn (5). We first randomly sampled an error term, ε_S , from a normal distribution with mean equal to zero and variance equal to the original MSE_S value for that allometric equation. We then replaced MSE_S by ε_S in Eqn (5), calculated a value for the model error term, ε_M , from this equation, added this value back to the original allometric equations, and then applied these equations to all trees using that specific allometric equation. We repeated the iteration 1000 times to calculate the CV for each output estimator.

i-Tree Eco estimates BVOC emissions based on the processes and protocols developed by the US Environmental Protection Agency (Hanna et al., 2005). The process consists of two steps: (1) estimating standardized emissions by multiplying the base genus emission rate by leaf biomass; and (2) converting standardized emissions to actual emissions based on environmental correction factors. These standard processes are also adopted by several other models, such as the Model of Emissions of Gases and Aerosols from Nature (Situ et al., 2014), and the Global Biosphere Emissions and Interactions System (Zheng et al., 2010). Therefore, rather than examining uncertainty of the modeling processes, we focused on the uncertainty derived from model parameters. We assumed that model parameters following specific distributions, used MC to randomly sample parameter values, and then estimated BVOC emissions with these parameter values. The CVs were then calculated using the output from 1000 iterations. The assumed distributions of these parameters were obtained from the literature (Hanna et al., 2005) and are presented in Table 5.2.

| Parameter | Original value in Eco | Unit | Distribution | Mean | SD |
|-----------|-----------------------|---------------|--------------|--------|--------|
| cT1 | 95000 | J*mol-1 | Lognormal | 95000 | 20000 |
| cT2 | 230000 | J*mol-1 | Lognormal | 230000 | 150000 |
| TM | 314 | К | Normal | 314 | 3 |
| cL1 | 1.066 | dimensionless | Normal | 1.06 | 0.2 |
| α | 0.0027 | µmol-1*m2*s | Lognormal | 0.0027 | 0.0015 |
| β | 0.09 | K-1 | Lognormal | 0.09 | 0.02 |

Table 5.2 Statistical information of main model parameters to estimate BVOC emissions

3.1.4 Total uncertainty

In addition to estimating the input, model and sampling uncertainties for each Eco output estimator, we also calculated the total uncertainty. Assuming the input, model and sampling uncertainty is independent, we estimate the CV of total uncertainty as:

$$CV_{Total} = \frac{\sqrt{(CV_{Input} * Estimate)^{2} + (CV_{Model} * Estimate)^{2} + (CV_{Sampling} * Estimate)^{2}}}{Estimate}$$
(6)

4 Results

Table 5.3 displayed the results for uncertainty analyses for leaf area (LA) and leaf biomass (LB) estimators. The uncertainty magnitudes were expressed by the CV values. Since LB was calculated by multiplying LA and a species-specific constant value, LA and LB displayed almost identical results. The following description focused on LA. For LA, the magnitudes of total uncertainty across 16 cities averaged 12.4%, and ranged from 8.1% to 18.5%. For LA estimator, sampling uncertainty primarily contributed to the magnitude of total uncertainty, while input and model uncertainties had much smaller impacts. The maximum magnitudes for both input and model uncertainties for LA estimator were less than 2% across all 16 cities. In contrast, the magnitudes of sampling uncertainty were greatly higher, with average values being 12.3% for LA. In addition, Sampling uncertainty varied largely across different cities. For LA, the range is from 8.0% (Chicago, IL) to 18.5% (Austin, TX).

