Characterizing tree cover change in response to urban greening initiatives using an in situ tree inventory, WorldView-2 and LiDAR data in Worcester, Massachusetts

Isabel Miranda

Fall 2016

Honors Thesis

And accepted on the recommendation of

John Rogan Ph.D., Advisor

Abstract

Characterizing tree cover change in response to urban greening initiatives using an in situ tree inventory, WorldView-2 and LiDAR data in Worcester, Massachusetts

Isabel Miranda

Urban tree cover extent in the Greater Worcester area has changed dramatically over the last seven years following the discovery of the invasive wood-boring Asian Longhorned Beetle (ALB) in 2008. The ALB eradication strategy caused the removal of 30,000-plus host trees, to date. The majority of the ALB host trees (>80%) were removed from two neighborhoods in north Worcester (i.e., Burncoat and Greendale). In response to the ALB eradication strategy, a multi-agency urban reforestation effort involving the City of Worcester, Massachusetts Department of Conservation and Recreation (DCR), and Worcester Tree Initiative (WTI) began in 2010. This study characterizes the amount of tree cover change between the start of the tree planting initiatives, 2010, and the present day, 2015, in Burncoat and Greendale neighborhoods. WorldView-2 satellite imagery (0.5 m) is used in concert with in situ tree inventory and 1 m airborne LiDAR data to create a 2015 tree cover map using an object-based classification approach. The 2015 tree cover map is compared for areas of gain and loss to an existing tree cover map from 2010. Overall 7.52% of the study area showed an increase while 0.46% of the area showed loss. The DCR tree planting from 2010 to 2012 contributed to a 1.75% in gain in tree cover. The results of this study will help inform agencies (e.g. DCR and WTI) engaged in monitoring urban tree cover

the utility of a top-down approach integrating fine spatial resolution imagery with LiDAR and GIS layers (e.g. impervious surface) to understand the early impacts and success of reforestation efforts.

John Rogan, Ph.D.
Advisor

Deborah Martin, Ph.D.
Assistant Advisor

Academic History

Name: Isabel Miranda **Date:** Fall 2016

Baccalaureate Degree: Bachelor of Arts in Geography, expected graduation May 2017

Source: Undergraduate School of Geography, Clark University **Date:** Fall 2016

Acknowledgements

I would like to thank John Rogan and Deborah Martin from the Graduate School of Geography at Clark University for all their guidance and support. I would also like to thank Arthur Elmes for helping me with any questions and problems I had during my research.

Contents

Introduction

Trees are an important component of the urban landscape providing ecological services to cities and their residents (Nowak and Dwyer, 2007) including reduction in storm water runoff, household energy use, noise pollution, and improved air quality (Nowak and Dwyer, 2007; Merry et al., 2014; O'Neil-Dunne et al., 2014). In addition to the environmental benefits provided by trees, their societal benefits include reduced crime levels, increased property value, reduced personal stress, enhanced landscape beautification, and sense of place (McPherson et al., 2005; Hostetler et al., 2013; Senanayake et al., 2013). To both maintain and enhance the socio-environmental benefits of urban trees, regular monitoring of tree cover abundance is critical to understanding how tree cover, and therefore, ecological servicing from trees are changing (Nowak and Greenfield, 2012). Traditionally field measurements are used for accessing annual, multi-annual tree cover inventories; however, adopting remotely sensed imagery by managers of urban forests presents increased efficiency and lower cost of forest inventories and management (Dwyer et al., 2002; Plowright et al., 2016; Roman et al., 2013).

Maintaining an inventory of tree cover and change, through maps, allow for the birds-eye view of the spatial distribution of tree cover change across a study area (McGee et al., 2012; Tanhuanpää et al., 2014). It is important to map and characterize tree cover change over time because tree cover in cities and their neighborhoods constantly changes as a result of the myriad natural and/or anthropogenic forces (Nowak and Greenfield, 2012). Natural forces of tree cover change largely include tree growth (Tanhuanpää et al., 2014), tree mortality due to insects/disease (Poland and McCullough, 2006), senescence (Nowak, 1993) or severe weather events (Danko et al., 2013; Hostetler et al., 2013). Anthropogenic forces impacting tree cover include new tree planting, tree removal and tree mortality from either direct or indirect human actions (Nowak and Greenfield, 2012). Direct human actions consist of new urban development where tree cover is replaced by impervious surfaces such as buildings and roads and indirect human actions such as exhaustive air pollution and natural gas pipeline leaks (Nowak and Greenfield, 2012; O'Neil-Dunne et al., 2014; Phillips et al., 2013).

Several approaches have been used to map tree cover and tree cover change in cities, including bottom-up ground-based inventory, and top-down aerial photography and satellite imagery (Merry et al., 2014). A bottom-up approach provides tree inventories with information such as age structure, species composition and biomass that are all important for understanding the conditions of the urban forest. However, bottom-up approaches such as traditional field surveys are expensive costing as much as $3.00 per tree (Wood 1999), and time consuming (McGee et al., 2012). The money invested into forest management is about five times greater for urban than exurban forests because of the personnel, materials and time that is needed to conduct a comprehensive inventory of tree cover (McPherson 1993). Tree inventories are expensive because of the detail records to characterize each tree and because of increased travel times due to urban forests having more trees that are dispersed across a city or neighborhood (Wood 1999). Furthermore, trees grow and are removed causing inventories in cities and neighborhoods to become less representative of the urban forest over time. According to Roman et al (2013)., the most common challenge for thirty-two local urban forestry organizations was resource limitations, followed by lack of staff time and funding. Therefore, using remotely sensed data and GIS data layers to monitor tree cover change allows for a better cost and time effective alternative methods (Plowright et al., 2016; O'Neil-Dunne et al., 2014).

True-color aerial photography approaches include methods such as crown cover scale that divides the photo into polygons where samples of polygons are used to visually interpret tree cover

(Nowak et al., 1996). Additionally, the dot method creates sample locations in aerial photographs in a systematic or random fashion where for each dot the land cover underneath is recorded to calculate tree cover (Nowak et al., 1996; Merry et al., 2014). Aerial photography was used to map tree cover change in Detroit and Atlanta from 1951 to 2010 using a point and polygon-based approach. This method is similar to the dot and crown cover scale methods and yielded to 50.2% tree cover in Atlanta comparable to the 2009 estimate (51.6%) by Nowak and Greenfield in 2012 that used paired aerial photographs to access changes in tree cover (Merry et al., 2014).

Using fine spatial resolution imagery of 1 m spatial resolution or less is also emphasized in analyzing land/tree cover change within a heterogeneous landscape (Al Kofhai et al., 2012; Zhou, 2013; Stueve et al. 2015). Land/tree cover maps made using the 30m National Land Cover Dataset (NLCD) were compared to land cover maps made using aerial photography from United States Geological Survey High-resolution Orthoimagery program and Woolpert Inc. of 0.5 and 0.3m spatial resolution (Stueve et al. 2015). Fine-resolution products could more accurately reveal a more complex landscape of conifer trees, deciduous trees, roads, buildings and grass in a variety of patch sizes and shapes while coarser resolution represents a simple landscape with broader shapes (Basu et al., 2015; O'Neil-Dunne et al., 2014; Stueve et al., 2015). Furthermore fine-resolution imagery generated a land cover map with accuracies of ≈92 percent rather than ≈68 % percent made with a coarse spatial resolution, 30m, land-cover map (Stueve et al., 2015). Therefore, fine-resolution multispectral imagery allows for fine scale heterogeneity in the landscape to be identified when mapping tree cover within suburban and urban locations (O'Neil-Dunne et al., 2014; Stueve et al., 2015; Zhou, 2014).

