Urban Tree Canopy Change Assessment Using Object-Based Image Analysis: An Application in Maple Grove, MN

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Abstract

Global population is on the rise and urban population density is growing. Urban areas are developing at a rapid pace, especially in the construction of new housing. Land is being developed at the cost of forest cover which is causing a reduction of the environmental benefits that urban tree canopies provide. In this project, object-based image analysis (OBIA) is used to conduct a temporal urban forest canopy change assessment in Maple Grove, MN. The OBIA methodology in this project focuses on using spatial, spectral, and textural image features in place of LiDAR data to classify forest cover. Image segmentation and classification was done using Trimble's eCognition Developer 9.5 software. Results of the project found a 1.26% increase in overall tree canopy cover over the assessment period. Accuracy of the project was investigated using an error matrix and 100 randomly generated checkpoints for each of the two classes in each classification year, totaling 400 points. The overall classification accuracy was determined to be 85.5% for 2008 and 89.5% for 2017. Overall, the results show accurate classification of urban tree canopy relative to other studies conducted in the OBIA tree cover field. This project provides results for effective, low cost, and routine canopy assessments that community stakeholders can use to proactively monitor canopy health and preserve their environmental service benefits for the community.

Introduction

Background

As the world population continues to grow, urban expansion and development will be a major force of change to the natural landscapes of cities. Urbanized land in the lower 48 states is expected to more than double in size from 67.6 million acres to 163.1 million acres by 2050 (Nowak and Greenfield, 2018). One inevitable side effect of urban expansion is change to the urban tree canopy. It is estimated that urban tree loss costs society conservatively $100 million annually due to loss of service benefits (Nowak and Greenfield, 2018). Urban forests provide service benefits including: moderating climate, reducing building energy usage, mitigating water runoff, and enhancing human well-being (Nowak and Dwyer, 2007 as cited in Nowak and Greenfield, 2018). Even with all the benefits trees provide, the continental United States is losing urban forest cover at a rate of 0.9% which is the equivalent of four million trees per year. This loss is a consequence of land development, storms, and old age (Nowak and Greenfield, 2012).

Development plays a large role in urban tree canopy changes. Urban areas currently account for over 50% of the world's population and will likely absorb a

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large part of future population increases. (United Nations, 2010 as cited in Lin, Meyers, and Barnett, 2015). Residential areas make up a larger percentage of many urban areas overall land area and therefore play an important role urban ecosystems (Lee, Longcore, Rich, and Wilson, 2017). Green cover loss in residential neighborhoods due to single family development is one of the biggest contributors to urban forest loss across metropolitan areas (Lee *et al.*, 2017). As a city's population grows, new development quickly follows in the form of new and larger homes, apartments, roads, retail stores, parking lots, and other impervious elements, often at the cost of natural green space and tree cover.

Nowak and Greenfield (2018) found that between 2009 and 2014 impervious cover from new development grew by 0.6% or 167,000 acres annually. Based on the results of the Nowak and Greenfield (2012) study, new development accounted for 71% of the new impervious areas added to urban areas across the USA.

Project Value and Importance

With all of the pressure new development places on the urban forest canopy, it is important that managers and stakeholders regularly assess how it is being affected. Especially as population density increases it is important to monitor how green infrastructure and ecosystem services are affected (United Nations, 2010 as cited in Lin, Meyers, and Barnett, 2015). Because of its service benefit value, tree canopy cover is an important part of a community's green infrastructure, and understanding how it is changing can help communities maintain or improve their service benefits. Tree cover assessments can be used to determine direction and rate of urban forest and impervious cover changes (Nowak and Greenfield, 2018).

Historically tree cover assessments were conducted by sending people out into the field to physically count and classify trees. The process of manually counting trees is extremely labor intensive and costly for a city to conduct on a regular basis. However, there is a need to assess tree canopy changes overtime to better understand the influences and impacts of canopy changes from urban development. New methods of remote sensing allow for more accurate and cost-effective assessments of urban tree canopies over time (Guo, Morgenroth, Conway, and Xu, 2019). These new methods are made possible using geospatial software and the growing amount of high-quality remote sensing data.

Object-Based Image Analysis Classification

One specific type of analysis that is used for conducting temporal tree canopy change is object-based image analysis (OBIA). OBIA is a preferred method for land cover classification over pixel-based classification. OBIA allows for large scale classification of buildings and ground cover (Ossola and Hopton, 2018). OBIA is a process in which like pixels within an image are grouped together into an object based on specified characteristics. These objects can then be overlaid with other datasets to conduct an accurate and automated classification of an image.

A dataset that is typically used in OBIA is Light Detection and Ranging (LiDAR) data. This type of data is beneficial because of its ability to measure elevation of the ground terrain. However, LiDAR data for a project area can be difficult to obtain due to its high collection cost for city and state scale projects. In many cases, there is not LiDAR data available within the timeframe required by a tree cover analysis.

In place of LiDAR data, other image properties can be used to classify tree cover, including spectral, spatial, and textural features. According to Haralick, Shaunmugam, and Dinstein (1973), spectral, textural, and contextual are three fundamental elements in human interpretation of imagery. These three features are used as part of the OBIA methodology to classify city scale imagery. Being able to classify large datasets, such as an entire city or county in relatively short periods of time can allow communities all over the world to conduct temporal analysis through OBIA.