| | Leaf area (CV: %) | | | Leaf biomass (CV: %) | | | | |
|--------------------|-------------------|----------|-------|----------------------|-------|----------|-------|-------|
| City, State | Input | Sampling | Model | Total | Input | Sampling | Model | Total |
| Atlanta, GA | 0.4 | 9.2 | 1.4 | 9.3 | 0.4 | 8.7 | 1.4 | 8.8 |
| Austin, TX | 1.6 | 18.5 | 0.7 | 18.5 | 1.0 | 13.9 | 0.7 | 14.0 |
| Boston, MA | 0.5 | 9.7 | 1.6 | 9.9 | 0.5 | 9.7 | 1.7 | 9.8 |
| Casper, WY | 1.1 | 15.2 | 1.2 | 15.3 | 1.2 | 16.3 | 1.5 | 16.4 |
| Chicago, IL | 0.4 | 8.0 | 1.4 | 8.1 | 0.4 | 8.0 | 1.5 | 8.1 |
| Gainesville, FL | 0.6 | 13.5 | 1.0 | 13.6 | 0.6 | 12.0 | 1.0 | 12.1 |
| Golden, CO | 1.1 | 17.1 | 1.7 | 17.2 | 1.1 | 18.5 | 1.9 | 18.6 |
| Houston, TX | 0.3 | 9.4 | 1.5 | 9.6 | 0.4 | 9.9 | 1.5 | 10.0 |
| Los Angeles, CA | 0.7 | 8.9 | 1.6 | 9.1 | 0.7 | 8.8 | 1.7 | 8.9 |
| Milwaukee, WI | 0.6 | 9.8 | 1.3 | 9.9 | 0.7 | 10.4 | 1.4 | 10.5 |
| Minneapolis, MN | 0.9 | 11.4 | 1.1 | 11.5 | 0.9 | 11.7 | 1.2 | 11.8 |
| New York, NY | 0.7 | 11.0 | 1.7 | 11.3 | 0.7 | 10.9 | 1.8 | 11.1 |
| Omaha, NE | 0.6 | 11.8 | 0.9 | 11.8 | 0.6 | 14.3 | 1.0 | 14.3 |
| Phoenix, AZ | 0.8 | 13.0 | 1.8 | 13.1 | 0.9 | 14.5 | 1.8 | 14.6 |
| Pittsburgh, PA | 0.9 | 15.4 | 0.3 | 15.4 | 0.9 | 15.6 | 0.3 | 15.6 |
| Washington, DC | 0.7 | 14.1 | 0.5 | 14.1 | 0.7 | 13.3 | 0.5 | 13.4 |
| Mean | 0.7 | 12.2 | 1.2 | 12.4 | 0.7 | 12.3 | 1.3 | 12.4 |
| Standard deviation | 0.3 | 3.1 | 0.5 | 3.1 | 0.3 | 3.1 | 0.5 | 3.0 |

Table 5.3 Uncertainty magnitudes for leaf area and leaf biomass

Table 5.4 contained the results for carbon storage and sequestration. The average magnitude of total uncertainty across 16 cities for carbon storage was 13.5% (ranging from 8.7% to 19.1%), while for carbon sequestration the average total uncertainty was 11.1% (ranging from 6.9% to 17.5%). Among the three sources of uncertainty, sampling uncertainty played the most dominant role, model uncertainty had a small influence, and input uncertainty had a negligible effect. By comparing the magnitudes of sampling, input, model and total uncertainties for carbon storage and sequestration, we can clearly see that total uncertainty was primarily impacted by sampling uncertainty.