Unfortunately, using true-color aerial photography to measure tree cover change is challenging when low spectral separability makes it difficult to locate trees, distinguish individual trees and neighboring features such as lawns, as well as the shadows casted by tree crowns and tall buildings (Li and Shao, 2014; Merry et al., 2014; Tanhuanpää et al., 2014). Furthermore, manual photointerpretation and field-based methods used for mapping tree cover are laborious and sample-driven, lacking wall- to wall information of information (O'Neil-Dunne et al., 2014).

Numerous studies have demonstrated that integrating remotely sensed datasets through geographic object based image analysis (GEOBIA) is an effective wall-to-wall method for tree canopy mapping (O'Neil-Dunne et al., 2014). Datasets such as LiDAR (Light Detection and Ranging) point cloud data, LiDAR derivatives (e.g. digital elevation model, normalized digital surface), multispectral imagery (e.g. National Agricultural Imagery Program that includes three visible bands and one NIR band) and GIS files (e.g. roads) provide an effective way to analyze tree cover change using object-based image analysis (OBIA) (Stueve et al., 2013; Zhou, 2013; O'Neil-Dunne et al., 2014; Parent et al., 2015).

O'Neil-Dunne et al., (2014) mapped tree canopy in urban and suburban landscapes in over 70 communities in North America. Focusing on Virginia Beach as a case study orthoimagery of 0.15m, high quality LiDAR acquired in 2012 permitting 0.4m LiDAR derivatives, and thematic building footprints were used to map tree cover and change in Virginia Beach from 2004 to 2012. LiDAR derivatives such as the normalized digital surface model (nDSM) allowed for tall objects to be distinguished using a threshold of 0.61m for the initial segmentation as well as for small shrubby trees to be identified near coastal locations for the creation of the tree cover map (O'Neil-Dunne et al., 2014). The incorporation of LiDAR is particularly useful for dense urban areas where shadowing effect of buildings is problematic with the use of spectral imagery and therefore provides more accuracy in mapping tree cover for an urban forest (Plowright et al., 2016). The integration of high quality LiDAR, high-resolution orthoimagery and thematic building foot prints produced a map with more than 90% overall accuracy showing a 3.1% gain in tree cover (O'Neil-Dunne et al., 2014).

Zhou (2013) used 0.6m color-infrared imagery from Emerge Inc. including green, red and near-infrared bands along with LiDAR data to map land-cover in a suburban location of Baltimore County. The study used an intensity difference layer derived from the first and last return of LiDAR data assisting to classify different land-cover types as the intensity of the laser pulses indicate the reflectance of the surface feature (Chen and Gao, 2014; Zhou, 2013). Because trees have a larger proportion of intensity edge points than buildings do, this is reputedly an efficient feature to use for distinguishing buildings from trees (Chen and Gao 2014; Zhou 2013). The integration of OBIA and a combination of LiDAR height and intensity data has achieved a 92% accuracy (Zhou, 2013). Additionally, LiDAR was used to assess urban tree conditions within the city of Surrey, Canada (Plowright et al., 2016). This study particularly focused on LiDAR's capacity to estimate tree height and crown density as indicators of tree condition. The relationships between tree heights measured in the field and tree heights measured with the LiDAR data resulted in a Pearson correlation coefficient of $r = 0.927$ with $p < 0.001$ showing that tree height estimates were successfully detected (Plowright et al., 2016). The crown density was measured by using percentage of non-ground LiDAR returns and the coefficient of variation of return height (Plowright et al., 2016). From this study airborne LiDAR proves to be an effective tool to detect trees in an urban environment and measure indicators of tree condition (Plowright et al., 2016). LiDAR has opened several opportunities to urban forestry by locating exact tree locations and conditions to produce a more comprehensive urban tree dataset for monitoring the urban forest (Plowright et al., 2016)

As LiDAR data have recently become widely available it provides an opportunity for land cover and tree cover mapping at fine scales especially in conjunction with multispectral imagery (O'Neil-Dunne et al., 2014). LiDAR derivatives can assist in separating bare ground from non-ground (e.g. buildings and trees), however, LiDAR data can be costly, $74 per square km (Rogan and Chen, 2004) and are not always available for research projects at a particular study area making an automated approach for monitoring tree cover change difficult (O'Neil-Dunne et al., 2014; Zhou, 2014).

Within the last 10-15 years remote sensing technologies have advanced allowing for more computerized mapping of detailed tree cover at resolutions for 1-2m or less which represent forest-urban landscape at finer scales (Stueve et al., 2013). In addition, despite the success of the GEOBIA approach which seeks to approach tree cover mapping by using existing data sources available such as LiDAR, multispectral imagery and thematic GIS layers, GEOBIA techniques have not been widely documented (O'Neil-Dunne et al., 2014). Past GEOBIA literature focused on the development of segmentation algorithms and focused less on these methods accommodating for a tree cover data across large areas in a timely and cost effective manner to facilitate with time series analysis (O'Neil-Dunne et al., 2014) This paper seeks to use the experimental approach, GEOBIA, that allows for a flexible method for characterizing tree cover change in neighborhoods of Worcester, Massachusetts, by integrating a variety of quality remote sensing and GIS data sources.

This study maps tree cover gain, loss and persistence in the northern Worcester, MA from 2010 to 2015 using geographic object based image analysis (GEOBIA), 0.5 m WorldView-2 imagery, 1m LIDAR and in situ data to characterize and map tree cover. From 2008 to 2010 tree cover loss in Worcester, Shrewsbury, Boylston, W. Boylston and Holden, Massachusetts was caused 47% by conversion to developed land types (residential or bare soil), 25% by USDA tree removal for the ALB eradication, 15% by to timber harvest and 6% by a December 2008 ice storm (Hostetler et al., 2013). The city of Worcester experienced the greatest proportion of tree canopy loss due to the USDA tree removal (60%) with the majority of trees (>80%), predominantly maples (*Acer*), removed from neighborhoods Burncoat and Greendale (Palmer et al. 2014). In response the Department of Conservation and Recreation (DCR), the Worcester Tree Initiative (WTI) and the city of Worcester initiated tree planting programs in Worcester in 2010 (Danko et al., 2013; Palmer et al. 2014). This paper is motivated by the need to estimate the change in tree cover in Burncoat and Greendale, identify locations of gain and loss and estimate and locate the tree cover gain contributed by the DCR to quantify and monitor the success of the DCR tree planting initiatives.

Study Area

The study area is comprised of Burncoat and Greendale neighborhoods located in the northeastern part of the city of Worcester (see Figure 1). Burncoat and Greendale encompass 8.1 km^2 (8% of the city of Worcester) and the dominant land-cover consists residential areas with 53.2% and mixed species of hardwood and coniferous forests with 11.6% (MAFOMP, 2011). Before the ALB infestation the urban forest consisted of mainly species in the maple family (*Aceraceae*) as 4 out of the 5 street trees planted in Worcester (Freilicher et al., 2008). The most abundant species consisted of 60.83% Norway maple (*Acer platanoides*), 9.61% Sugar Maple (*Acer saccharum),* 6.43% Red maple (*Acer rubrum*), 2.13% Sliver Maple (*Acer saccharinum)* and 2.06% Littleleaf linden (*Tilia cordata*) (Freilicher et al., 2008). In 2008 the ALB infestation caused approximately 30,000 host trees to be removed of which more than 80% of the trees were removed from Burncoat and Greendale (Palmer et al. 2014). As a response to the large amount of tree removal tree planting programs by the Department of Conservation and Recreation (DCR), Worcester Tree Initiative and the city of Worcester were established. From 2010 to 2012 there was a high concentration of trees, 12423, planted in Burncoat and Greendale neighborhoods (Manley et al., 2012). Therefore, within the past seven years Burncoat and Greendale encountered major changes in cover due to the ALB eradication effort and the resulting tree planting programs.

