Urban Tree Canopy Assessment Using Geospatial Technologies:

A Case Study of the Town of Lincoln, Ontario

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Abstract

Urban trees provide important benefits to communities, from mitigating stormwater to improved air quality. Municipalities across Ontario encounter a decline in their urban tree canopy (UTC). UTC assessment is essential for the management of urban trees, especially in the context of climate change. However, quantifying the canopy remains a challenge, given that tree crowns are difficult to assess from the ground. Geospatial technologies provide a suitable alternative to costly, ground-based assessments. Still, they typically require a significant investment in resources, including technical expertise and equipment. For many small- and medium-sized municipalities facing the realities of climate change, these investments are cost-prohibitive.

This study aimed to assess the UTC within the Town of Lincoln, Ontario, using geospatial technologies. The first objective was to estimate canopy cover and distribution using image classification as the main approach. The second objective was to assess the proficiency of a low-cost method based on image interpretation (i.e., i-Tree Canopy) to calculate canopy cover compared to the main approach. The third objective was to examine the possibility of using the canopy goal designated by the Niagara Official Plan as a standard canopy goal. This research study produced three main results. First, the image classification indicated that the tree canopy covers 21% of the Town. Second, this study demonstrated that the results from the main approach are similar to those obtained from i-Tree Canopy. Given the similarity between these approaches, this study concluded that the lower-cost i-Tree Canopy method could be combined with other methods to prepare accurate and affordable canopy assessments for resource-limited municipalities. Finally, this study concluded that canopy goals should account for local differences based on geographic location. This study makes a valuable contribution to the literature as it informs management of canopy resources in communities with limited resources. Outcomes from this study can also better inform tree-canopy goals and policies with a cost-effective method that requires minimal expertise. The ability to conduct UTC assessment in smaller communities is critical in mitigating the impacts of climate change facing most of these communities.

Keywords: urban forest, remote sensing, i-Tree Canopy, canopy goals, climate change

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List of Abbreviations

CLI	Canada Land Inventory
CMA	Census Metropolitan Areas
ELC	Ecological Land Classification
ES	Ecosystem Services
EMS	Electromagnetic Spectrum
ENVI	Environment for Visualizing Images
FAO	Food and Agriculture Organization
FCC	False-colour Composite
GHG	Greenhouse Gas
GIS	Geographic Information Systems
LiDAR	Light Detection and Ranging
LULC	Land-use and Land-cover
MA	Millennium Ecosystem Assessment
MLC	Maximum Likelihood Classification
NbS	Nature-based Solutions
NIR	Near-infrared
SOLRIS	South Ontario Land Resource Information System
SDGs	Sustainable Development Goals
SE	Standard Error
TCC	True-colour Composite
UHI	Urban Heat Island
USDA	The United States Department of Agriculture
UTC	Urban Tree Canopy

1. Introduction

1.1 Background

Urbanization is a relatively new phenomenon in human history. Today, half the world's population lives in cities. Compared to 1950, the urbanization rate has increased by 20% globally (UN Department of Economic and Social Affairs [DESA], 2019). Urbanization alters existing social and demographic structures, attracts public and private investments, and changes the spatial distribution of land-use and land-cover (LULC) to accommodate and support a growing population. Urbanization is also directly connected to the three dimensions of sustainability: environmental, societal, and economical. It boosts social and economic progress while giving less priority to protecting environmental resources, such as urban trees, wetlands, and biodiversity. Therefore, rapid urbanization may involve tradeoffs between environmental, societal, and economic dimensions of sustainability (Boone & Fragkias, 2013).