Project Area

For the purposes of this project, the City of Maple Grove, MN (Figure 1) was chosen because of its suburban location within the Twin Cities Metropolitan Area (TCMA). The TCMA is the largest urban area within the state of Minnesota with the cities of Minneapolis and Saint Paul at its center. Maple Grove is located approximately 11 miles from downtown Minneapolis. In addition to it being a suburban city, Maple Grove has a 20-year trend of increasing population and residential development.

According to the Community Profile for Maple Grove (2019), Maple Grove has gone from a population of 50,365 in the year 2000 to 66,903 people in 2018. The population is expected to increase to 89,700 by the year 2040. The number of housing units within the city has increased from about 17,700 in 2000 to over 26,500 units in 2018. The city has a total area of 35 square miles or 22,429 acres. These characteristics are all consistent with areas that have sustained high urban tree cover changes as described by literature. Based on the population and housing increases that Maple Grove has experienced in the past 20 years, it is important that its tree canopy is measured so that community leaders can understand if their development and forestry policies have been effective at preserving the service benefits of the tree cover over time.

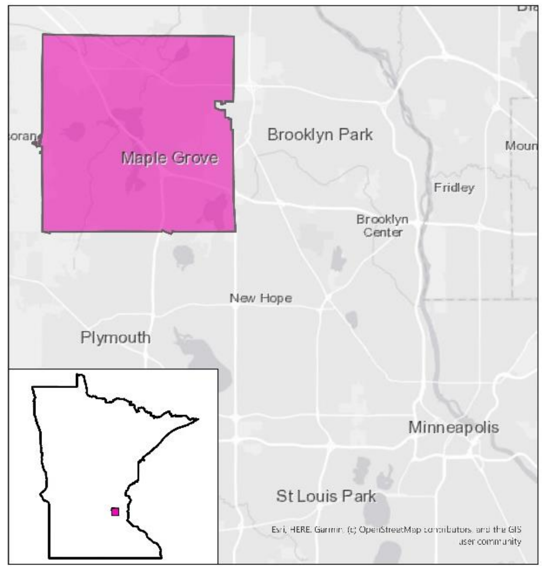

Figure 1. Location of the City of Maple Grove within the State of Minnesota. Maple Grove is a suburb of the Minneapolis and Saint Paul Metropolitan Area. Maple Grove, MN is approximately 11 miles from downtown Minneapolis.

Project Overview

This project explores the changes to tree canopy cover over 10 years within the growing suburban city of Maple Grove, MN. An OBIA approach for classification of high-resolution aerial imagery is used in this project. This project tests the classification accuracy of using a combination of spectral, spatial, and textural properties of the image as a substitute for the traditional LiDAR based dataset. The results of this project not only explore the changes in tree canopy for Maple Grove, but also whether this method is a viable option for conducting regular and accurate assessments in urban tree canopy change.

Methods

The methodology below outlines a rule set for conducting an OBIA of urban tree canopy cover with Trimble eCognition Developer 9.5 software using freely acquired National Agriculture Imagery Program images (NAIP). This also includes an assessment of the accuracy of the spectral, spatial, and textural image features used in tree canopy classification.

Data

This project used two sets of US Department of Agriculture (USDA) NAIP multispectral images as the primary source for deriving classification data. NAIP imagery was chosen because of its 1-meter per pixel resolution which will aide in the detection of finer image details such as individual trees. The imagery was downloaded from the United States Geologic Survey (USGS) Earth Explorer website. A 1.5 square mile sample of the 2017 NAIP imagery in pictured in Figure 2.

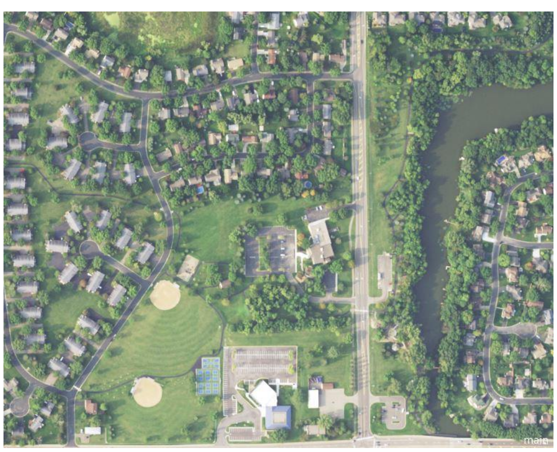

Figure 2. A sample section of the 2017 NAIP imagery pre-segmentation. This image represents approximately 1.5 square miles of area.

The goal of the project is to assess urban canopy cover change over a 10-year period. Due to the availability and frequency of NAIP imagery, the available data that met the timeframe requirements of this project was from July 2008 and August 2017. Imagery for both years consisted of six, 4-band multispectral GeoTIFF images each with a 1-meter resolution. Because this project focuses on tree canopy change, it is important that the imagery used includes a near infrared band (NIR) which can be used to identify vegetated areas. After the images were downloaded, Esri ArcGIS Pro was used to create one Mosaic Dataset for each year. Each mosaic was then exported to a raster file and clipped to the Maple Grove, MN city boundary. In addition to NAIP imagery, the Minnesota Department of Natural Resources 2012 Hydrology Dataset was downloaded from the Minnesota Geospatial Commons for use as reference data during classification of the images.

Object-Based Image Analysis

An Object-based image analysis (OBIA) method was used for this project. OBIA uses software to segment an image into larger groupings of pixels, or objects, based on algorithms in the software that compare spectral and spatial characteristics of each pixel.