Data

In Situ Data

DCR tree planting points used in this study are a subset of the trees planted after the ALB eradication effort. The location of 12,423 of trees planted by the DCR from Fall 2010 to Spring 2012 are used for a comparison between locations of tree cover gain that are attributed to the DCR tree planting. The top five trees planted in the dataset consist of the White Fir, American Arborvitae, Kousa Dogwood, Japanese Tree Lilac and Colorado Spruce and were primarily planted on Burncoat Street, Skyline Drive, Shawnee Road and Cheyenne Road.

GPS points for trees planted by the DCR, which were used to compare tree cover gain and loss polygons within the study contributed by the DCR, were incorrectly demarcated because of human or mechanical error. Therefore, when comparing DCR tree planting points to areas of gain and loss a visual estimation of which gain and loss polygons aligned with each tree planting point were made.

LiDAR

The LiDAR data is used to create LiDAR mask that masks out canopy higher than zero meters and separates areas of ground from non-ground. The LiDAR mask was used for the process of creating the 2015 tree cover map allowing for detection of smaller crown trees.

Between Fall of 2013 and Spring of 2014, airborne LiDAR data covering the city of Worcester's boundaries were collected under a contract by Woolpert (Dayton, OH). The discrete return LiDAR system used were a Leica ALS70 and an Optech ALTM Gemini LiDAR sensor attached to Cessna 404 and Cessna 310 aircraft. The Leica ALS70 and Optech ALTM Gemini LiDAR sensor have an average single pass flight line swath of 0 to 1.5 m x altitude (variable). For the Leica ALS70 sensor it was acquired at 200 – 3500 m altitude with a maximum pulse rate of 500 kHz with 7 returns per pulse. The Optech ALTM Gemini LiDAR sensor was acquired at a 150 – 4,000 m altitude and has a maximum pulse rate of 167 kHz with 4 returns per pulse. Once the sensor calibration, data acquisition and GPS processing phases were complete the individual flight lines were processed used to derive a raw "point cloud" LAS file that matched the overlapping flight lines, generated statistics for evaluation comparisons and made any adjustments needed to remove any residual systematic error. The LAS files were filtered to create a ground and non-ground class and once all data was imported and classified and survey ground control data was used for a vertical accuracy assessment.

World-View 2 imagery

WorldView-2 imagery for this study was collected from Digital Globe (https://www.digitalglobe.com/) and used to create a 2015 tree cover map through the process of segmentation. The multispectral imagery was pan-sharpened using the panchromatic band that allowed for a 0.5m resolution. The time and date of acquisition is 15:40 on May 7th 2015 and the swath is 16.4 by 16.4 km. The spectral resolution ranges from 0.4 to 10.4 micrometers.

2010 Tree Canopy

2010 tree canopy was used in the study compare tree cover gain and loss between the 2010 tree cover map and 2015 tree cover map. The 2010 tree cover map was created by the

University of Vermont Spatial Analysis Lab. This map was made by applying an object based classification scheme to 1 m NAIP imagery collected during July 2010.

Impervious Surface

The impervious surface layer represents impervious surfaces (e.g. buildings, roads, parking lots, and concrete) covering the Commonwealth of Massachusetts. The surface was extracted using a semi-automated technique by Sanborn Map Company using 50cm Vexcel UltraCam near infrared orthoimagery collected in April 2005 for the Color Ortho imagery project. The impervious surface layer was used to mask out all the buildings from the LiDAR Mask leaving predominantly tree cover. This layer was overlaid with the segmentation classification to create the 2015 tree cover map.

Methods

Step 1: Creating a Tree Cover Map for 2015

The character of the urban forest is heterogeneous and spans from stands of hundreds of trees to trees along streets to individual trees in residential and institutional lawns. Therefore, to account for this complexity of the urban forest, an object-based approach is conducted through an Object-based Image Analysis by conducting an image segmentation of high resolution imagery. Unlike traditional pixel-based classifiers, an object-oriented approach takes into account more than the average spectral signature of an object such as the object shape and the spatial pattern of the objects in the landscape (McGee et al., 2012). The segmentation process is a supervised classification method that groups adjacent pixels together into segments based on their spectral similarity creating spectrally homogenous segments (McGee et al., 2012). This study uses the TerrSet GIS software package (Eastman 2015) to subdivide the raster bands into homogenous groups that represent the same objects. There are three steps for the tool: (1) creation of a variance image through a user defined filter based on all input raster across a moving window (2) creation of segments based on a watershed process that groups pixels which have low variance (3) merging of adjacent segments through the similarity of segment mean value and standard deviation defined by the user-specified threshold. The user defines the four parameters (e.g. window width and similarity tolerance) and tests the optimal values for the segmentation parameters through a visual comparison in a false color composite. TerrSet also needs a pixel-based classification along with the segmentation-based classification to assign classes to the image segments, for this paper a maximum likelihood classification approach was used (see Figure 2).

Segmentation was tested within three different locations of Burncoat and Greendale by altering the parameters of window and tolerance and compared to Google Earth imagery and the false color composite to see if tree cover segments were homogenous, without any pixels of buildings or roads. The segmentation results were later used to enhance the 2015 tree cover map produced with a maximum likelihood classification approach. In addition, a LiDAR mask was created by masking out canopy higher than zero meters that separates areas of ground from non-ground; therefore, the LiDAR mask includes mainly buildings and tree cover excluding objects at ground level such as grass or roads. The LiDAR mask was helpful in detecting smaller crown trees as well as detecting trees that would have otherwise been misclassified due to the similarity in spectral signature of grass, shadows and trees. Furthermore, the impervious surface layer was used to mask out all the buildings from the LiDAR Mask to aggregate the trees detected from the LiDAR mask (see Figure 2).

Step 2: Creating a Tree Cover Change Map from 2010 to 2015

The study focuses on detecting tree cover change through the presence of a tree in a location in 2010 and comparing it to 2015. Therefore, tree cover gain and loss is not calculated by analyzing the change in tree crown width but rather if the tree-crown was present or not at a particular location between the two years. Since the 2010 and 2015 tree cover maps were produced with different data sources the 2010 tree cover map was first split into smaller polygons using the tree cover polygons from the 2015 tree map. Next, the tool “select by location” in ArcMap was used to acquire areas of no change, gain and loss. Using the “select by location” tool allowed for an entire tree polygon to be selected, indicating the presence or no presence of tree cover, rather than detecting gain or loss in tree crown width (see Figure 2).

Results

An accuracy assessment of the 2015 tree cover map was conducted using Google Earth imagery with 200 stratified sample points, stratified by areas classified as tree cover and not tree cover on the map. An overall accuracy of 93.2% with an error of commission of 0.066% and an error of omission of 0.068%. Sample points of tree cover were misclassified as dirt, pavement, edge of roofs and shadows. The tree cover change map from 2010 to 2015 indicates a greater percentage of areas in gain than loss, 7.52% areas of gain and 0.46% areas in loss of tree cover (figure 3).