A small percentage of the planet's surface is currently covered by urban areas (0.5%). However, it is predicted that by 2030 the total global urban area will be tripled (UN Development Programme [UNDP], 2016). From 2009 to 2019, the degree of urbanization in Canada increased by 0.7% (Plecher, 2020). According to the 2016 Canadian census, southern Ontario is the most densely populated region in Canada. With more than 12.7 million residents, the region accommodates approximately one-third of Canada's population of 35.1 million. Southern Ontario is home to over 94% of Ontario's total population of 13.4 million people, compared to approximately 780,000 in northern Ontario (Statistics Canada, 2017a). This increase in population is due to many factors, including more arable land in the south, its moderate climate, different transportation routes (water, land, and air), proximity to populated areas of the midwestern and northeastern United States, as well as a long history of early European settlement and colonialism (Chapman & Putnam, 1984).

Cities have significant ecological footprints. They produce 70% of the world's greenhouse gases and consume 80% of the world's energy (UN Human Settlement Programme [HABITAT], 2011). In addition to the enormous greenhouse gas production, climate change impacts such as erosion, landslides, and flooding are exacerbated in urban areas by displacing forests, farmlands, wetlands and replacing porous soil with impervious surfaces (Mullaney et al., 2015).

Urbanization is an inevitable modern phenomenon. More job opportunities, better health and education facilities, the concentration of capital, and specialized human recourses have made cities an ideal destination for populations (UNDP, 2016). Despite the negative impacts of urbanization on the environment, there are still opportunities to achieve sustainable, equitable, and inclusive urban communities. Well-managed, sustainable urbanization takes advantage of the natural potential to mitigate the environmental degradation and adverse drawbacks of population growth. Nature-based solutions (NbS), such as trees and wetlands, are substitutes to traditional approaches and have gained particular attention in recent years to solve environmental, societal, and economic challenges, such as climate change, food insecurity, environmental injustice, and natural catastrophes (Brears, 2020). NbS are less expensive to establish and maintain than conventional infrastructure, are environmentally friendly, and accessible to small communities (Cohen-Shacham et al., 2016).

Utilizing the abundant ecosystem services of trees to confront climate change and achieving sustainability requires knowledge of the current tree canopy. The urban tree canopy (UTC) is defined as the "leafy, green, overhead cover from trees that community groups, residents, and local governments maintain in the landscape for beauty, shade, fruit production, wildlife habitat, energy conservation, stormwater mitigation, and a host of public health and educational values" (United States Department of Agriculture [USDA], 2019, p. 1).

UTC assessment provides information on the available canopy cover and the spatial distribution of trees. This information can be used to protect the current canopy, monitor changes over time, set policies to protect existing trees, and devise plans to enhance the canopy in the future. Further, map output products generated from UTC assessments can be integrated with ancillary data (e.g., watershed/flood information, topographic data, population density) for improved urban and environmental planning (McGee et al., 2012; USDA, 2019).

Many large cities worldwide have conducted UTC assessments, and the condition of their tree canopy is being monitored regularly. The need for smaller cities and even semi-urban areas to conduct these assessments is also growing (The Food and Agriculture Organization [FAO], 2016). Existing research suggests that trees located in smaller communities (including low-income neighborhoods) are in poor condition (Basman, 2002; Gerrish & Watkins, 2018). The problem of providing funding for the expertise, human resources, and technical requirements deprives small communities of the useful information provided by a UTC assessment (Gerrish & Watkins, 2018).

Current research suggests that smaller communities and local municipalities can benefit from establishing formalized partnerships with other organizations and institutions to address contemporary environmental challenges (McGee et al., 2012). The Brock-Lincoln Living Lab (a partnership between Brock University and the Town of Lincoln) is an example of a partnership that provides additional resources and expertise to help a local municipality address these challenges. Living labs are experimentation environments where producers and beneficiaries create real-life solutions integrating innovation and research (European Network of Living Labs [ENoLL], 2016).