| | Carbon storage (CV: %) | | | | Carbon sequestration (CV: %) | | | |
|--------------------|------------------------|----------|-------|-------|------------------------------|----------|-------|-------|
| City, State | Input | Sampling | Model | Total | Input | Sampling | Model | Total |
| Atlanta, GA | 0.0 | 9.1 | 0.8 | 9.1 | 0.0 | 8.5 | 0.8 | 8.5 |
| Austin, TX | 0.0 | 10.0 | 0.4 | 10.0 | 0.0 | 7.9 | 0.4 | 7.9 |
| Boston, MA | 0.0 | 10.7 | 1.0 | 10.7 | 0.0 | 9.0 | 1.0 | 9.0 |
| Casper, WY | 0.1 | 19.1 | 1.4 | 19.1 | 0.0 | 14.6 | 1.7 | 14.7 |
| Chicago, IL | 0.0 | 8.7 | 0.7 | 8.7 | 0.0 | 6.8 | 0.7 | 6.9 |
| Gainesville, FL | 0.0 | 18.1 | 0.6 | 18.1 | 0.0 | 15.2 | 0.7 | 15.2 |
| Golden, CO | 0.1 | 18.1 | 1.5 | 18.2 | 0.0 | 15.3 | 2.1 | 15.5 |
| Houston, TX | 0.0 | 10.4 | 0.5 | 10.4 | 0.0 | 8.5 | 0.5 | 8.5 |
| Los Angeles, CA | 0.0 | 10.4 | 0.8 | 10.4 | 0.0 | 8.3 | 2.0 | 8.5 |
| Milwaukee, WI | 0.0 | 14.2 | 1.1 | 14.3 | 0.0 | 9.5 | 1.3 | 9.6 |
| Minneapolis, MN | 0.1 | 15.9 | 2.2 | 16.0 | 0.0 | 12.6 | 2.4 | 12.8 |
| New York, NY | 0.0 | 12.6 | 1.6 | 12.8 | 0.0 | 10.0 | 1.2 | 10.1 |
| Omaha, NE | 0.0 | 13.0 | 1.2 | 13.0 | 0.0 | 10.5 | 1.1 | 10.5 |
| Phoenix, AZ | 0.1 | 15.9 | 0.5 | 15.9 | 0.0 | 12.3 | 0.6 | 12.4 |
| Pittsburgh, PA | 0.0 | 16.5 | 1.6 | 16.6 | 0.0 | 17.3 | 2.4 | 17.5 |
| Washington, DC | 0.0 | 12.1 | 1.2 | 12.2 | 0.0 | 9.9 | 2.6 | 10.3 |
| Mean | 0.0 | 13.4 | 1.1 | 13.5 | 0.0 | 11.0 | 1.4 | 11.1 |
| Standard deviation | 0.0 | 3.5 | 0.5 | 3.5 | 0.0 | 3.2 | 0.8 | 3.2 |

Table 5.4 Uncertainty magnitudes for carbon storage and sequestration

For BVOC emissions, the total uncertainty average was 40.7% (range is from 30.4% to 57.6%) for isoprene and 25.0% (range is from 16.7% to 32.9%) for monoterpenes (Table 5.5). The magnitudes of uncertainty for BVOCs were much larger than the corresponding values for both leaf and carbon estimators. All three sources of uncertainty played important roles for estimating total uncertainty for BVOC emissions. When examining the average values of uncertainty for isoprene, the order of uncertainty magnitude was model (26.8%) > sampling (24.0%) > input (17.3%); for monoterpene emissions, the order of average uncertainty magnitude was sampling (17.8%) > input (12.2%) > model (11.1%).

For both isoprene and monoterpene emissions, sampling uncertainty had the largest standard deviation (SD) across the 16 cities (last row in Table 5.5). For isoprene emissions, input uncertainty had a larger SD than model uncertainty, while the opposite was observed for

monoterpene emissions. This is probably because input uncertainty is due to the spatial variability of both temperature and PAR for isoprene emissions, while only spatial variability of temperature affects input uncertainty for monoterpene emissions. When looking at input uncertainty of isoprene emissions, the majority of cities had similar magnitudes except for Omaha, NE. This is probably because the spatial variability of PAR in Omaha, NE (SD 539.7 μ mol/m2/s) is much larger than that of other cities in this study (SD of approximately 100-250 μ mol/m2/s). For the input uncertainty of monoterpene emissions, the average magnitude across 16 cities was 12.1%. The lowest input uncertainty of monoterpenes, 7.9%, was in Golden, CO, which is due to the low spatial variability of temperature (SD of 0.9 °C compared with an average SD of 1.2 °C for other cities) in this relatively small city.

Surprisingly, the SD of model uncertainty for isoprene emissions, which is derived from 5 model parameters, was less than that for monoterpene emissions, which is only due to the change of one model parameter. This relatively large SD for model uncertainty of monoterpene emissions is primarily driven by several cities (e.g., Austin, TX and Houston, TX) that have relatively small CVs. When looking at model uncertainty of these two cities, the variability due to the model parameters is comparable to other cities. However, the majority of genera in Austin, TX have low base emitting rates (< 1 ug/g/hr), and the majority of trees in Houston, TX have very low leaf biomass. i-Tree Eco calculates BVOC emissions by multiplying genus base emitting rates, leaf biomass volumes and environmental correction factors; a narrow distribution of either base emitting rates or leaf biomass volumes could result in a low magnitude of model uncertainty.

