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Estimation of urban woody vegetation cover using multispectral imagery and LiDAR

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ABSTRACT

Urban vegetation is an important resource in built up environments, and estimation of urban canopy cover arising from trees and shrubs is an important metric in assessments of landscape quality. We used an image classification approach to estimate urban vegetation cover consisting of trees and shrubs only within two medium-sized cities in the United States. Four-band aerial imagery with 1 m spatial resolution, a vegetation index derived from this imagery, and two LiDAR-derived maps were used to examine the added value of LiDAR for this purpose. The classification results showed that using LiDAR derived data along with multispectral data or LiDAR derived data by itself improved the process of identifying woody vegetated areas compared to aerial imagery alone. For Tallahassee, Florida, overall accuracy of six major classes (water, developed, woody vegetation-consisting of trees and shrubs only, bare ground, grass and shadow) ranged from 51% to 69% among all scenarios. The user's accuracy of vegetation class was 69% when using aerial imagery only. Adding LiDAR derived data into the classification increased the user's accuracy of vegetation class between 16% and 24%. Aggregating land cover classes into two major classes (woody vegetation-including trees and shrubs only, and non-vegetation-including developed, water, shadow, grass, and bare ground) resulted in over 80% overall accuracy and user's accuracy across several scenarios. For Tacoma, Washington, the overall accuracy was between 60% and 73% for six major land cover classes. Similar to Tallahassee, using aerial imagery alone produced the lowest user's accuracy of the woody vegetation class (67%) while scenarios including LiDAR plus visible imagery resulted in over 80% of user's accuracy of woody vegetation class. Additionally, the overall accuracy for two major classes (woody vegetation and non-vegetation) was over 80%. The user's accuracy of the woody vegetation class using LiDAR integrated data or LiDAR data by itself exceeded 80%, while using NAIP imagery alone the user's accuracy was 70%. For both cities, estimates of woody vegetation using NAIP imagery alone were greater than the estimates of woody vegetation in other scenarios. Our results also suggest that LiDAR-derived information seemed to improve the overall accuracy of the six-class and two-class land cover classification results, when compared to using NAIP imagery alone for this purpose, but improvement was not consistently very significant.

1. Introduction

Urban population growth has had an important impact on land cover change processes around the world (Berland, 2012). Since 1950, the world's urban human population has grown rapidly from 746 million to 3.9 billion (54% of the total world population), partly due to increases in population and partly due to the expansion of the urban land designation. Based on the continuing urbanization and overall growth of the world's population, it is projected that by 2050, 66% of all people will live in urban areas (United Nations, 2015). In the United States, the population increased from 281.4 million to 308.7 million between 2000 and 2010, and over 83% now live in urban areas (Berland, 2012; Mackun et al., 2011). While urbanization facilitates employment and other opportunities, it also increases the need for infrastructure such as educational facilities, health services, roads, and cultural amenities (Berland, 2012; United Nations, 2015), and exerts pressure upon the urban forests (McPherson et al., 2011; Nowak, 1993). For example, many urban areas in the United States were created from landscapes once previously forested; in the 1990s about 0.4 million hectares (ha) of forested land was converted to urban areas through

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urbanization (Alig et al., 2003).

Urban vegetation refers to all trees and shrubs within an urban area (Berland, 2012; Nowak et al., 2010), and this vegetation resource can represent a significant component of the urban environment. Urban vegetation provides fundamental biophysical and socioeconomic benefits to humans, including recreational opportunities and aesthetic values that improve health, improve overall enjoyment, and increase the value of neighborhoods. Urban vegetation also can reduce energy use, facilitate cooling effects, improve water and air quality, and improve biodiversity (Leuzinger et al., 2010; Mariappan et al., 2015; McGee et al., 2012; Mincey et al., 2013; Nowak et al., 2001; Nowak et al., 2008; Pasher et al., 2014; Richardson and Moskal, 2014; Singh et al., 2012; Ucar et al., 2016; Walton et al., 2008). Hence, accurately quantifying urban vegetation cover is crucial for proper management of vegetated areas within a city to help sustain or improve ecosystem services and quality of life (Nowak et al., 2008; Richardson and Moskal, 2014; Walton et al., 2008).

Remote sensing technologies such as aerial photography, satellite imagery, and airborne LiDAR (Light Detection and Ranging) are increasingly used to assess urban vegetation cover. When captured at an appropriate spatial resolution during an appropriate time of year, the use of these technologies can be more cost and time effective than field based inventories of urban vegetation cover (Mariappan et al., 2015; McPherson et al., 2011; Nowak et al., 1996; Singh et al., 2012). For instance, Nowak (1993) conducted a study using panchromatic aerial photographs spanning nearly 50 years to estimate long-term changes of urban forests in Oakland, California. Merry et al. (2014) also used digital aerial photography for a similar long-term change study of urban forests in Detroit, Michigan and Atlanta, Georgia. Nowak and Greenfield (2012) estimated tree cover change in 20 cities in the United States using stereo pairs of aerial photographs. McGee et al. (2012) also estimated urban tree cover in Winchester, Virginia using digital aerial photography.