For this project Trimble's eCognition Developer 9.5 software was used to conduct the OBIA. eCognition allows the user to create a structured iterative workflow for analysis of multiple types of datasets and can create customized rulesets for image segmentation, classification and refinement within the software (McGinty, McGinty, and Ramsey, 2017). Within eCognition the images are segmented based on the desired segmentation algorithm and user-defined settings for the specific algorithm. In this project, Multiresolution Segmentation was chosen as the optimal algorithm based on similar methods in previous studies (Zhou and Troy, 2008; Walker and Briggs, 2007; Moskal, Styers, and Halabisky, 2011; McGinty *et al*., 2017). Multiresolution Segmentation starts with individual pixels and merges neighboring homogeneous pixels together into objects in a bottom up process over several iterations. Typically, OBIA uses spectral and/or textural characteristics of pixels to determine their similarity (McGinty *et al*., 2017). This process runs until the smallest difference in homogeneity in adjacent objects exceeds the scale parameter set by the user in which case the process stops, and the result is a segmented image (Karakis, Marangoz, and Buyuksalih, 2004). The other user defined settings within eCognition's segmentation process include image layer weight, shape and compactness. Weighting the shape setting higher decreases the influence color has on the segmentation process. By weighting compactness higher there is more potential for the resulting objects to be more compact in size (eCognition Developer 9.5). This is important when trying to detect small groupings of trees within the image.

Suitable settings for scale, shape, compactness, and image layer weight are adjusted and evaluated by the user to determine the best fit for the images (McGinty *et al*., 2017). Previous OBIA forest cover studies have used various scale, shape, and compactness settings. Scale settings ranged from 10 - 30, shape settings ranged from 0.0 - 0.3, and compactness from 0.5-0.8 (Moskal *et al*., 2011; Zhou and Troy, 2009; Walker and Briggs, 2007). The multiresolution segmentation settings for this project are detailed in Table 1. The settings in Table 1 resulted in 593,440 objects for the 2017 imagery and 604,485 objects for the 2008 NAIP imagery. A 1.5 square mile sample of the segmentation results are pictured in Figure 3.

Table 1. eCognition 9.5 multiresolution segmentation settings. Settings are controlled by the user. Scale determines the threshold at which the segmentation process should stop. Shape determines how the algorithm uses color to create objects. Compactness controls the size of the objects. Layer weights can be used to add more preference to one band or thematic layer over another.

Level 1 Segmentation	
Scale	20
Shape	0.2
Compactness	0.8
Layer Weights	Red =1 Green = 1 Blue = 1 NIR = 1

Figure 3. A sample of the objects created with the NAIP 2017 imagery from the segmentation process in Trimble eCognition Developer 9.5. This image represents approximately 1.5 square miles.

Classification

After the image has been segmented the objects can then be classified based on the specific textural and spatial characteristics of each object. The following workflow in Figure 4 shows the rule set used to classify both the 2008 and 2017 imagery. Before the classification of image objects was done, a Normalized Difference Vegetation Index (NDVI) was generated for each set of imagery. The NDVI is calculated by:

$$\text{NDVI} = \frac{(\text{NIR Band} - \text{Red Band})}{(\text{NIR Band} + \text{Red Band})}$$

The first step in classification is to separate objects in *shadowed* areas within the image from *non-shadowed*. This is done because of the different spectral properties that similar features have when they are in shaded areas. Objects are separated based on brightness, defined as the channel mean value of the green, red, and NIR layers (Zhou and Troy, 2009). Previous studies using eCognition have a range of threshold values for separating *shadow* and *non-shadow* objects. In Walker and Briggs (2007), a threshold of greater than 0.12 on a 0 to 1 scale was used to determine if an object was *non-shadow*. Zhou and Troy (2008) used a value 30 to define *shadow* and *non-shadow* and a value of 65 was used by Platt and Schoennagel (2009) to represent "dark forest." Average brightness amongst images may vary so thresholds can be adjusted slightly up or downward in an effort to visually match tree cover within the image (Platt and Schonnagel, 2009). For the purposes of this project a brightness threshold of 60 was selected.

Next, *non-shadowed* and *shadowed* objects were divided into *vegetation* and *non-vegetation*. The objects with a NDVI value <0 were immediately categorized as *non-vegetation* (Zhou and Troy, 2009). Based on the threshold of 0.08 used Zhou and Troy (2008) and, in an effort to eliminate *non-vegetation* objects that might have had a minimal positive NDVI value, a threshold of >0.08 was used to classify objects as *vegetation*.

After categorizing objects as *vegetation* further criteria are needed to separate tree canopy from other types of ground cover. This project used several textural and spatial characteristics of objects to classify them as *trees*. Texture was chosen as a primary classification feature because Haralick *et al. (*1973) identified it as an important feature when classifying objects within imagery. Texture is one of the most important spatial features of an aerial image and it is a distinctive feature of land cover classes (Kupidura, 2019; Tuominen and Pekkarienen., 2004). Texture is the spatial relationship that gray-levels of the image pixels have to one another (Haralick *et al*., 1973). Image texture is measured using a Gray Level Co-Occurrence Matrix (GLCM). Gadkari (2004) quotes Haralick *et al*. (1973) stating GLCM is "a two-dimensional histogram of gray levels for a pair of pixels, which are separated by a fixed spatial relationship." Texture, specifically contrast, was chosen as the primary classifier in Stage 1 of the *trees* or *non-trees* argument because there is a moderate correlation between forest attributes and the GLCM contrast and entropy features (Tuominen and Pekkarienen, 2004).