This study is being undertaken within the context of Brock-Lincoln Living Lab; it provides the necessary expertise, computer equipment, and software for the Town of Lincoln to acquire a baseline dataset of their tree canopy. Conducting a UTC assessment provides the Town with information that can be used to monitor and enhance the tree canopy over time. This study focuses on small communities (such as the Town of Lincoln) that can benefit from formalized partnerships to address their canopy needs. This is particularly important as these communities simultaneously adapt to the impacts of climate change (e.g., increased flood events). In this study, two different geospatial approaches to the assessment of urban trees are examined. The term geospatial technology describes the use of “several different high-tech systems and tools that acquire, analyze, manage, store, or visualize various types of location-based data” (Shellito, 2018, p. 2). This study examines the extent to which low-cost geospatial technologies, such as i-Tree Canopy (a publicly available software based on image interpretation with low technical complexities), can be used in place of image classification, a higher cost and more technically complex geospatial technology. If the results obtained from these two approaches coincide, the more accessible method (i-Tree Canopy) can be used for rapid UTC assessment or pre-studies in urban and regional planning.

1.2 Study Purpose and Objectives

The purpose of this research study is to undertake an UTC assessment in the Town of Lincoln, Ontario, Canada. Urban tree canopy assessment measures a community’s tree canopy cover and is substantial for understanding the extent of a community’s forests and tree resources (USDA, 2019). As many ecosystem services are directly correlated to the mass of healthy leaves, the proportion, area, and spatial distribution of the tree canopy serves as crucial information for increasing these services and targeting areas where they are most needed (McGee et al., 2012). The objectives of this study are:

1. Determine the percentage and the area of the Town of Lincoln under urban tree canopy cover and the spatial distribution of the canopy across urban areas within the study area using a traditional remotely sensed image classification approach. This approach has long been used to successfully map land-use and land-cover types and monitor their change over time; it is very technical, requires specialized hardware/software, and is both cost- and time-consuming. Given that this method has proven to be effective in UTC assessment, it was chosen as the main method used in this study;
2. To implement UTC assessment using a low-cost image-interpretation method (i.e., i-Tree Canopy) and compare the results to the image classification approach. In addition to identifying the benefits and challenges of this approach, other affordable and precise UTC assessment methods for small-to-medium sized communities will be discussed; and
3. To examine the suitability of the canopy goal outlined in the Niagara Official Plan to serve as the potential canopy goal to increase resilience and adaptation to climate change and achieve sustainability. Achieving a reasonable canopy goal requires assessing current canopy cover and then prioritizing the most suitable locations to plant new trees depending on the environmental, social, and economic need assessments. Setting policies in urban tree management should protect the existing canopy and achieve the canopy goal.

UTC assessments are not limited to large urban areas and can be applied in any geographical location, regardless of being urban or rural. Small communities can benefit from trees just as much as urban communities. Maintaining or increasing the ecosystem services provided by trees requires a canopy assessment, often overlooked in small communities due to a lack of expertise and budget. This study is unique because it provides an accurate, rapid, and practical solution to implementing UTC assessment in a small community at the frontline of confronting the impacts of a changing climate.

1.3 The Study Area

Located in the Regional Municipality of Niagara between the southern shore of Lake Ontario and the Niagara Escarpment (Figure1.1), the Town of Lincoln has a moderate climate with mild winters for its abundant orchards, vineyards, and crops. The Region is located in the heart of Ontario's wine country and contributes significantly to the wine industry in Niagara. Lincoln, one of the twelve local municipalities within the Niagara Region, serves Beamsville, Campden, Jordan, Jordan Station, Prudhommes, Vineland, and Vineland South.

