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Research article

Uncertainties in mapping forest carbon in urban ecosystems

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ABSTRACT

Spatially explicit urban forest carbon estimation provides a baseline map for understanding the variation in forest vertical structure, informing sustainable forest management and urban planning. While high-resolution remote sensing has proven promising for carbon mapping in highly fragmented urban landscapes, data cost and availability are the major obstacle prohibiting accurate, consistent, and repeated measurement of forest carbon pools in cities. This study aims to evaluate the uncertainties of forest carbon estimation in response to the combined impacts of remote sensing data resolution and neighborhood spatial patterns in Charlotte, North Carolina. The remote sensing data for carbon mapping were resampled to a range of resolutions, i.e., LiDAR point cloud density – 5.8, 4.6, 2.3, and 1.2 pt s/m^2, aerial optical NAIP (National Agricultural Imagery Program) imagery – 1, 5, 10, and 20 m. Urban spatial patterns were extracted to represent area, shape complexity, dispersion/interspersion, diversity, and connectivity of landscape patches across the residential neighborhoods with built-up densities from low, medium-low, medium-high, to high. Through statistical analyses, we found that changing remote sensing data resolution introduced noticeable uncertainties (variation) in forest carbon estimation at the neighborhood level. Higher uncertainties were caused by the change of LiDAR point density (causing 8.7–11.0% of variation) than changing NAIP image resolution (causing 6.2–8.6% of variation). For both LiDAR and NAIP, urban neighborhoods with a higher degree of anthropogenic disturbance unveiled a higher level of uncertainty in carbon mapping. However, LiDAR-based results were more likely to be affected by landscape patch connectivity, and the NAIP-based estimation was found to be significantly influenced by the complexity of patch shape.

1. Introduction

Urban forests can provide a myriad of ecosystem services, such as air pollution reduction, biodiversity preservation, climate amelioration, water quality improvement, and leisure enhancement to improve public health and human development (Dwyer et al., 1992; Wear et al., 1998; Tyrväinen and Miettinen, 2000; Alvey, 2006; Nowak et al., 2013). In North America, municipal governments play a vital role in protecting, planting, and maintaining trees that grow on public lands (e.g., street and park trees). A number of cities have developed urban forest management plans (e.g., Charlotte, Seattle, Baltimore, and NYC) to address the growing challenge of declining forest health and extent due to rapid urban development (City of Baltimore 2007; City of Seattle, 2013; City of New York 2014). However, the majority of urban trees actually grow on private lands with limited site accessibility. City managers are facing a common challenge that a municipal-scale forest conservation plan needs to be developed using forest inventories that are biased to street and park trees (Clark et al., 1997).

Remote sensing offers an ideal tool to provide spatially explicit characterization of urban forest with minimum field efforts to address this challenge. Recently, the advances in sensor technology allow the practitioners to retrieve both the forest horizontal structures (e.g., canopy cover – the horizontal extent of canopies

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per unit land area) and vertical structures (e.g., tree height and carbon storage). Although canopy cover has been a popular parameter to imply the effectiveness of forest management, carbon storage is drawing increasing attention, because it can describe tree growth (e.g., old *versus* young, healthy *versus* damaged) in a more accurate way (Singh et al., 2015a,b). Knowing how much carbon is stored by urban forest can further assists in developing effective climate change mitigation efforts, such as supplying marketable carbon emission offsets in a carbon trading program (Poudyal et al., 2010).

The nature of fragmented development in an urban setting often leads to small, isolated tree patches surrounded by abiotic components. Therefore, high-spatial resolution (hereafter *h-res*) remote sensing data is particularly beneficial for urban forest management. Forest carbon estimation requires accurate answers to two questions: where are the trees? And how much carbon is stored in the spotted trees? The first question can be well addressed by h-res optical sensors, because they have the capacity to differentiate complex land cover types (e.g., forest *versus* building) based on the distinct spectral, spatial, and/or temporal characteristics of fine-scale ground objects (Blaschke et al., 2014). Once trees are located, structural data such as small footprint LiDAR point clouds are ideal to extract plant vertical structure, including understory vegetation (Shrestha and Wynne, 2012; Singh et al., 2015b).

While theoretically promising, applying h-res remote sensing to map forest carbon storage at the municipal scale is often restrained by limited budget, as the costs associated with h-res data acquisition and processing remain high. A potential solution is to use coarser-resolution data. But, can such data still generate satisfactory results meeting the needs of urban forest management? Previous efforts exploring the resolution-accuracy relationship mainly focused on natural forests (e.g., Treitz et al., 2012; Jakubowski et al., 2013). However, studying the similar topic in an urban setting has received less attention (Singh et al., 2015a). This is because urban environments are highly fragmented where neighborhoods vary by levels of forest fragmentation. It is likely that the neighborhood development patterns (e.g., low *versus* high built-up density) further complicate the resolution-accuracy relationship in an urban setting.