Contrast is the difference between the highest and lowest gray levels for a set of contiguous pixels. It measures the local variations in an image (Gadkari, 2004). Trees vary in height, color, shape, and reflectivity, and in theory should have higher degrees of variation in their GLCM values relative to other more homogeneous ground cover types. In Stage 2 of the tree canopy classification rule set, both texture and spatial features were used for further refinement of the *trees* and *non-tree* categories.

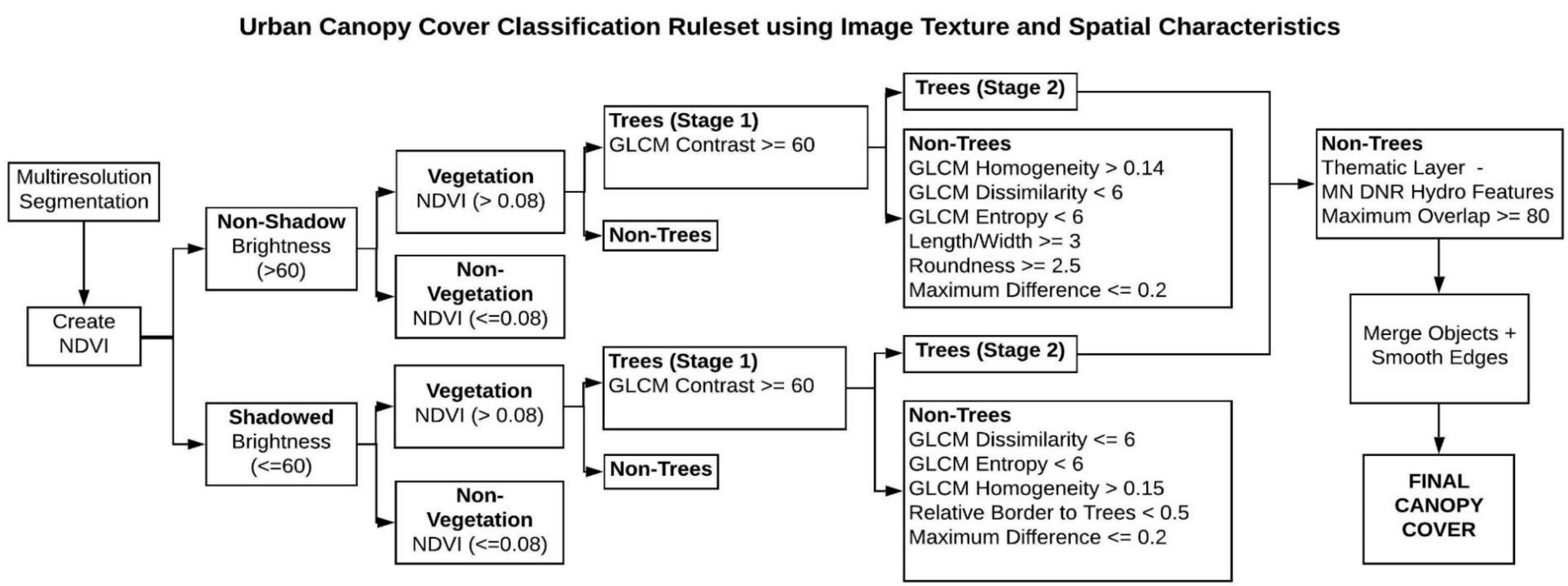

Figure 4. Urban tree canopy classification rules using texture and spatial characteristics of objects to classify as tree or non-tree. Classification of both 2008 and 2017 imagery was done in Trimble eCognition Developer 9.5. Ruleset based on a study focused on inventorying human-dominated forest ecosystems by Zhou and Troy (2008).

GLCM Entropy, Dissimilarity, and Homogeneity were all chosen as parameters in the classification process. Entropy measures the disorder or complexity in an image; complex textures tend to have higher entropy levels when compared to more homogeneous textures (Gadkari, 2004). Again, because of its variation in spectral and hyperspectral features, tree cover should present as higher entropy pixels relative to other types of ground cover. Dissimilarity is a feature similar to contrast except that it uses a different linear pattern of the GLCM. Homogeneity is inversely correlated to contrast. The smaller the difference in gray tones, the higher the homogeneity value (Gadkari, 2004).

In addition to texture, length/width of the object helped to remove long fence lines and grass medians. Proximity to other classes, relative border to other classes, and maximum difference were all used to further improve accuracy of classifications (Moskal *et al*., 2011).

Once all the objects were classified according to the ruleset, objects classified as *trees* were merged. After the objects were merged, the Pixel-Based Object Resizing (PBOR) function was used to “smooth” the edges of the classified object. The PBOR function grows and shrinks the edges of the object by filling in or subtracting individual pixels along the border which results in a “smooth” boundary and improves the shape of the object when exported to a map. The result of the OBIA using the above ruleset within eCognition is pictured in Figure 5.

Accuracy Assessment

The accuracy of the canopy cover classification was measured using a stratified random sampling method. To assess accuracy the classified tree canopy

Figure 5. Forest canopy classification results from 2017 NAIP Imagery using eCognition multiresolution segmentation. Area represents approximately 1.5 square miles.

data was compared to visually interpreted data. Accuracy assessments compare classified land cover to other verification data, which can include field samples or image interpretation (Aronoff, 2005 as cited in McGinty *et al.*, 2017). A classified forest cover polygon layer was exported from eCognition Developer 9.5 for each project year and opened in ESRI ArcPro. In order to effectively measure accuracy, both canopy and non-canopy classifications must be assessed. A polygon feature was created for the entirety of Maple Grove, and then the Erase tool was used to remove the area classified as tree canopy from the Maple Grove polygon.