| | Isoprene emissions (CV: %) | | | | Monoterpene emissions (CV: %) | | | |
|--------------------|----------------------------|----------|-------|-------|-------------------------------|----------|-------|-------|
| City, State | Input | Sampling | Model | Total | Input | Sampling | Model | Total |
| Atlanta, GA | 16.2 | 11.2 | 23.4 | 30.5 | 12.0 | 10.0 | 5.8 | 16.7 |
| Austin, TX | 14.6 | 34.6 | 22.5 | 43.8 | 11.1 | 13.0 | 2.4 | 17.3 |
| Boston, MA | 17.3 | 17.9 | 31.6 | 40.3 | 11.8 | 13.8 | 17.9 | 25.5 |
| Casper, WY | 15.1 | 20.2 | 25.0 | 35.5 | 11.1 | 29.3 | 10.1 | 32.9 |
| Chicago, IL | 19.3 | 21.0 | 29.2 | 40.9 | 13.4 | 10.1 | 15.5 | 22.8 |
| Gainesville, FL | 14.1 | 17.7 | 23.6 | 32.7 | 10.3 | 15.4 | 6.0 | 19.5 |
| Golden, CO | 11.1 | 30.6 | 27.5 | 42.6 | 7.9 | 29.0 | 13.4 | 32.9 |
| Houston, TX | 16.2 | 11.3 | 23.1 | 30.4 | 11.8 | 15.4 | 5.2 | 20.1 |
| Los Angeles, CA | 23.4 | 17.0 | 26.5 | 39.2 | 16.5 | 15.4 | 12.4 | 25.8 |
| Milwaukee, WI | 16.6 | 26.9 | 31.1 | 44.4 | 11.4 | 14.8 | 17.4 | 25.5 |
| Minneapolis, MN | 16.1 | 45.3 | 31.6 | 57.6 | 10.6 | 19.7 | 17.8 | 28.6 |
| New York, NY | 16.9 | 18.3 | 26.0 | 36.0 | 11.9 | 19.0 | 11.5 | 25.2 |
| Omaha, NE | 33.0 | 30.2 | 28.1 | 52.8 | 18.0 | 16.4 | 13.9 | 28.0 |
| Phoenix, AZ | 12.9 | 37.9 | 27.0 | 48.3 | 12.9 | 26.1 | 7.2 | 30.0 |
| Pittsburgh, PA | 16.2 | 27.5 | 25.8 | 41.0 | 11.5 | 20.6 | 11.1 | 26.1 |
| Washington, DC | 17.2 | 16.8 | 26.0 | 35.3 | 12.1 | 17.0 | 10.6 | 23.4 |
| Mean | 17.3 | 24.0 | 26.7 | 40.7 | 12.1 | 17.8 | 11.1 | 25.0 |
| Standard deviation | 5.0 | 9.7 | 3.0 | 7.6 | 2.3 | 5.9 | 4.8 | 4.9 |

Table 5.5 Uncertainty magnitudes for isoprene and monoterpene emissions

5 Discussion

It is either infeasible or cost prohibitive to measure tree variables (e.g., leaf area and leaf biomass) and tree-derived ecosystem services, especially across an entire city. Urban forest models provide valuable tools to estimate tree structure and their ecosystem services. Although the estimators provided by the models are beneficial to the planning and management of urban trees, they contain uncertainty. For the total uncertainty of leaf and carbon estimators, our results indicate this uncertainty is primarily driven by sampling uncertainty (Tables 5.3 and 5.4). In contrast, for isoprene and monoterpene emissions, the relationships between total uncertainty and each source of uncertainty across our 16 study cities are more complicated. As shown in Figure 5.2, the ratios of each source of uncertainty



to total uncertainty varied greatly across the 16 cities for both isoprene and monoterpene emissions. These large variations prevent an effective generalization across cities.