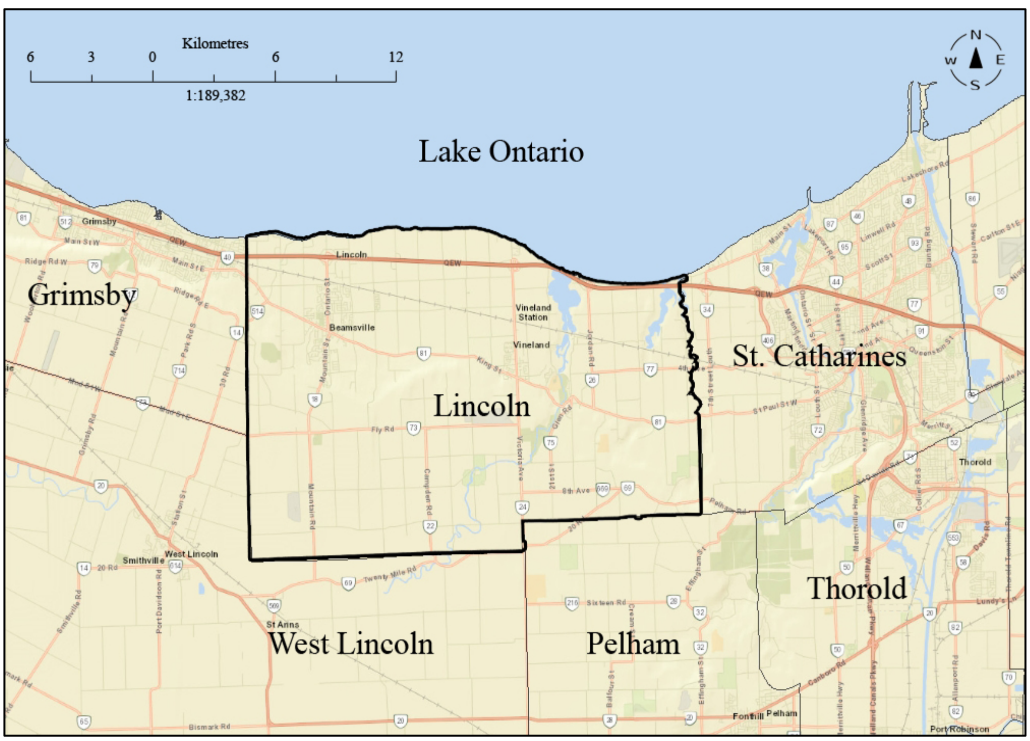

Figure 1.1
Map of the Town of Lincoln, Ontario
Adapted from *Statistics Canada, 2016*

Like many other parts of the world and Canada, Niagara Region also faces climate change impacts (e.g., flooding, strong winds, and droughts). In Lincoln, the most critical impacts of climate change are the flooding of households, properties, infrastructure, and challenges resulting from more frequent occurrences of extreme heat (Niagara Adapts, 2020). As a shoreline community, erosion creates challenges like evacuating parts of the Town and costly damages to the road networks that were not seen decades ago (DeCock-Caspell & Vasseur, 2021). According to Lincoln's 2016 census profile, the Town has a population of 23,787; that represents a population growth of 5.8% from 2011. This compares to the provincial average of 4.6% and the national average of 5% (Statistics Canada, 2019). Over the past five years, the Town's population growth rate has been higher than most municipalities within the Niagara Region (Figure 1.2). Lincoln will face a 32% population increase by 2041 (Town of Lincoln, 2019). This increase represents an addition of 7,640 new residents to the Town's current population.

New residents increase demands on the environmental, cultural, economic, and social landscape of the Town. Environmental needs, such as space requirements for construction purposes, are particularly problematic as they often impact natural assets such as forests and wetlands. Covering the soil with impermeable layers (e.g., asphalt, concrete) in cities is a problem that significantly increases stormwater runoff (Mullaney et al., 2015). The adverse effects of urbanization can be exacerbated when combined with climate change impacts. The Town of Lincoln is eager to use urban tree ecosystem services to adapt to climate change in the Brock-Lincoln Living Lab partnership. UTC assessment provides an opportunity to understand the current state of trees, adopt appropriate policies to protect them, and make optimal use of urban trees as NbS to confront climate change and other environmental crises. UTC assessments provide an opportunity to determine a baseline dataset from which gaps in the canopy can also be identified. Using information gleaned from this assessment, NbS can be implemented to address socio-environmental negative impacts.