The result was a “non-canopy” classified polygon. Based on Congalton (1991), a minimum sample size of 50 points per class is needed to assess accuracy of land cover classification. For this project 100 points were used for each class for a total of 200 points for each project year. Additional points were used because of the large scale of the project and because only two classes were used. The Create Random Points tool was used to generate points within each class for both datasets. Visual interpretation of each point was conducted using the 2008 and 2017 imagery.

An error matrix was created to assess the overall accuracy of the OBIA classification process. For each random point the classification derived from the eCognition classification as well as the results of the visual interpretation of the NAIP imagery were summarized and placed into an error matrix. The results of the error matrix provide key metrics for assessing the overall accuracy of the data. These metrics include user's error, producer's error, overall accuracy, and overall kappa coefficient.

Results

The results of this project will focus on the overall change in tree canopy cover in Maple Grove, MN and the accuracy of the OBIA method used to classify land cover as either tree canopy or non-canopy

Canopy Cover Change

Overall change to canopy cover was assessed by measuring the total area of the canopy cover and non-canopy cover polygons derived from the OBIA classification process. Figure 6 shows final tree canopy cover of the entire project area for 2008 and 2017. The pixel count of each classification polygon was used to determine total area. Each pixel within the polygon represents one square meter, based on the original NAIP image resolution. The pixel area was then converted to acres and square miles for comparison at varying scales. As shown in Table 2, total canopy cover in 2008 was calculated at 4,990.52 acres or 22.31% of the overall area. Total canopy cover in 2017 was calculated at 5,053.52 acres or 22.47% of the city's overall area. The boundary Maple Grove remained unchanged between 2008 and 2017. The overall area of the 2008 and 2017 tree canopy remain relatively consistent over the 9- year period. The net change was a positive 1.26% between 2008 and 2017 with an increase in canopy cover of 63 acres (Table 3).

Accuracy Assessment

The results of the accuracy assessment are based on the error matrices in Tables 4 and 5. The key metrics in the error matrices are producer's accuracy, user's

Table 2. 2008 and 2017 total area for canopy cover and non-canopy cover derived from OBIA classification using 1-meter NAIP imagery.

Total Area Based on Classification Type				
	Pixel Area (m^2)	**Acres**	**Miles^2**	**Total Area (%)**
2008 Canopy Cover	20,195,920	4,990.52	7.80	22.31%
2008 Non-Canopy	70,318,404	17,376.38	27.15	77.69%
2017 Canopy Cover	20,450,864	5,053.52	7.90	22.47%
2017 Non-Canopy	70,573,922	17,439.52	27.25	77.53%