Aerial photography has a few limitations for these types of assessments that include the amount of ground coverage per image (unless bundled into a composite), the temporal revisiting periods, and the image acquisition cost. For these reason, some land cover change analyses in urban areas have been conducted with satellite imagery (Zhang et al., 2010). While larger areas are typically captured per image and while the temporal revisit period may be shorter, the use of the satellite imagery for urban canopy cover estimation is not without its limitations, as it may lack the spatial detail necessary to identify patchy vegetation cover (Nowak and Greenfield, 2012; Walton et al., 2008; Zhang et al., 2010). However, advances in satellite technology facilitate opportunities to describe urban vegetation cover (Zhang et al., 2010), such as with high spatial and spectral resolution satellite imagery provided through the IKONOS, QuickBird, GeoEye, and Worldview programs. These types of satellite imagery have been used to estimate urban vegetation cover in Seattle, Washington (Parlin, 2009), Baltimore and Annapolis, Maryland (Galvin et al., 2006; Irani and Galvin, 2003), Nanjing City, China (Zhang et al., 2010), Atlanta, Georgia (Goetz et al., 2003), New York City (Bhaskaran et al., 2010), and Phoenix, Arizona (Myint et al., 2011).

More recently, airborne LiDAR (Light Detection and Ranging) technology has been employed for vertical feature description due to its ability to generate 3 dimensional point cloud data. Airborne LiDAR is a laser system that compares travel time differences of laser pulses emitted by an airborne sensor, interacting with earth objects, and returning to the sensor (Jia, 2015; Parmehr et al., 2016; Singh et al., 2012; Yan et al., 2015). In addition to describing the topographic profile of the Earth's surface, LiDAR data can be useful in estimating the urban vegetation canopy because it can help eliminate the effects of relief displacement and shadows (Yan et al., 2015). Other natural resource applications (estimating forest inventory, deriving leaf area index, assessing tree canopy characteristics, etc.) also can benefit from the information provided by LiDAR data (Parmehr et al., 2016; Singh et al., 2012; Yan et al., 2015). In particular, the LiDAR data can contribute to studies in urban environments, such as estimations of impervious surfaces and assessments of infrastructure and environmental quality (Basgall, 2013; Chen et al., 2012; Hartfield et al., 2011; Jia, 2015; Parmehr et al., 2016), as well as individual tree detection, although it may be limited in cases where trees and shrubs of different crown classes reside due to decreased penetration of LiDAR through the vegetation profile (Hamraz et al., 2017).

One disadvantage of LiDAR data is that it lacks spectral information common to other types of imagery in the visible or near infrared spectrum, which may restrict its usefulness in land cover assessments in urban areas (Singh et al., 2012; Yan et al., 2015). Therefore, studies have been conducted on integrating LiDAR data with aerial or satellite imagery, providing descriptions of both radiometric and geometric data features. Hartfield et al. (2011) assessed the feasibility of combining multispectral aerial imagery and LiDAR-derived height information to improve a land use/land cover classification in Tucson, Arizona. The overall accuracy of a supervised classification process employed, which used only the 4-band multispectral data and Normalized Difference Vegetation Index (NDVI), was 84%. By adding LiDAR-derived height information to the supervised classification process, a 5% increase in classification accuracy was achieved. Singh et al. (2012) used Landsat and LIDAR data to assess large-area urban land cover in North Carolina and found that this increased the overall accuracy by 32% when compared to only using LiDAR, and by 8% when compared to only using Landsat data. Chen et al. (2012) used NDVI and LiDAR for building detection in an urban area (Nanjing, China), and estimated that of the total numbers of buildings in the area, 90% were correctly identified in LiDAR. Moreover, Jia (2015) conducted a study which combined LiDAR data and multispectral data for classification of an urban area in Sweden, and achieved a 95% overall accuracy in land cover class estimation, which was 6% higher than when only multispectral data was used, and 7% higher than when only LiDAR data was used. In general, it seems that integrating LiDAR data into multispectral imagery for urban land use classification can be helpful in discriminating between structurally variable land covers.

Urban areas include impervious surface features such as buildings and roads, along with bare ground, open areas and vegetation (trees, shrubs and grass). Our interest is in estimating canopy cover provided by trees and shrubs which will hereafter be described as woody vegetation or urban woody vegetation. Since the use of multispectral data (aerial photography or satellite imagery) itself may not be sufficient for distinguishing heterogeneous land cover in urban areas, and since LiDAR data seems to add value to the classification process, we embarked on a study to utilize both. The objective was to assess whether the addition of the LiDAR data increased the accuracy of urban woody vegetation cover, consisting of trees and shrubs only, estimates when using a pixel-based supervised classification method.

2. Methodology and data

2.1. Study areas

Tallahassee, FL and Tacoma, WA are located in different regions of the United States (Fig. 1), and contain different vegetation cover. Tallahassee is in the humid, southern part of the United States, where prevalent natural tree species are pines (*Pinus* spp.) and oaks (*Quercus* spp.). Tacoma is in the Pacific Northwest of the United States, where prevalent natural tree species are mainly conifers (Douglas-fir (*Pseudotsuga menziesii*) and western hemlock (*Tsuga heterophylla*)). Each city has a variety of trees planted along streets that may not be typical of the native tree species. In addition to their different locations, these two cities were selected based on the temporal consistency of multispectral U.S. Department of Agriculture National Agricultural Imagery Program (NAIP) and LiDAR data available for this project. Further, each city is comparable in terms of population size; the estimated 2010 human