The DCR tree planting contributed 1.75% in gain and of the total tree cover loss 0.032% were trees that the DCR planted from 2010 to 2012. Kernel density was used to create a density surface of each occurrence of tree cover gain (See Figure 4). In addition, Optimized Hotspot Analysis tool was used to further examine significant clusters of tree cover gain that visually appear clustered on the density surface map by counting the number of tree cover gain occurrences within fishnet polygons. The Optimized Hotspot Analysis output was used to examine locations of significant tree cover gain clusters, where hotspots indicate high densities of tree cover gain are near other high densities of tree cover gain (see figure 6). The Optimized Hotspot Analysis output indicated significant clusters (>99% confidence level) of tree cover gain along roads and front/backyards extending around and beyond Clark Street and Burncoat Street in Burncoat (see zoom in on Figure 6). Additionally, other significant clusters of high tree cover gain density are located by Burncoat Preparatory School, forested areas by Garrison Avenue and forested locations in the north of Burncoat near West Boylston Street. In the north of Greendale there are significant clusters of tree cover gain density extending from Maiden and West Boylston Street in Greendale (see zoom in on Figure 6).

In addition, the tree planting by the DCR in Burncoat attributed to tree cover gain on E Mountain Street and Cobblestone Lane in both the front/backyard of Burncoat (see figure 8). Within Greendale tree planting by the DCR contributed to tree cover gain along Kendrick Avenue and near Price Chopper on Hunnewell Road (see figure 8). In addition, six locations, Dixfield Road, Hunnewell Road, Bristol Street, Granville Avenue, Calumet Avenue, and Whispering Pine Circle were chosen across Burncoat and Greendale from the tree cover gain hotspots to compare the tree cover gain in the front and backyards. A visual count concluded 59% tree cover gain occurred in the backyards.

A density surface was calculated for tree cover loss using Kernel density (see Figure 5) indicating the magnitude of tree cover loss per unit area from the centroid point of a tree cover loss polygon. Figure 5 indicates high densities of tree cover loss in the southern part of Greendale by West Boylston Street and Fraternal Avenue (south of Abby Kelly Foster charter public School). The Optimized Hotspot Analysis output indicated significant hotpots (>99% confidence level) of tree cover loss in the southern part of Greendale by West Boylston Street and King Phillip Road (See figure 7). Additionally, six locations used to analyze tree cover loss in front and backyards are spread out across the study area and include Dixfield Road, Hunnewell Road, Ivernia Road, Granville Avenue Calumet Avenue, and Whispering Pine Circle. A visual count of tree cover loss polygons at the six locations concluded that 87% of the tree cover loss occurred in the front yard.

In Burncoat tree cover loss occurred on St Marke Road near the Worcester Country Club and on Fairhaven road south of Quinsigamond College (see Figure 9). Examples of tree cover loss in Greendale are on Granville Street in the backyards and on King Philip Road in the front yard (see Figure 9). However, unlike some tree loss in Granville Street the loss in tree cover on King Philip Road were not trees the DCR planted. Overall the majority of tree cover loss in Burncoat and Greendale occurred in the front yards while the majority of tree cover gain occurred in the backyards. 61.5% of the tree cover loss polygons are in Greendale and 38.5% of tree cover loss polygons in Burncoat, with Burncoat having approximately more than 26 ha of tree cover than Greendale.

Discussion and Conclusions

The purpose of this study was to characterize tree cover change from 2010 to 2015 in Burncoat and Greendale using LiDAR and WorldView-2 satellite imagery. The results demonstrate that there is more tree cover gain than loss within the study area, with DCR tree planting from 2010 to 2012 contributing to 1.75% of tree cover gain. Of the total tree cover loss 0.032% were trees that the DCR planted from 2010 to 2012. Tree cover gain and loss was seen in both the front/backyards of homes near Quinsigamond Community College, Burncoat

Preparatory School, Dodge Park and Price Chopper. However, the majority of tree cover gain occurred in front yards while the majority of tree cover loss occurred in backyards.

Additionally, only tree planting points from 2010 to 2012 by the DCR were acquired and therefore further tree planting by the DCR from 2012 onwards was not used as a comparison between the gain and loss polygons in the study area. Hence, tree cover gain and loss could be further contributed by the DCR. In addition to the DCR the WTI and city of Worcester also initiated tree planting programs that contribute to tree cover gain. This analysis suggests that social implications (neighborhood effect), policy implication and land ownership patterns influenced the targeting of tree planting over in specific locations of the study area. Targeted planting suggests an explanation for hotspots of tree cover gain in the study area.

This study uses multi-source GIS data, a GEOBIA approach, which relies on existing public investments in LiDAR, multispectral imagery and thematic GIS layers reducing data acquisition costs (O'Neil-Dunne et al., 2014). This allows for research covering large geographic extents to be performed quickly and at a lower cost than using field survey and inventory, as well as accommodates for datasets that vary in quality and content by using a combination of LiDAR and imagery to differentiate trees from buildings and other urban structures (Hostetler et al., 2013). With increasing use and advances in airborne LiDAR technology more urban forest managers will be able to integrate high resolution multispectral imagery with LiDAR technology to better monitor the changes in tree cover in the landscape, improve allocation of resources for tree planting programs and investigate further into locations of gain or loss in tree cover.

In addition, detection of tree cover is lost and an increase in errors of omission and commission when working with rasterized LiDAR rather than raw LiDAR point clouds (Zhang et al.2015; Zhou et al., 2013). Even though LiDAR allows for increase efficiency of urban tree inventories by detecting large and small crown trees, its accuracy is dependent on the sensor's pulse rate and the pulses' hit location. Consequently, LiDAR may mischaracterize and miss the crowns of some trees, particularly obstructed trees by fences or sheds or trees right next to buildings (Zhou et al., 2013).

This study encourages a top-down approach to monitoring urban tree cover change by integrating data from different data sources using high spatial resolution satellite imagery, LiDAR and GIS thematic layers (e.g. impervious surface). The results can assist future research and urban forest managers as tree cover mapping estimates are essential for ecosystem service models to determine environmental impacts of tree cover in the urban landscape. Additionally, this research demonstrates a multi-source GIS approach that can accommodate for using different data sources for time series analysis while providing a more efficient and less expensive method towards monitoring tree cover change over large extents.

References

Al-Kofahi, S., Steele, C., VanLeeuwen, D., & Hilaire, R. S., (2012), Mapping land cover in urban residential landscapes using very high spatial resolution aerial photographs. *Urban Forestry & Urban Greening*, *11*(3), 291-301.

Basu, S., Ganguly, S., Nemani, R. R., Mukhopadhyay, S., Zhang, G., Milesi, C., & Cook, B., (2015), A Semiautomated Probabilistic Framework for Tree-Cover Delineation From 1-m NAIP Imagery Using a High-Performance Computing Architecture. *Geoscience and Remote Sensing*, *IEEE Transactions on*, *53*(10), 5690-5708.

Chen, Z., and Gao, B, (2014), An object-based method for urban land cover classification using Airborne Lidar data. *Selected Topics in Applied Earth Observations and Remote Sensing, IEEE Journal of*, *7*(10), 4243-4254.

Danko III, J., Rogan, J., DeLauer, V., & Martin, D., (2013), Using the past to manage the future: Asian Longhorned Beetle (ALB) narrative timeline for the Worcester outbreak. Clark University Honors Thesis.

Freilicher, M., Kane, B., Ryan, H., & Bloniarz, D. (2008). A report on the status of Street trees in Worcester, Massachusetts: University of Massachusetts at Amherst.

Hostetler, A. E., Rogan, J., Martin, D., DeLauer, V., & O'Neil-Dunne, J. (2013). Characterizing tree canopy loss using multi-source GIS data in Central Massachusetts, USA. *Remote Sensing Letters*, *4*(12), 1137-1146.