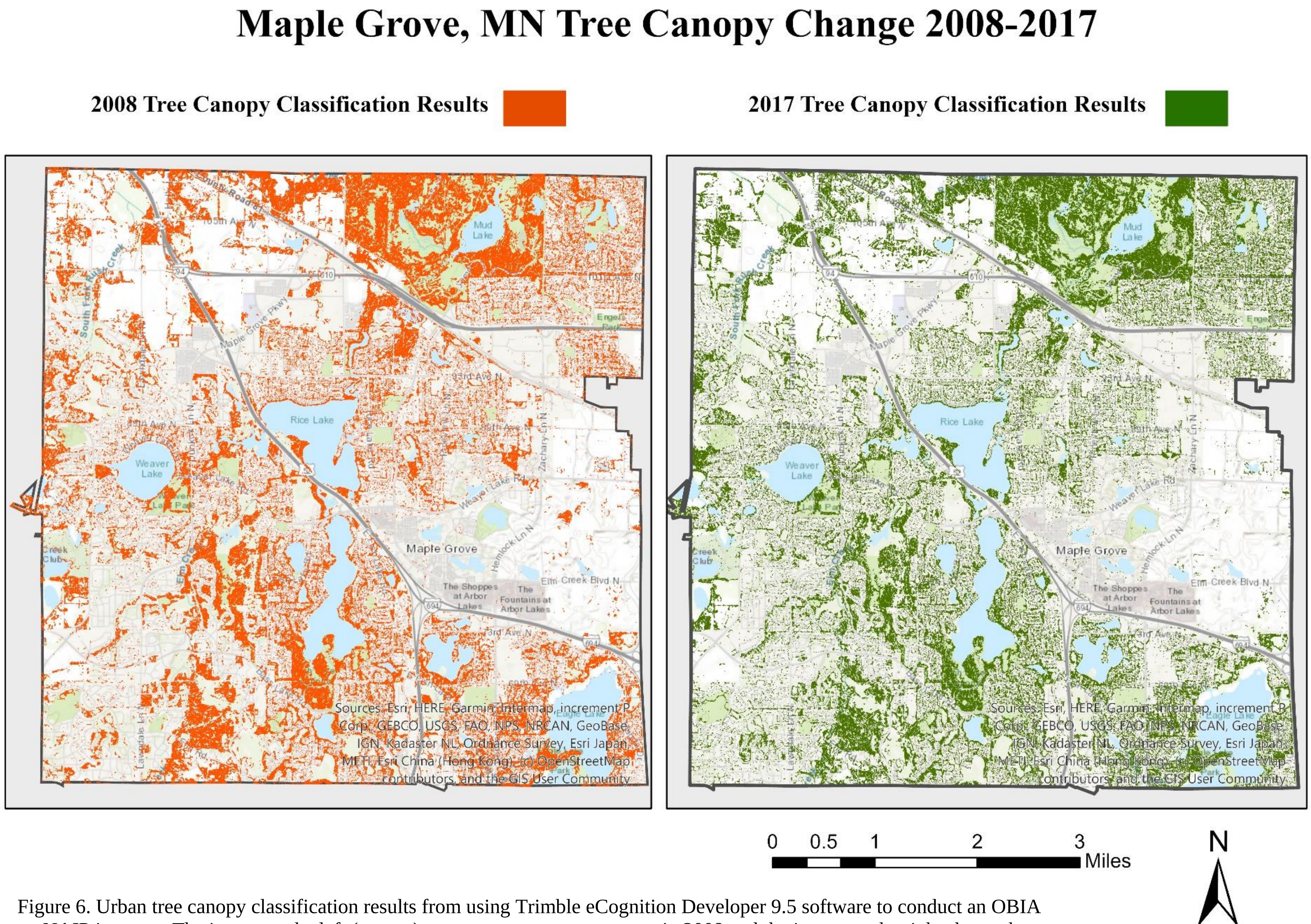

Figure 6. Urban tree canopy classification results from using Trimble eCognition Developer 9.5 software to conduct an OBIA on NAIP imagery. The image on the left (orange) represents tree canopy cover in 2008 and the image on the right shows the tree canopy in 2017.

Table 3. Overall tree canopy change in Maple Grove, MN between 2008 and 2017.

Canopy Cover Change 2008-2017			
Meters^2	**Acres**	**Miles^2**	**% Change**
254,943	63.00	0.10	1.26%

Table 4. Error Matrix for OBIA classification of 2008 NAIP imagery using Trimble eCognition Developer 9.5.

2008 Canopy Classification			
Classification	**Reference** Canopy	No-Canopy	**User's Accuracy**
Canopy	81	19	81.00%
No-Canopy	10	90	90.00%
Producer's Accuracy	89.01%	82.57%	
Overall Accuracy	**85.50%**		
Overall Kappa	**0.71**		

Table 5. Error Matrix for OBIA classification of 2017 NAIP imagery using Trimble eCognition Developer 9.5.

2017 Canopy Classification			
Classification	**Reference** Canopy	No-canopy	**User's Accuracy**
Canopy	86	14	86.00%
No-Canopy	7	93	93.00%
Producer's Accuracy	92.47%	86.92%	
Overall Accuracy	**89.50%**		
Overall Kappa	**0.79**		

accuracy, overall accuracy, and kappa coefficient. Producer's accuracy reflects the probability that a pixel from the reference data is properly classified. User's accuracy is a measure of the reliability that a pixel in the classified data was correctly classified (Congalton, 1991). The other metric produced by the error matrix in the kappa coefficient. The overall kappa coefficient estimates how well classes are represented in the classification, and the actual, or interpreted ground data (Conchedda, Durieux, and Mayaux, 2008). The higher the kappa coefficient the more agreement there is between the classification and the actual ground cover.

Overall accuracy is a calculation of the total correctly classified points compared to the total number of points classified. In this project the overall accuracy for the 2008 OBIA classification was 85.5% and the kappa coefficient was 0.71. The 2008 tree canopy classification had a producer's accuracy of 89.01% and a user's accuracy of 81%. Producer's accuracy for non-canopy classification was 82.57% and user's accuracy was 90%. This shows that the method used in the OBIA classification was more reliable at classifying non-canopy versus canopy ground cover.

The results of the 2017 OBIA classification show an overall accuracy of 89.50% and a kappa coefficient of 0.79. The producer's and user's accuracy for the 2017 tree canopy classification 92.47% and 86%. Non-canopy classification had a producer's accuracy of 86.92% and a user's accuracy of 93%. In the case of 2017 image classification, the OBIA method appears to have a good ability to properly classify ground cover in NAIP imagery. Overall, the 2017 imagery had a higher level of classification accuracy than the 2008 imagery.

Discussion

The three main objectives of this project were to: (1) measure the reliability of OBIA as an effective method of identifying urban tree canopies in metropolitan areas; (2) determine if OBIA can be effective if no temporal LiDAR data is available for the project area; (3) determine if the project area saw a loss in canopy cover between 2008 and 2017 due to the increase in development from population growth.

OBIA for Urban Canopy Assessments

Utilizing an OBIA process to accurately classify and measure urban canopy cover shows good promise based on the results of this project. Overall classification accuracy for 2008 and 2017 achieved 85.5% and 89.5% and kappa coefficients of 0.71 and 0.79. These results are within the range of expected results based on similar studies using OBIA to classify ground cover without LiDAR data. Moskal *et al*. (2011) achieved an overall accuracy in an OBIA of NAIP imagery of 79.7%, a kappa coefficient equal to 0.74, user's and producer's accuracy for tree cover of 80.5% and 93.9%. Walker and Briggs (2007) had an overall accuracy of 81.0%, a kappa coefficient of 0.63, tree cover user's accuracy of 96.0%, and a producer's accuracy of 76.0% for an OBIA of urban forests in Phoenix, AZ. McGinty *et al*. (2017) used OBIA to map riparian land cover and achieved an overall accuracy of 94.43% and 0.9486 kappa coefficient. When mapping change in mangrove ecosystems Conchedda *et al.* (2008) achieved an overall accuracy of 85.7% and a kappa coefficient of 0.83. The tree cover classification in that study produced a user's accuracy of 97.4% and a producer's accuracy of 99.5%. When the results of other studies are compared to this project for Maple Grove, MN, the accuracy of the tree canopy classification is slightly higher than other studies analyzing urban tree cover. On the other hand, the accuracy is lower when compared to other studies where the urban environment is not a factor.