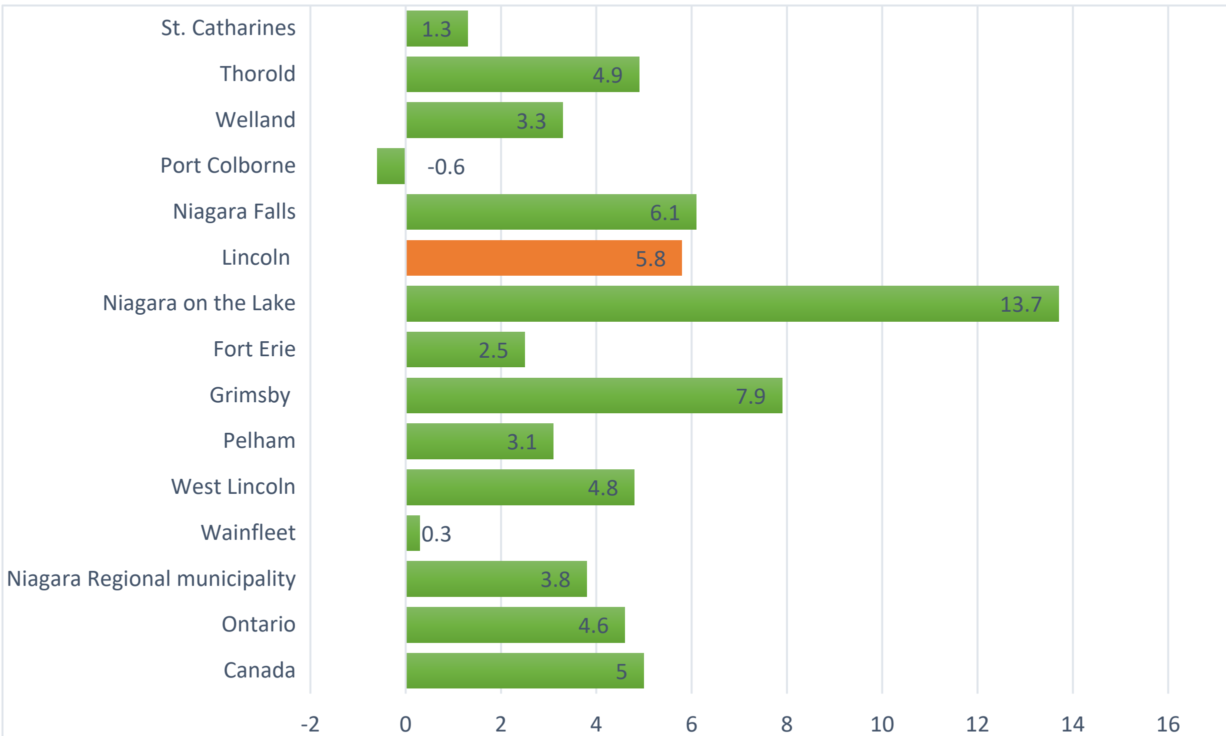

Figure 1.2
Niagara Region's Municipalities Population Change (% from 2011 to 2016)

Note. Adapted from *Statistics Canada, 2017b*

1.4 Thesis Outline

This thesis has been organized into six chapters. Chapter 1 introduces the research problem, background information, and the purpose and objectives of this research study. The context, rationale, and expected contributions of this research study are also included in this chapter. In Chapter 2, a comprehensive review of the relevant literature on urban tree canopy assessment using geospatial technologies is provided. This chapter situates this research study within the context of the broader literature on the UTC and UTC assessments.

The approaches used in this study and a detailed description of the data and methods used are provided in Chapter 3. The chapter includes a detailed description of the data acquisition process, image pre-processing, and the analytical techniques performed on the remotely sensed data. It also includes a discussion of techniques used to classify and assess the accuracy of results obtained from image classification and describes an alternative (i.e., more affordable) method for performing canopy assessments (i.e., i-Tree Canopy).