Figure 5.2 The ratios between each source of uncertainty and total uncertainty for BVOC emissions across 16 cities

In addition to the regression fitting errors, various aspects of applying these equations could also increase model uncertainty. Each equation is developed based on observational data that have specific ranges and are collected at specific locations. As we are not privy to the data from which these equations were developed, we may be applying these equations to predict values outside the range of the data used to develop them and in different climatic conditions, both of which are likely to increase the magnitude of uncertainty (McPherson et al., 2016). In addition, the selection of allometric equations can also contribute to uncertainty. The selection of an incorrect equation (due to species misidentification) or an average genus equation (due to the lack of a species-specific model) is likely to introduce errors in model predictions (Van Breugel et al., 2011). When quantifying carbon estimators for open-grown trees, i-Tree Eco adopts a correction factor of 0.8 to forest-derived equations. The correction factor is based on a study on urban trees in Chicago that open-grown trees have on average

20% less biomass than traditional forest trees (Nowak, 1994). However, several studies reported that this standard correction approach may result in either over-estimation or underestimation of carbon storage (McHale et al., 2009; Aguaron and McPherson, 2012). More studies related to urban tree versus rural tree carbon storage are warranted.

Compared with the empirical approaches for leaf and carbon estimators, i-Tree Eco quantifies BVOC emissions based on mechanistic processes. This mechanistic approach is based on a comprehensive database of genus based emission rates. Our reported magnitudes of model uncertainty of BVOC emissions are based on examining variability of model parameters while ignoring the uncertainty of the base emission rate database. The results of this experiment indicate that the magnitudes of model uncertainty derived from model parameters could be low if the study area primarily has species with a similar base emission rate.

Input variables for i-Tree Eco include tree structure and meteorological variables. The input uncertainty due to tree structure measurements is most likely low because we adopted the criteria of the USDA Forest Service's FIA national core field guide to represent tree structure uncertainty. The criteria are set up for experienced urban forestry practitioners. Many urban forest programs employ citizen scientists to collect tree attribute data (Roman et al., 2017), which may result in larger measurement errors and input uncertainty than the results reported in this study. In addition, some circumstances, such as multi-stemmed trees, leaning trees, and trees on slopes, may also increase measurement errors. More studies and criteria to measure tree structure for these special cases are needed (Magarik et al., 2020). Unlike tree structure measurements, meteorological variables contribute greatly to input

uncertainty. i-Tree Eco first estimates standardized BVOC emissions at a temperature of 30 °C and a PAR flux of 1000 μ mol*m⁻²*s⁻¹, and then converts these emissions by multiplying by temperature and light and correction factors which are calculated based on local temperature and PAR values, which are impacted by the spatial uncertainty of these variables.

For all 16 cities, sampling uncertainty for BVOC emissions is larger than that for leaf and carbon estimators, while the sampling uncertainty for leaf and carbon estimators have similar magnitudes. The plots across most cities have a wide range of tree densities. Tree variables that most impact leaf and carbon estimators are crown height and width, and DBH, respectively. For BVOC emissions, the sampling process results in the variability of both leaf biomass estimators and genus based emission rates; the differences of base emission rates across species can be up to a factor of 70 for isoprene, and 8 for monoterpenes (Nowak et al., 2002). These two confounded effects result in relatively large sampling uncertainty for BVOC emissions.

6 Conclusions

This study developed an uncertainty framework to quantify the magnitudes associated with input, sampling, and model uncertainties. We developed and applied an uncertainty framework to a network of 16 cities across the US to examine the uncertainty magnitudes and variability of several forest structure and ecosystem services estimators from i-Tree Eco. The average magnitude of total uncertainty across 16 cities is 12.4% for leaf area, 12.4% for leaf biomass, 13.5% for carbon storage, 11.1% for carbon sequestration, 40.7% for isoprene emissions, and 25.0% for monoterpene emissions. For leaf and carbon estimators, the total
uncertainty is primarily driven by sampling uncertainty while input and model uncertainties have much smaller effects; the magnitudes of all three sources of uncertainty relative to the total uncertainty are comparable across the 16 cities. In contrast, all input, sampling, and model uncertainties contribute to the total uncertainty for isoprene and monoterpene emission estimators, and there are large variations in these three sources of uncertainty across 16 cities.

Our findings for input, sampling, and model uncertainties have important implications for future field data collection, sampling design, model development and application. We suggest improving the spatial representation of meteorological variables, and establishing measurement criteria to reduce the uncertainty of field measurements. Since sampling uncertainty is important for all i-Tree Eco estimators, future studies on improving sampling strategies for field data collection and utilizing auxiliary information to reduce sampling uncertainty are warranted. Regarding model uncertainty, we suggest developing urban- and species-specific allometric relationships when not available. We believe our analyses and our suggested future directions could improve our understanding of model output as well as how to incorporate model output in decision-making, and advance the science of urban forest modeling.