While the goal of this project was to assess the accuracy of urban tree canopy classification using an OBIA method without LiDAR data, it should be noted that there are many examples within the literature that support the benefits of LiDAR data to the overall accuracy of a land cover classification process, especially when assessing tree cover. One example is Zhou and Troy (2008) which achieved an overall accuracy of 92.3% and overall kappa of 0.899 when including LiDAR data in their OBIA. User's accuracy and producer's accuracy were 97.7% and 94.4% for coarse vegetation, such as trees, for that study. The use of LiDAR is an important tool for assessing tree cover because it can effectively separate the taller trees from other herbaceous ground cover such as grass, small shrubs, and marshland. The reason that this project focused on using image texture and other spatial and spectral elements was because of a lack of LiDAR data for temporal analysis. In Minnesota, there is only comprehensive LiDAR data publicly available between 2011 and 2013. Unless the person or group researching changes to tree cover can wait for another public LiDAR mission to be flown or fund LiDAR data collection privately at the city scale, additional methods of accurate tree canopy assessment are needed.

The design of the process used in this project for segmentation and classification within eCognition Developer 9.5 achieved an expected level of accuracy. However, there are several areas where error has influenced the classification of tree cover. One source of error is the nine-year time gap between the NAIP imagery. The space in time likely led to spectral differences within imagery that influenced segmentation and classification of the image. Moskal *et al.* (2011) identified three main categories of error in OBIA assessment of urban tree cover: spectral content, spatial detail, and temporal availability of imagery. The project detailed in this paper likely suffers from some of these same sources of error. The NAIP imagery selected for this project was chosen because it was the image pair that most closely corresponded to the ten-year timeframe of the project. In an ideal situation, this image pair would be from the same month, or even the same week, in order to minimize error due to changes in sunlight, shadows, chlorophyll fluorescence of vegetation, etc. Even though the images used were within one calendar month of each other, potential error from changes in the spectral characteristics of the ground cover influences how the eCognition multiresolution segmentation algorithm groups pixels into objects. Because the initial segmentation process in this project relies solely on the spectral and NIR and does not use LiDAR or other inputs, it is sensitive to changes in spectral content. The way that the pixels are grouped into objects determines their textural properties which are a central part of the classification ruleset in this project.

During the classification process, visual inspection of spectral, textural, and spatial characteristics of image objects were performed to monitor for large scale classification error. While the overall classification proved to be accurate, there were several common conditions within the imagery that effected classification. Examples of features that created confusion within the classification process included algae covered patches on ponds which had similar values compared to grass. Individual trees within residential yards were sometimes grouped into the same object as lawn cover, which made it impossible to classify individual trees effectively.

Texture was one of the key elements of the classification rule set used in this project. As discussed above, texture calculations in eCognition are based on Haralick's GLCM principals. Each object's contrast, entropy, dissimilarity, and homogeneity value are relative to its neighbors within the image. The textural features used in this project achieved an accuracy comparable to other studies in the field; however, while they are capable of successfully classifying tree canopy, they also are vulnerable to error. For example, there were several cases where patches of grass along boulevards and right of ways generated a high level of contrast and entropy and low homogeneity which were similar to the tree cover values. This similarity led to misclassification of several objects. Other examples where textural properties created the potential for misclassification included tall marsh grasses, narrow strips of grass between two structures, and fence lines. In an effort to correct these misclassifications, the project used spatial features of these objects to try and reject them from the tree canopy classification. In the case of grass strips along boulevards and backyard fence lines, the ruleset created a maximum length/width ratio to eliminate long and narrow objects, which did not share the more rounded characteristics of trees.

Local Canopy Cover Change

This project found a 1.26% increase in the total canopy cover within Maple Grove, MN between 2008 and 2017. While no existing studies were found specifically for Maple Grove, there are several studies that have surveyed tree cover change within Minnesota. Norwak and Greenfield (2018) used a paired point analysis to conduct a temporal tree cover analysis for each of the 50 states. They found that Minnesota had a mean change in tree cover of 0.0% between 2009 and 2014. In a previous study Norwak and Greenfield (2012) found an absolute change in tree cover in Minneapolis of -1.1% or 74.1 acres between 2003 and 2008. Yuan, Sawaya, Loeffelholz, and Bauer (2005) found a relative change in forest cover in the seven county Minneapolis and Saint Paul Metropolitan Area of -7.9 % between 1986 and 2002.

Maple Grove adopted their current Forest Preservation Management Plan in 2002 and it consists of eleven priorities. Priory two calls for the establishment of a reforestation program and priority four takes steps to confirm the health of the forest through regeneration and replication of native species (City of Maple Grove, 2020). This program was started at a point when, according to Yuan *et al.* (2005), the metropolitan area was experiencing a reduction in forest cover. The other two studies listed above show forest cover loss stabilizing in Minneapolis and Minnesota between 2003 and 2014. Given the positive direction of other studies in Minnesota and the goals of Maple Gove, it is possible that the 1.26% increase in forest cover found in this project is a realistic achievement for the city.