Chapter 4 presents the results obtained from the data-analysis methods used in this study, including the results from applying the maximum-likelihood classification algorithm to select bands of remote-sensing data. It also includes results achieved from the use of i-Tree Canopy. An assessment of the accuracy of these results is also presented in this chapter.

The fifth chapter provides an interpretation of the results gained from data analyses, including a comparison of the results of the two UTC assessment approaches used in this study. The outcomes from these results are critical for small communities facing an increasing need to conduct UTC assessments using more affordable techniques. Current canopy estimates are discussed and compared with the Niagara Official Plan's desired canopy cover, based on the new Niagara Region 2019 Official Plan (Niagara Region, 2019). The compatibility of the official plan's goal with what is typically considered a canopy goal is also discussed.

A summary of the findings and limitations of this research study, along with recommendations for further research on UTC assessments in small- to medium-sized communities, is provided in Chapter 6.

2. Literature Review

2.1 Introduction

This chapter provides a review of the relevant literature on assessments of the urban tree canopy (UTC) covering the period from 2000 to the present. It consists of a discussion of the best approaches and practices in urban tree canopy assessment. Based on their technical specifications (e.g., sensor resolution), a review of the most suitable remote-sensing datasets for UTC assessments is also provided. This literature review offers critical information to guide this research by informing this study's data acquisition and analysis phases (i.e., objectives 1 and 2). It is also used to identify existing gaps in the literature. To satisfy objective #3 of this study, the remainder of the literature review was dedicated to reviewing existing research studies on setting canopy goals. This part of the review is particularly important as the optimal canopy goals should be specifically tailored to the needs of a community and strengthen sustainable development in a region.

Peer-reviewed journal articles and reference books were used for the technical part of the image classification method, mainly related to objective one. Since using i-Tree Canopy is a relatively new method, few studies have been published using this method. Most of the existing papers using this method have been published in reports from municipalities conducting UTC assessments; some of these have been undertaken in collaboration with academic institutions. This study intends to contribute to this gap in the literature on using i-Tree Canopy in UTC assessment and especially its comparison with a pixel-based approach (i.e., image classification).

Urban tree canopy coverage is one of the most important types of cover in LULC studies; however, it wasn't the main focus of these studies prior to 1990. In 2003, the concept of ecosystem services was popularized by the United Nations Millennium Ecosystem Assessment (Millennium Ecosystem Assessment, 2003). Since then, it has enhanced communities' desire to use trees in urban areas as nature-based solutions, especially for increasing sustainability and adapting to climate change. In 2003, the US Department of Agriculture (USDA) established the first study on urban tree canopy coverage for the City of Baltimore (Irani & Galvin, 2003). Since then, based on information obtained from the UTC assessment, other studies on urban trees have been conducted. Results of the current study can be used as primary data to determine the canopy goal, prioritize suitable areas for canopy expansion, track changes in the canopy, and examine the ecosystem services provided by urban trees. Today, canopy cover maps are often combined with other city planning geographic information system (GIS) datasets to meet different urban needs concerning the tree canopy.

2.2 Best Practice in Urban Tree Canopy Assessment

Non-field estimates of tree canopy cover can be obtained using two different approaches: classification of remotely sensed imageries and image interpretation (e.g., Leff, 2016; Nowak, 2017; USDA, 2019). Remote sensing is defined as "the science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area, or phenomenon under investigation" (Lillesand et al., 2015, p. 1). Over the past 15 years, remote-sensing technologies have frequently been used to measure the existing UTC and evaluate the potential of the UTC from a perspective directly above the tree canopy (e.g., McGee et al., 2012; Walton et al., 2008). The most common remote-sensing dataset used for this purpose has included the use of either air- or space-borne multispectral and/or hyperspectral imagery. At present, the use of very high spatial resolution (pixel sizes of $<1m^2$) multispectral data, combined with Light Detection and Ranging (LiDAR) data for object-based image classification, is considered the gold standard for UTC assessment with approximately 95% accuracy (USDA, 2019). The extraction of features in object-based classification is based on spatial, spectral and texture attributes (Im et al., 2008).