Li, X., & Shao, G., (2014), Object-based land-cover mapping with high resolution aerial photography at a county scale in midwestern USA. *Remote Sensing*, *6*(11), 11372-11390.

MAFOMP (2011). Massachusetts Forest Monitoring Progam. Worcester, MA: Clark University.

Manley, M., Rogan, J., Martin, D., & DeLauer, V. (2012). A Multi-Scale Assessment of Urban Forest Biodiversity: Tree Replanting as a Driver of Street Tree Composition. Clark University Honors Thesis.

McGee, J. A., Day, S. D., Wynne, R. H., and M.B. White. 2012. Using Geospatial Tools to Assess the Urban Tree Canopy: Decision Support for Local Governments. *Journal of Forestry*, *110*(5), 275-286.

McPherson, E. G. 1993. Monitoring Urban Forest Health. *Environmental Monitoring and Assessment*, *26*(23), 165-174.

McPherson, E. G., Simpson, J. R., Peper, Maco, S. E., & Xiao, Q., (2005), Municipal forest benefits and costs in five US cities. Journal of Forestry, 411-416.

Merry, K., Siry, J., Bettinger, P., & Bowker, J. M., (2014), Urban tree cover change in Detroit and Atlanta, USA, 1951–2010. *Cities*, *41*, 123-131.

Nowak, D. J. (1993)., Historical vegetation change in Oakland and its implications for urban forest management.

Nowak, D. J., & Dwyer, J. F., (2007), Understanding the benefits and costs of urban forest ecosystems. In *Urban and community forestry in the northeast* (pp. 25-46). Springer Netherlands.

Nowak, D. J., & Greenfield, E. J., (2012), Tree and impervious cover change in US cities. *Urban Forestry & Urban Greening*, *11*(1), 21-30.

Nowak, D. J., Rowntree, R. A., McPherson, E. G., Sisinni, S. M., Kerkmann, E. R., & Stevens, J. C, (1996), Measuring and analyzing urban tree cover. *Landscape and Urban Planning*, *36*(1), 49-57.

O'Neil-Dunne, J., MacFaden, S., & Royar, A., (2014), A Versatile, Production-Oriented Approach to High-Resolution Tree-Canopy Mapping in Urban and Suburban Landscapes Using GEOBIA and Data Fusion. *Remote Sensing*,*6*(12), 12837-12865.

Palmer, S., Martin, D., DeLauer, V., & Rogan, J., (2014), Vulnerability and adaptive capacity in response to the Asian Longhorned Beetle infestation in Worcester, Massachusetts. *Human Ecology*, *42*(6), 965-977.

Parent, J. R., Volin, J. C., & Civco, D. L., (2015), A fully-automated approach to land cover mapping with airborne LiDAR and high resolution multispectral imagery in a forested suburban landscape. *ISPRS Journal of Photogrammetry and Remote Sensing*, *104*, 18-29.

Phillips, N. G., Ackley, R., Crosson, E. R., Down, A., Hutyra, L. R., Brondfield, M., ... & Jackson, R. B., (2013). Mapping urban pipeline leaks: Methane leaks across Boston. *Environmental pollution*, *173*, 1-4.

Plowright, A. A., Coops, N. C., Eskelson, B. N., Sheppard, S. R., & Aven, N. W. (2016). Assessing urban tree condition using airborne light detection and ranging. *Urban Forestry & Urban Greening*, *19*, 140-150.

Poland, T. M., & McCullough, D. G. (2006). Emerald ash borer: invasion of the urban forest and the threat to North America's ash resource. *Journal of Forestry*, *104*(3), 118-124.

Rogan, J., & Chen, D.,(2004). Remote sensing technology for mapping and monitoring land-cover and land-use change. *Progress in planning*, *61*(4), 301-325.

Roman, L. A., McPherson, E. G., Scharenbroch, B. C., and J. Bartens, J. 2013. Identifying Common Practices and Challenges for Local Urban Tree Monitoring Programs across the United States. *Arboric Urban. 39*, 292-299.

Stueve, K. M., Hollenhorst, T. P., Kelly, J. R., Johnson, L. B., & Host, G. E., (2014), High-resolution maps of forest-urban watersheds present an opportunity for ecologists and managers. *Landscape Ecology*, *30*(2), 313-323.

Senanayake, I. P., Welivitiya, W. D. D. P., & Nadeeka, P. M.,(2013), Urban green spaces analysis for development planning in Colombo, Sri Lanka, utilizing THEOS satellite imagery–A remote sensing and GIS approach. *Urban Forestry & Urban Greening*, *12*(3), 307-314.

Tanhuanpää, T., Vastaranta, M., Kankare, V., Holopainen, M., Hyyppä, J., Hyyppä, H., & Raisio, J., (2014), Mapping of urban roadside trees–A case study in the tree register update process in Helsinki City. *Urban Forestry & Urban Greening*, *13*(3), 562-570.

Wood, J. P. 1999. *Tree inventories and GIS in urban forestry* (Doctoral dissertation, Virginia Tech).

Zhou, W.,(2013), An object-based approach for urban land cover classification: integrating LiDAR height and intensity data. *Geoscience and Remote Sensing Letters, IEEE*, *10*(4), 928-931.

Zhang, C., Zhou, Y., and F. Qiu. 2015. Individual Tree Segmentation from LiDAR Point Clouds for Urban Forest Inventory. *Remote Sensing*, *7*(6), 7892-7913.

Zhao, C., & Sander, H. A., (2015), Quantifying and Mapping the Supply of and Demand for Carbon Storage and Sequestration Service from Urban Trees. *PloS one*, *10*(8), e0136392.