To inform effective urban forest management while reducing costs, this study aims to improve our understanding of the uncertainties in urban forest carbon mapping through assessing the joint impacts of remote sensing data resolution and neighborhood patterns. We integrated h-res remote sensing data from aerial photography and airborne LiDAR to estimate spatially explicit forest carbon distributions across the Charlotte metropolitan area of North Carolina, United States. The variation in carbon estimation was generated using multiple resolutions of data from aerial imagery and LiDAR point clouds, respectively. We further applied statistical modeling to quantify how such data resolution-induced variation was affected by urban spatial patterns at the neighborhood level.

2. Study area

Our study area covered the entire Charlotte–Mecklenburg County (CMC) of North Carolina, United States, with a size of 1415 km^2 centered at 35°15′N, 80°50′W (Fig. 1). Charlotte, the largest city in North Carolina, has earned the title of "The City of Trees", and is recognized as one of the "10 best cities for urban forests" by American Forests, the oldest national non-profit citizen conservation organization (American Forests, 2014). Forested landscapes of Charlotte are primarily comprised of secondary growth oak-hickory-pine trees (BenDor et al., 2014). According to the most recent city-maintained forest inventory, approximately 86% of all street trees (~180,000) in Charlotte are deciduous trees with 39% being large maturing species (trees that will grow >40') (City of Charlotte (2013)). Five dominant species, including crape myrtle (*Lagerstroemia* spp.), willow oak (*Quercus phellos*), red maple (*Acer rubrum*), callery pear (*Pyrus calleryana*), and dogwood (*Cornus florida*), represent 50% of the total street tree population, while the remainder is comprised of sugar maple (*Acer saccharum* Marsh.), sweetgum (*Liquidambar*), eastern redcedar (*Juniperus virginiana*), and pear (*Pyrus* spp.) (City of Charlotte (2013)). The trees on private lands, however, still lack detailed inventories compared to the street trees.

Since the mid-1980s, the Charlotte metropolitan area has become one of the fastest developing regions of the southeastern United States. According to U.S. Census Bureau (2015), CMC has grown in population from 0.4 million in 1980 to over 1 million people in 2014, a trend that is expected to continue. The rapid population growth, manifested by an urban geography of low, medium to high housing density, has replaced landscapes dominated by native forest and farmland with an array of developed land use types including managed treescapes and highly fragmented urban forests (BenDor et al., 2014).

3. Data

3.1. Field data

Field mensuration was conducted during 2010–2012 as part of the Charlotte ULTRA-Ex (Urban Long-Term Research Areas Exploratory) study designed to analyze socio-ecological interactions driving the persistence of private forest (Singh et al., 2015b). This research selected a total of 56 circular plots (0.04 ha each) across deciduous (25 plots) and coniferous (21 plots) forests. Those field plots were designed to cover a variety of major species types in the study area, such as Shagbark Hickory (*Carya ovata*), Sweet Gum (*Liquidambar styraciflua*), White Oak (*Quercus alba*), Tulip Poplar (*Liriodendron tulipifera*), Winged Elm (*Ulmus alata*), Willow Oak (*Quercus phellos*), Loblolly Pine (*Pinus taeda*), Mockernut Hickory (*Carya tomentosa*), Pignut Hickory (*Carya glabra*), Tulip Poplar (*Liriodendron tulipifera*), Red Maple (*Acer rubrum*), Short Leaf Pine (*Pinus echinata*), and Eastern Red Cedar (*Juniperus virginiana*). Within each plot, we measured geographic coordinate, tree diameter at the breast height (DBH), species composition, and merchantable tree height. If a plot consisted of over 75% deciduous or coniferous trees, we labeled the plot as deciduous or coniferous, respectively otherwise we labeled plots as mixed plots. We applied the classic Jenkins allometric equations (Jenkins et al., 2003) to calculate forest aboveground biomass (AGB) for all the field plots by following Godwin et al. (2015). Although we recognized that Jenkins equations were developed and complied for a larger areal extent of contiguous United States, the results were considered 'ground truth' due to the lack of local equations. McPherson et al. (2013) also argued that such errors are smaller than the high variation in tree growth in urban environments.

3.2. Remote sensing data

Two types of remote sensing data were utilized in this project, including LiDAR point clouds, and NAIP (National Agriculture Imagery Program) multispectral imagery. LiDAR data were acquired by the Storm Water Services Division of Charlotte-Mecklenburg County government office in April 2012, as part a long-term flooding monitoring project. Original data acquisition was carried out using Optech's ALTM Gemini 3100 LiDAR system (Optech Incorporated, Vaughan, Canada), at point densities of 1.0 pts/m^2 for the entire region and 5.8 pts/m^2 for forest-covered areas. We used a