While multispectral data provide the spectral characteristics of the canopy itself (typically expressed as spectral reflectance), LiDAR sensors provide important tree canopy structure information, including canopy height and texture. Using LiDAR and object-based image classification techniques, UTC assessments create canopy cover maps differentiating trees from shrubs (Agarwal et al., 2013). Since this approach typically requires considerable remote-sensing expertise, specialized and commercially available remote-sensing/GIS software (e.g., ENVI and ArcGIS), and significant hardware investments, it has not garnered widespread use for UTC assessment in most small- to medium-sized communities.

In larger cities, LiDAR has been successfully used to perform UTC assessments. For example, MacFaden et al. (2013) conducted a UTC assessment in New York City using fused LiDAR and high spatial resolution imagery. These data were used to evaluate New York’s current canopy and establish an accurate baseline dataset from which changes in the canopy could be detected (MacFaden et al., 2013). To date, this approach is the best option for studies assessing ecosystem services in addition to canopy cover.

The geospatial technologies used in UTC assessments are often influenced by project goals, budget, resources, and expertise. Using remote-sensing technologies, pixel-based image classification approaches are most widely used for extracting meaningful information about urban trees (e.g., vegetation type and percent cover). Digital image classification is the term used to refer to any data-reduction technique that attempts to place earth surface features with similar spectral characteristics into either computer or analyst-defined classes (Jensen, 2004). The overall goal of image classification is to automatically extract thematic information from image data (Lillesand et al., 2015). Analyst-defined (also known as a "supervised" classification), pixel-based classification approaches are commonly applied to multispectral remote-sensing data as these data are more accessible and affordable compared to hyperspectral data (Leff, 2016).

Several remote sensing research studies have compared different remote-sensing devices, pre-and post-processing tasks, data-analysis techniques, outcomes, and accuracies achieved in UTC assessments. For example, McGee et al. (2012) reviewed the geospatial tools used to examine UTC assessment; they described using different types of imagery in UTC assessments and presented the steps taken to determine canopy cover in the City of Winchester, Virginia, USA (McGee et al., 2012). Xie et al. (2008) discussed image classification for land-cover mapping, including familiarity with the types of sensors and their features and the image pre-processing tasks required to prepare images for image classification. In addition to assessing urban trees, the study also examined the possibility of differentiating tree species using their unique spectral reflectance characteristics (Xie et al., 2008).

Maximum efficiency in the object-based classification method requires particular spatial data (e.g., high-resolution fused LiDAR and hyperspectral data), the preparation of which may not be easily undertaken for all UTC assessments. In terms of technical complexity, this method also requires experienced personnel. Pixel-based classification approaches are an intermediate and most popular method in evaluating urban trees considering data acquisition costs and required experts. In most cities that have long followed a strategic plan to achieve sustainable urban forest, pixel-based UTC assessment is done at least once and preferably repeated every few years to monitor changes. As a pioneer in the UTC assessment program, the City of Baltimore, US, performed its first study on low-resolution national land-cover images using a pixel-based method, which found the canopy represented 20% of the total city area. O'Neil-Dunne's (2009) subsequent evaluation determined 27% cover using the same method with high spatial resolution (i.e., 1 m) aerial imagery at a parcel scale (O'Neil-Dunne, 2009). Using coarse spatial resolution images (e.g., 30 m pixel sizes) can cause canopy underestimations by up to 28% (Greenfield et al., 2009).