Figures

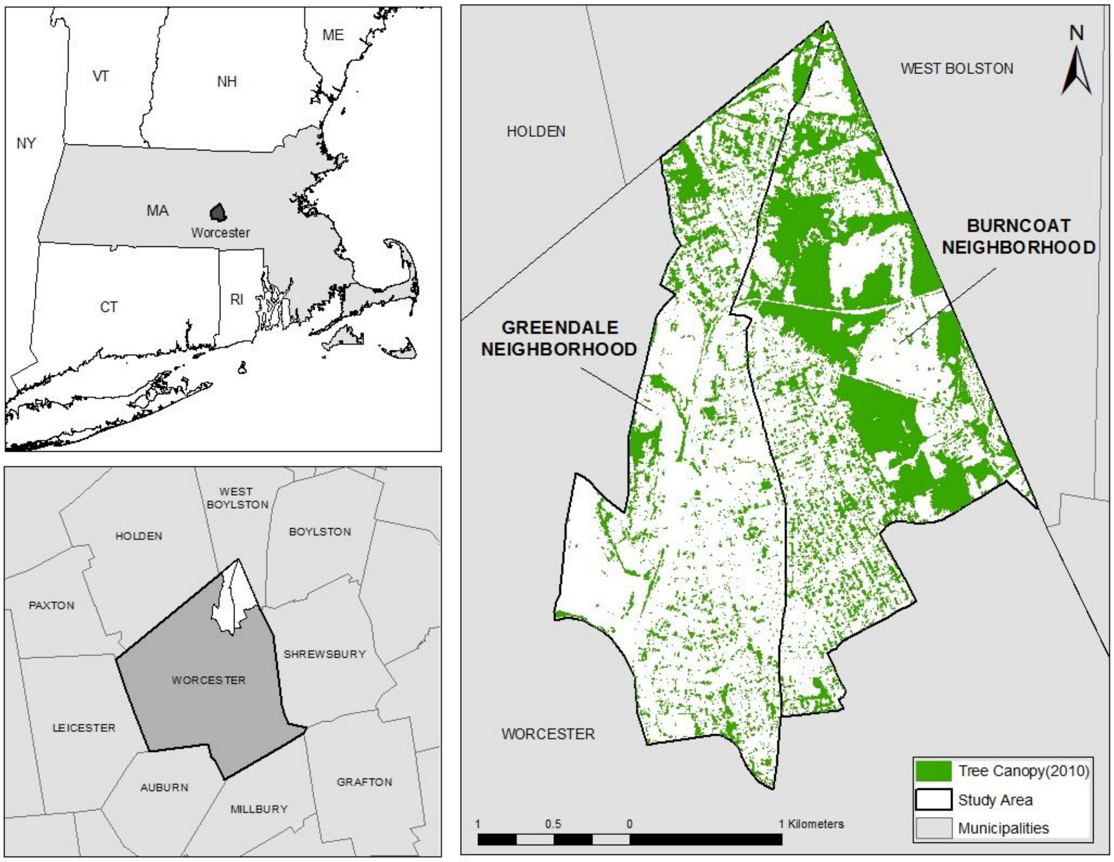

Figure 1: Study are of Burncoat and Greendale neighborhoods in Worcester, MA

Figure 2: Flow chart indicating process of segmentation and integration of LiDAR mask to create the 2015 tree cover map and a tree cover change map from 2010 to 2015.

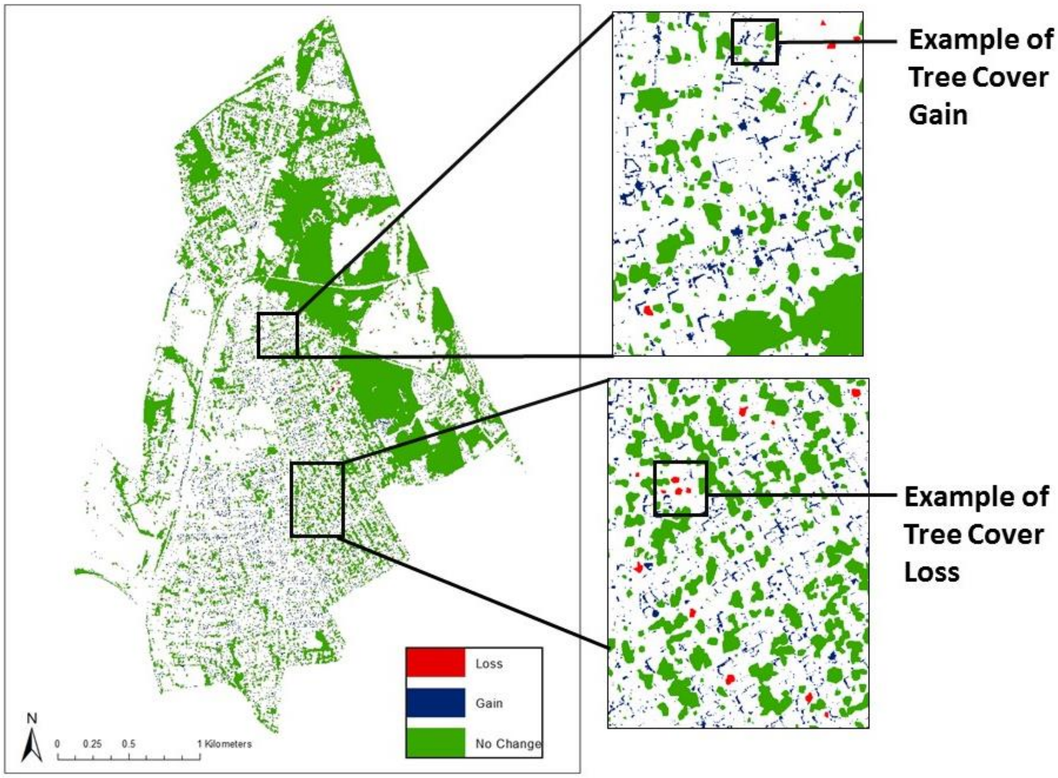

Figure 3: Tree cover change map from 2010 to 2015 indicating gain, loss and no change in tree cover

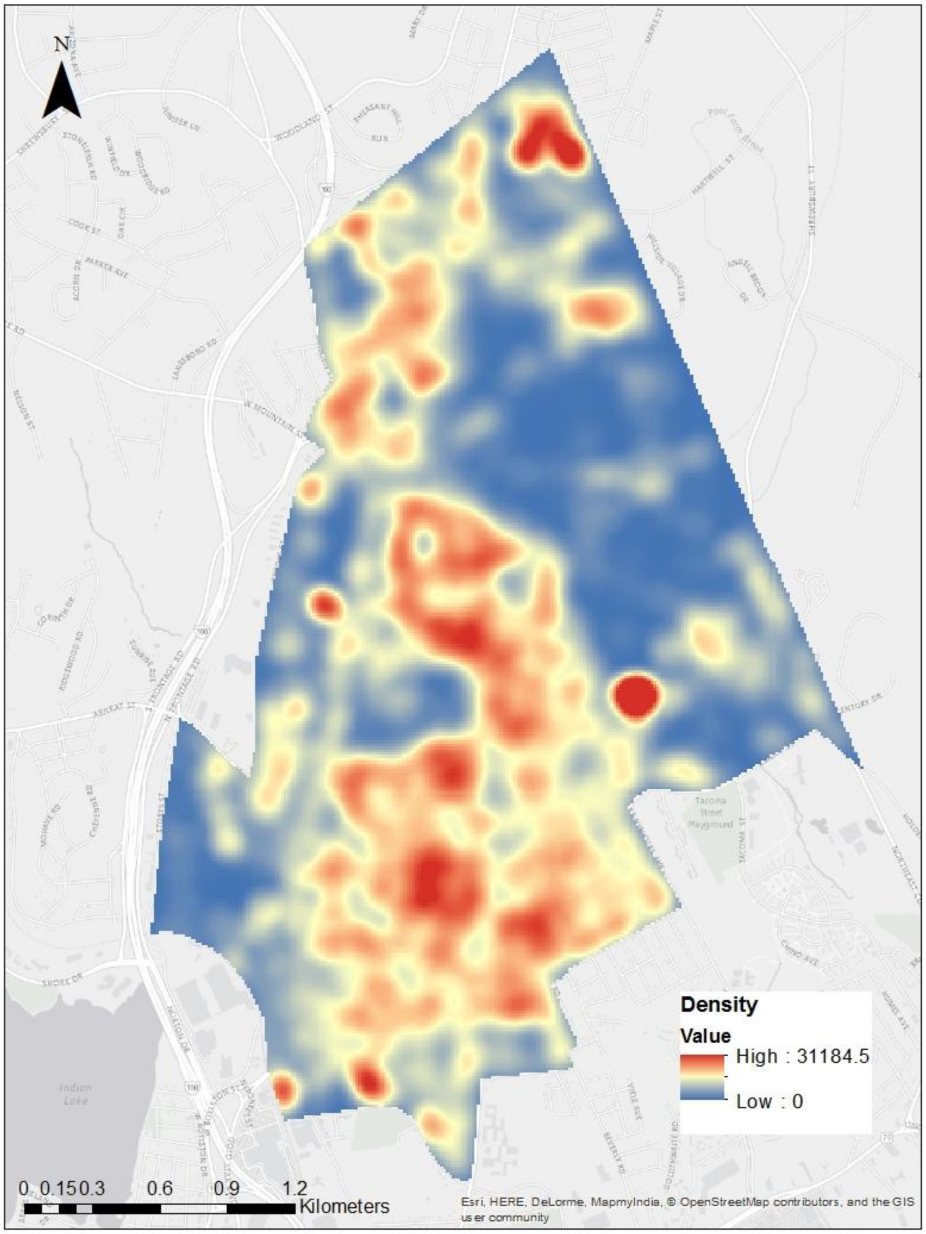

Figure 4. Density surface created using Kernel Density of incidents of tree cover gain in Burncoat and Greendale.