Upon further review of the canopy cover classification results, it was observed that the increase in tree canopy likely came from two sources. First, the continuing maturation and growth of existing trees within the city created an increase canopy area over the nine-year period. Secondly, canopy cover increases appear to have come from the conversion of agricultural land into residential neighborhoods. There are a few areas in the western part of the city that were fields in 2008 and had been converted to residential use by 2017. While the residential use typically causes the reduction of tree canopies, in this case the conversion brought new tree plantings in yards, and new parks and boulevards with tree growth that did not exist in the agricultural fields.

The final totals of the classified areas differ slightly. This is likely due to error created during the processing of the imagery for use in this project. This processing included combining the original imagery into mosaic datasets and clipping the mosaic to the project area. This process could result in small variations in total pixel count between the image years. Also, processing of the imported eCognition classification polygon within ArcPro could create error. The Erase function was used to separate area within Maple Grove classified as *non-tree* using the classified *tree* polygon. Again, due to small variations in the dataset, this could lead to slight differences in the overall area of ground cover classifications. The 2008 data resulted in a total area of 37.95 square miles and the 2017 data had a total area of 35.15 square miles. The official area of Maple Grove is 35.0 square miles. The 0.20 square mile difference in the calculated total areas could impact the results of the overall tree canopy change.

Direction of Future Studies

In order to improve classification accuracy of similar projects in the future, several areas within the methodology should be studied to see if they lead to increase classification accuracy. First, using a unique ruleset within eCognition for each project year could improve accuracy. In this project, one ruleset was applied to both 2008 and 2017 imagery. Given that the imagery spans a nine-year period, many factors could cause differences in spectral properties of the images. Date, time, flight path, camera lens, and sensor type could all play a role in creating enough difference within the imagery to justify the creation of unique rulesets for each dataset. For this project the NAIP imagery used was all flown on the same date in each of the two project years and were all 4-band images. Additional precautions would need to be taken to adjust the OBIA ruleset if images used within mosaic datasets were not all from the same flight mission.

Secondly, adding additional data into the segmentation process and classification collateral could improve accuracy. By including a GLCM in the segmentation dataset, pixel texture values could then be used to more accurately group similar pixels together instead of relying exclusively on spectral properties. For example, this might help to reduce the number of times when grass and tree cover are grouped together within an object due to similar spectral features. Additional thematic layers could be used to help reduce classification errors. Building footprints, national land use and land cover maps, and more robust wetland datasets could all be integrated as thematic layers within eCognition to theoretically provide improved classification accuracy.

Lastly, a multi-level segmentation approach could be explored in future projects that focuses on texture-based classification. Both Moskal *et al.* (2011) and Zhou and Troy (2009) used a multi-level segmentation approach. This process segments the objects into primitive objects at a fine scale and allows different thematic layers to be used within each of the segmentation levels (Zhou and Troy, 2009). Multi-level segmentation allows objects to be merged into larger polygons based on their class type and then re-segmented with a different set of user parameters (Moskal *et al.*, 2011). The goal is to achieve more homogeneous objects especially when trying to classify multiple land cover types. This process could be used to try an improve the segmentation of the NAIP imagery by generating objects that contain only tree cover.

Conclusion

Urban tree canopies provide important environmental service benefits to their communities. The world population continues to grow and with that, many cities are seeing their population densities increase. With increasing population comes increased development from housing, businesses, and community services. This development is having a negative impact on the overall tree canopy cover in communities around the globe. Monitoring changes to these tree canopies on a regular basis will be critical to preserving these benefits into the future. It is important to find improved methods for assessing changes to tree cover that can be conducted regularly at a reasonable cost.

The focus area of this project is Maple Grove, MN which has seen large population and housing growth over the last 20 years, making it a suitable area for studying how this growth has affected the overall tree canopy. To measure the change an OBIA ruleset was developed using spectral and spatial features combined with specific textural properties of the image. Texture is used in place of the more commonly used LiDAR datasets to classify the image. The OBIA was conducted in the Trimble eCognition Developer 9.5 environment using NAIP imagery and MN DNR water features datasets.

The results from the OBIA

methodology in this project yielded a positive increase of 1.26% of 63 acres in Maple Grove, MN. An accuracy assessment was conducted using an error matrix and visual interpretation of randomly generated check points. The error matrix concluded that the overall classification accuracy for the 2008 tree canopy was 85.5% and 89.5% for the 2017 tree canopy classification. When these findings were compared to other temporal studies conducted within Minnesota and the Maple Grove's forestry plan established in 2002, the results appear to be consistent with expectations.

Further studies should be conducted to try an improve the accuracy of OBIA using texture as a primary classifier. Integrating texture into the segmentation process as well as using additional thematic datasets could all potentially yield higher accuracy results.

Overall, OBIA can deliver relatively accurate results in urban tree canopy assessment. While further studies are needed, textural and spatial features appear to be a strong substitute for LiDAR data when it is unavailable or cost prohibitive. Using this type of methodology to conduct a temporal assessment on tree canopies can provide community stakeholders with data in a relatively short timeframe at a reduced cost compared to traditional methods. If reliable tree canopy change data can be generated on a regular interval, community stakeholders could more proactively manage tree cover in an effort to maximize the environmental service benefits that it produces.

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