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Chapter 6 Conclusions and future directions

1 Conclusions

This dissertation first presents a thorough review of urban forest models, and then performs sensitivity and uncertainty analyses for an urban forest model, i-Tree Eco. By employing field plot data, meteorological variables, and air pollution data, i-Tree Eco can quantify urban forest structure (e.g., leaf area and leaf biomass) and numerous forest-related ecosystem services (e.g., biogenic volatile organic compounds (BVOCs) emissions, carbon storage and sequestration, and air pollution removal). For the sensitivity analyses, we evaluated the relative impact of tree structure measures and meteorological variables on model outputs using Morris one-at-a-time and variance-based decomposition methods. For the uncertainty analyses, we assessed the uncertainties associated with input data, sampling methods and employed models by bootstrap and Monte Carlo simulations.

In Chapter 1, four hypotheses related to urban forest models and the sensitivity and uncertainty of i-Tree Eco were formulated. Below, each of these hypotheses is presented, and conclusions based on results from the experiments in Chapters 2 -5 are formulated.

Hypothesis 1: All the urban forest models are equally applied and are used to estimate similar ecosystem services.

In Chapter 2, we reviewed case studies of urban forest modeling practices over the past two-decades. Based on the identified 242 peer-viewed papers and 476 case studies, we performed a comparative analysis of the similarities and differences among urban forest models. We reached the conclusion that the most commonly used models are the i-Tree

toolset, ENVI-met, computational fluid dynamic models, and the Hedonic price model. In addition to the popularity of model, other characteristics of model applications were also summarized as follows: (1) the spatial distribution of case studies is primarily clustered in the US, Europe, and China, with the most popular units to model being streets and parks; (2) uncertainty assessments of urban forest models is limited; (3) spatially explicit models are critically important for estimating ecosystem services as well as for environmental management; (4) most case studies focus on the biophysical benefits of urban forests with few studies estimating economic and social benefits; and (5) linkages between urban forests and their social-psychological and health effects are less common due to subjectivity and uncertainty in expressing and quantifying human cultures, attitudes and behaviors. The review in Chapter 2 suggested that it is important to perform sensitivity and uncertainty analyses to increase the credibility of the modeling processes and to facilitate the effective use of model outputs in urban forest decision-making. The results presented in Chapter 2 lead to a rejection of this hypothesis; all urban forest models are not equally applied.

Hypothesis 2: All input variables contribute equally to the uncertainty of model outputs.

Chapter 3 employed a Morris one-at-a-time method and a variance-based decomposition method to analyze the relative impact of different i-Tree Eco inputs on outputs, and bin regression analyses to characterize the input-output relationships. Based on a case study in New York City in 2013, we made conclusions that: (1) genus has the largest influence on BVOC emissions by determining base emission rates and its high interactions with other input factors; (2) carbon storage shows a convex relationship with diameter at

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breast height (DBH), while carbon sequestration is sensitive to DBH, crown light exposure, and tree condition in a linear manner; and (3) dry deposition velocity is sensitive to leaf area index and relative humidity in a nearly linear fashion, and sensitive to temperature and PAR in a concave manner. Model outputs are affected by not only model inputs but also by model development (e.g., the adopted model equations and model parameters) and model applications (e.g., sampling strategy). It is necessary to fully and systemically explore various aspects of modeling practices to quantify the total uncertainty of model output estimators. The results presented in Chapter 3 lead to a rejection of this hypothesis; the impact of input variables on i-Tree Eco output varies widely.

Hypothesis 3: All three sources (input, model and sampling) of uncertainty contribute equally to the total uncertainty estimators.