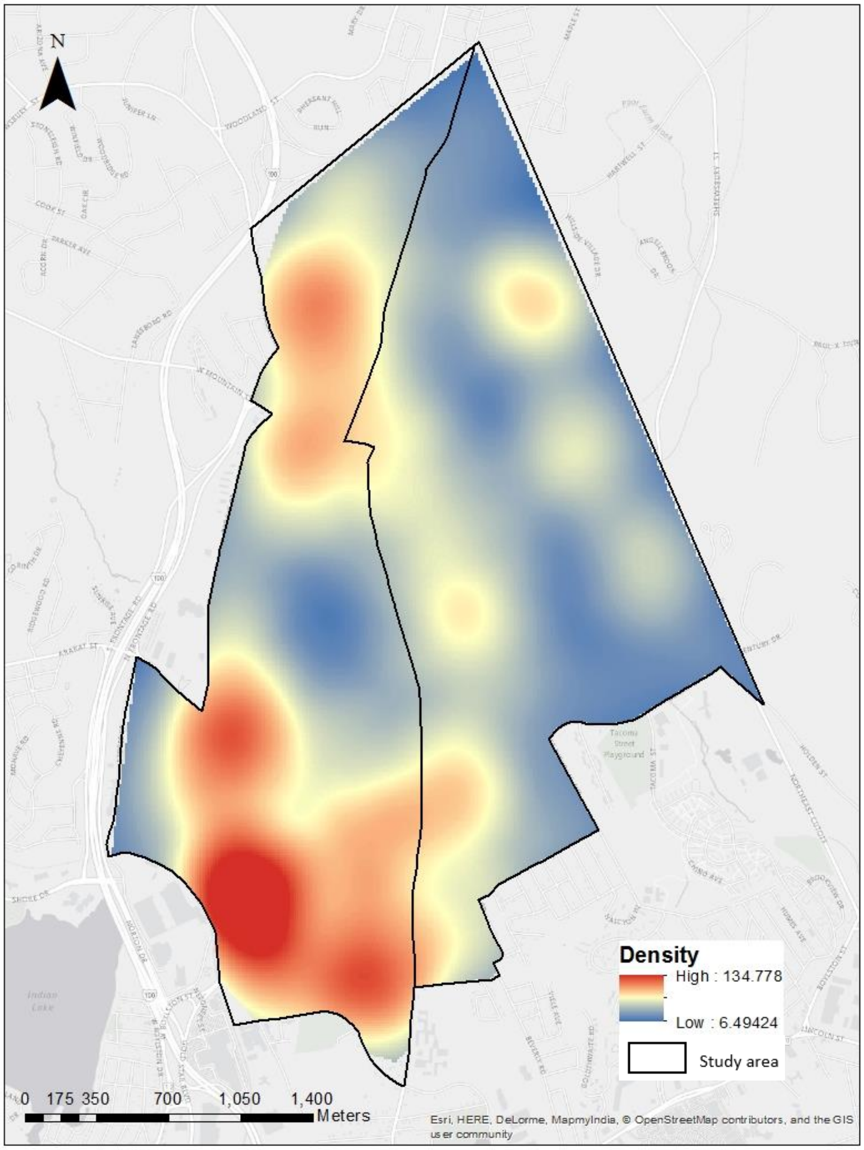

Figure 5. Density surface created using Kernel Density of incidents of tree cover loss in Burncoat and Greendale.

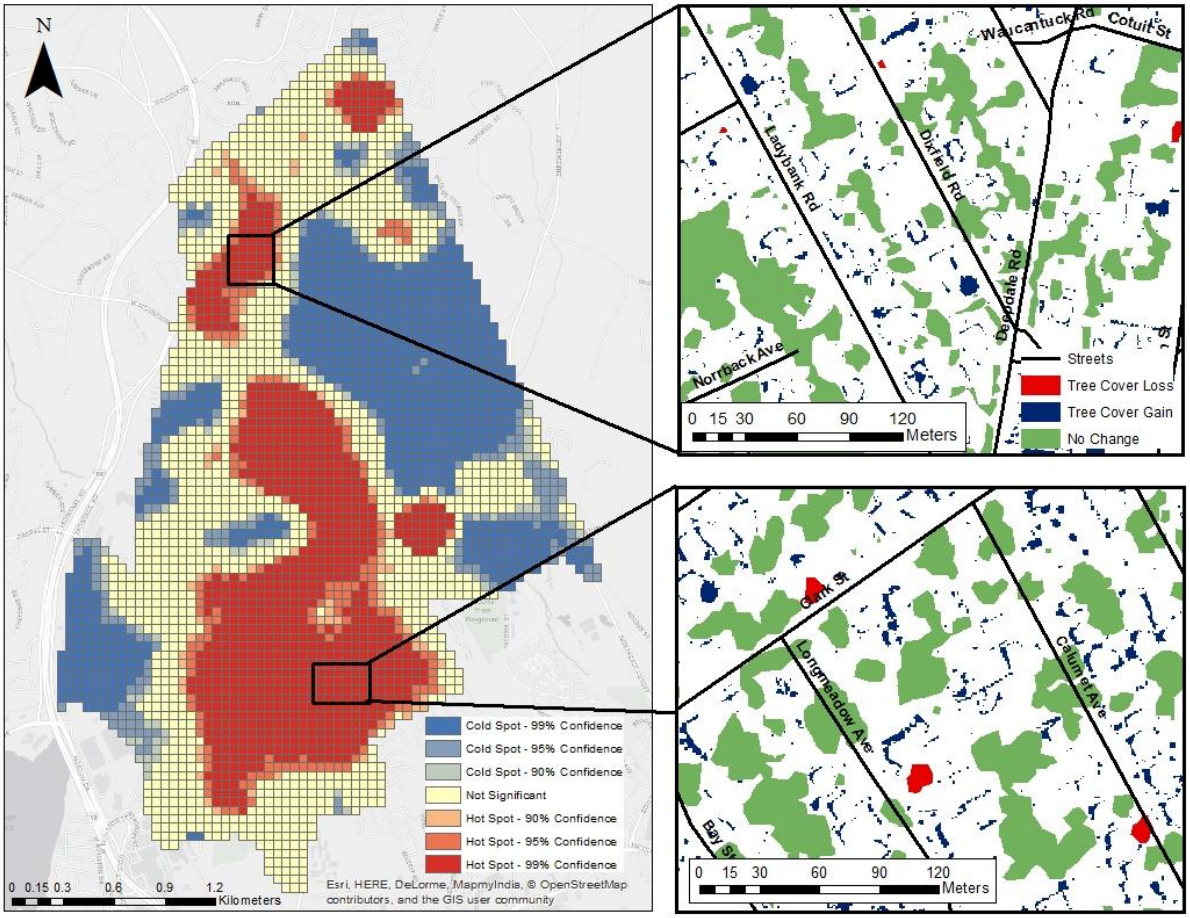

Figure 6. Optimized Hotspot Analysis in Burncoat and Greendale, highlighting hotspot locations of tree cover gain along Dixfield and Ladybank Road near West Boylston Street, Greendale (top right). Burncoat neighborhood hotspots of tree cover gain along Longmeadow and Calumet Avenue (bottom right).

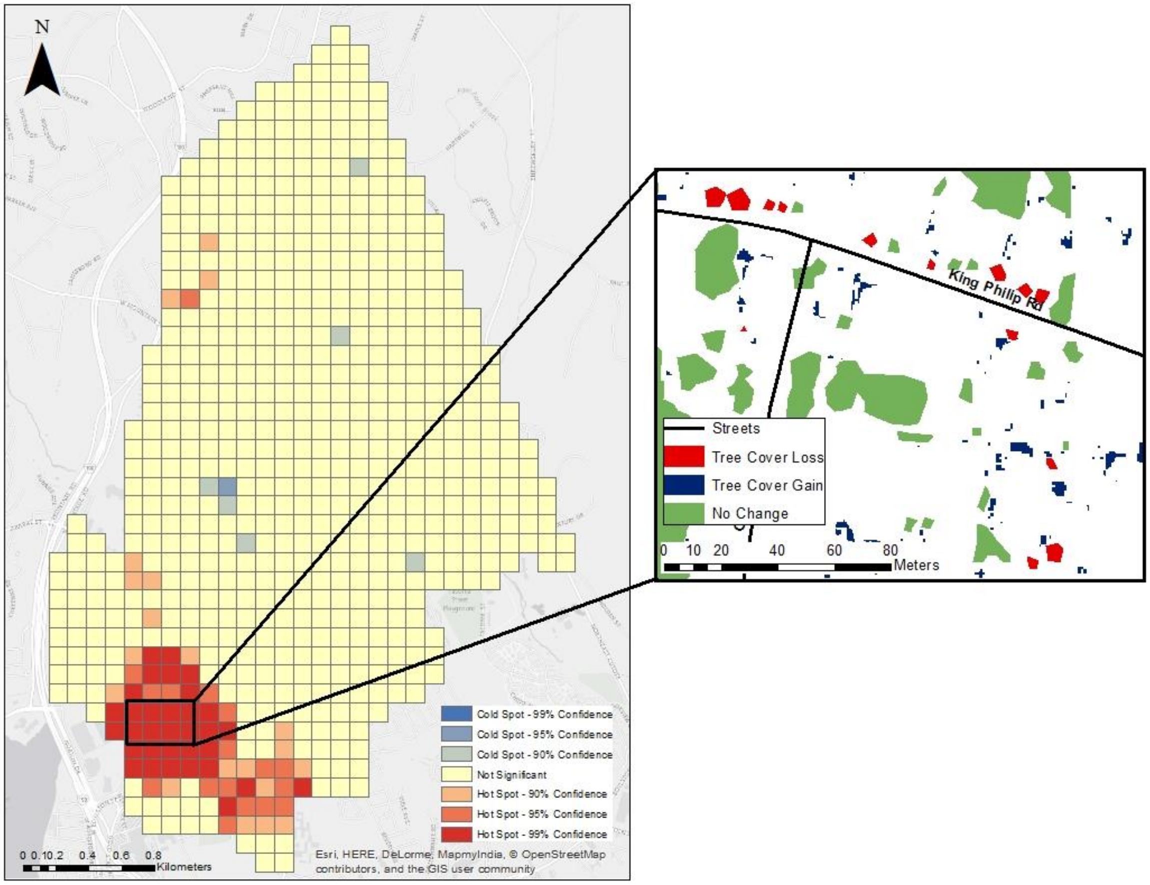

Figure 7. Optimized Hotspot Analysis in Burncoat and Greendale, highlighting hotspot locations of tree cover loss. Zoom in of tree cover loss hotspot location is on West Boylston Street intersecting with King Phillip Road and Andover Street.

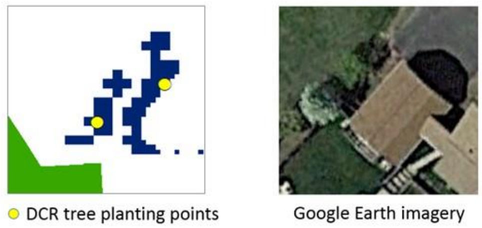

Figure 8.1. Tree cover gain due to DCR tree planting on E Mountain Street, Burncoat

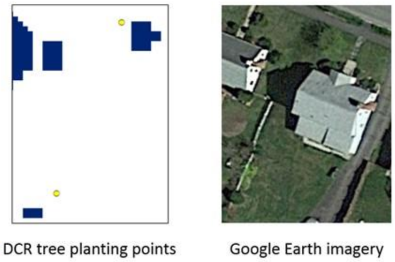

Figure 8.2. Tree cover gain due to DCR tree planting on Kendrick Avenue, Greendale

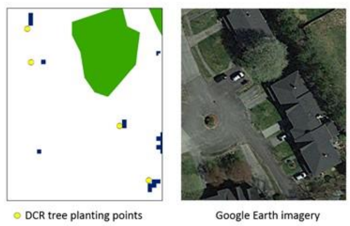

Figure 8.3. Tree cover gain due to DCR tree planting on Cobblestone Lane, Burncoat

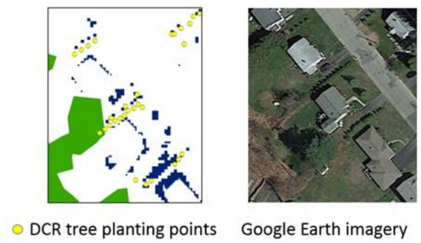

Figure 8.4. Tree cover gain due to DCR tree planting on Hunnewell Road (near Price Chopper), Greendale

Figure 8. Locations of tree cover gain in Burncoat and Greendale

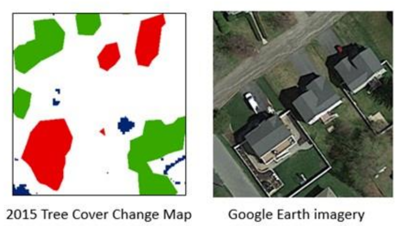

Figure 9.1. Tree cover loss on St Marke Street (near Worcester Country Club), Burncoat

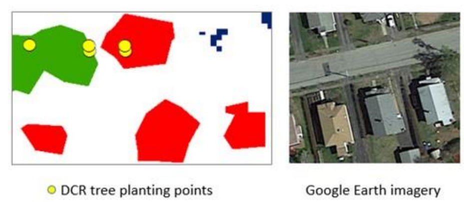

Figure 9.2. Tree cover loss on Fairhaven Street, Burncoat

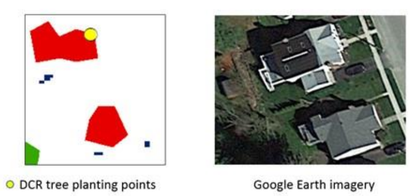

Figure 9.3. Tree cover loss on Granville Street, Greendale.

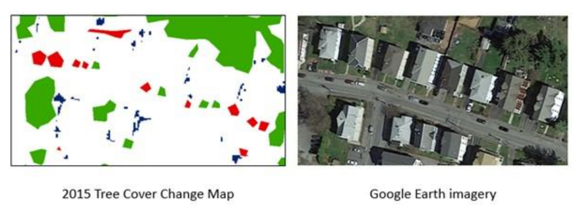

Figure 9.4. Tree cover loss on King Philip Road (near Saint-Gobain Abrasives Inc.), Greendale

Figure 9. Locations of tree cover loss in Burncoat and Greendale.