Chapter 4 developed an uncertainty framework to assess the uncertainties throughout the i-Tree Eco modeling process from input dataset collection, to urban forest characterization, to subsequent estimators of ecosystem services. This includes input, sampling and model uncertainties. We quantified uncertainty magnitudes by employing bootstrap and Monte Carlo simulations, and aggregated the three sources of uncertainty to derive an estimator of total uncertainty. Through a case study in New York City in 2013, we found the magnitude of total uncertainty is estimated as 11.3% for leaf area, 11.1% for leaf biomass, 12.8% for carbon storage, 10.1% for carbon sequestration, 36.0% for isoprene emissions, 25.2% for monoterpene emissions, 71.3% for nitrogen dioxide removal, 80.5% for sulfur dioxide removal, and 58.5% for ozone removal. For leaf and carbon estimators, the total uncertainty was driven by sampling uncertainty while input and model uncertainties have negligible effects. For BVOC emissions, all three sources of uncertainty contribute similarly to total uncertainty. For air pollution removal, the total uncertainty is driven primarily by both input and model uncertainties, while sampling uncertainty has a more moderate influence. The results presented in Chapter 4 and 5 lead to a rejection of this hypothesis; for leaf area, leaf biomass, carbon storage and carbon sequestration, sampling uncertainty overwhelms input and model fitting uncertainty.

Hypothesis 4: The characteristics of three sources of uncertainty (input, model and sampling) are consistent across 16 US cities.

Chapter 5 applied the same framework and methodology developed in Chapter 4 to a network of 16 cities across the US that have diverse social and ecological settings. The results show that the average magnitudes of total uncertainty across 16 cities are 12.4% for leaf area, 13.5% for carbon storage, 11.1% for carbon sequestration, 40.7% for isoprene emissions, and 25.0% for monoterpene emissions. For leaf and carbon estimators, the total uncertainty is primarily driven by sampling uncertainty, while input and model uncertainties have much smaller effects on total uncertainty. The magnitudes of all three sources of uncertainty are similar across the 16 study cities. In contrast, input, sampling, and model uncertainties contribute to the total uncertainty for isoprene and monoterpene emission estimators, and there are large variabilities in these three sources of uncertainty across the 16 study cities. The results presented in Chapter 5 lead to a rejection of this hypothesis; the three sources of uncertainty vary widely across our study cities.

2 Future directions

This dissertation focuses on sensitivity and uncertainty analyses for i-Tree Eco. We focused not only on model development, but also on input data collection, sampling processes, and model application. Because model outputs and their uncertainty are affected by every component of the modeling practices, our efforts were to attempt to assess the contributions of different drivers of model output uncertainty. Although we focus on evaluating i-Tree Eco, the developed methods and framework could be applied to other urban forest models which have similar structure and function, and the findings and conclusions have general implications for urban forest modeling practices. Based on a systematic literature review and case studies in 16 cities, we can make the following suggestions for urban forest modeling:

(1) Improve the spatial representation of meteorological weather and air pollutant concentration monitors. For some environmental variables (e.g., photosynthetically active radiation) that cannot be directly measured, it is important to develop improved methods for estimating these variables. Advances in remote sensing technologies may improve the spatial representation and estimation of some of these variables.

(2) Improve sampling strategies for field data collection, and examine the effects of different sampling strategies. For example, it is beneficial to compare the relative impacts of sampling method and sampling intensity, and the resulting uncertainty from the sampling strategy. Users should balance the cost of increased sampling with the resulting decrease in sampling uncertainty.

(3) Establish tree structure measurement criteria for citizen scientists.

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(4) Develop urban-specific and species-specific allometric equations to quantify leaf and carbon estimators, and compare allometric equations in i-Tree with other locally developed equations.

(5) Improve our understanding of the various roles model parameters play in the dry deposition process, and perform experiment to validate models of dry deposition removal by urban trees.

(6) Perform comparative studies of urban forest services and benefits in a wide area of study sites, including cities outside the US, to examine the consistency of model performance, assess commonalities in model outputs, and explore the ranges of model output uncertainty. In addition, it is also important to reveal major driving factors that drive the uncertainty magnitudes in particular cities, so that the results can be extrapolated and used in other cities.

(7) Perform numerous case studies where there are measurements to verify model outputs. For example, urban flux towers can be built to verify the accuracy of air pollution removal effects of i-Tree Eco. Such measurement networks are critical to the development of model improvement and the assessment of model estimators.

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Curriculum Vitae

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