Recognizing objects in the remotely sensed photographs based on elements of image interpretation (e.g., tone, shape, size, pattern, texture, association) is another approach to identifying and measuring target features. The principles of image interpretation have been developed for more than 150 years (Philipson, 1997). Interpretation of aerial photos is the most cost-effective means of estimating urban trees and other surface covers. Determining urban coverages from aerial photographs can be performed using several methods (i.e., crown cover scale, dot method, transect method, scanning method) (Nowak, et al., 1996). i-Tree Canopy, a web application designed by the USDA, uses the random-dot method to sample LULC in the study area of interest beneath a series of dots overlaid on Google Maps satellite imagery.

Although i-Tree Canopy is a simple, more cost-effective method for image interpretation, especially when compared to image classification, a few academic studies have been conducted on i-Tree Canopy as an approach to UTC assessment (https://canopy.itreetools.org/). Thus, one of this study's objectives is to perform a UTC assessment using i-Tree Canopy and compare these results with image classification methods for a small community.

Parmehr et al. (2016) compared results obtained using i-Tree Canopy with classification on fused LiDAR and multispectral images in Williamstown, a suburb of Melbourne, Australia. They highlighted the advantages and disadvantages (e.g., being quick, accurate, less complicated versus lack of visual presentation and non-spatial results) of i-Tree Canopy. They stated that despite the shortcomings of i-Tree Canopy, the program's capabilities and relative acceptable accuracy outweigh its disadvantages (Parmehr et al., 2016). This study showed only a 1% difference with the results achieved in i-Tree Canopy (i.e., image interpretation) and the image classification method used as the primary approach of this study. The accuracy obtained in their study may not necessarily be achieved in other geographic locations since the resolution of Google Maps imagery differs from one place to another, which may cause different land-cover types to be misidentified. Thus, the results across other areas cannot be compared.

There are two fundamental differences between Parmehr's study and the current study. The geographic area identified in the Parmehr et al. study (i.e., Williamstown) is a dense suburban area in Melbourne, Australia. In contrast, most of the land in the current study is devoted to agricultural land uses. Differences between land-use and mixed land-cover types in agricultural areas may affect the results obtained by i-Tree Canopy. Second, their study was performed using an object-based algorithm that used fused multi-spectral and high-end LiDAR data not available in most UTC assessments due to its high cost and required expertise (Parmehr et al., 2016).

The only other research study comparing i-Tree Canopy (an image interpretation approach)image classification was conducted by Hwang and Wiseman (2020).Their study was performed in an urban area (i.e., Urbanized College Campus) and it evaluated i-Tree Canopy's results with two image classification approaches. First, low-resolution imagery was used in an automated classification approach using i-Tree Landscape. Second, an unsupervised classification approach was performed on a multispectral image (i.e., three visible bands and one near-infrared band) with 1 m spatial resolution. i-Tree Landscape is another software package developed by the USDA for image classification based on the United States national land-cover data. It is not available for use outside of the USA. Although the approach used in this study, along with the study location differ from the current study, , it revealed an important point about i-Tree canopy's suitability for UTC assessment. Classification of high-resolution images in their study showed higher levels of agreement with i-Tree Canopy than image classification on low-resolution imagery (Hwang & Wiseman, 2020).

In addition to making a contribution to the limited body of literature on i-Tree Canopy, this study also makes significant practical implications for municipalities and local authorities using i-Tree Canopy.. The proven suitability of i-Tree Canopy as a method for quickly assessing the urban canopy helps to better inform other researchers undertaking similar studies by providing them with fundamental information about the canopy coverage.

2.3 Prioritizing the Tree Canopy

In 1997 American Forests established a universal 40% canopy goal after surveying the tree canopy in several US cities. While a worthy exercise at the time, existing research has suggested that tree canopy goals are hard to define broadly because opportunities to expand the tree canopy vary between cities, even with similar climates or land-uses (Leahy, 2017). Today, the canopy goal is not just a numeric value to pursue. Canopy goal setting is a collaborative, need-based, suitability-based procedure that fulfills the socio-environmental needs of communities, is in the most suitable locations and sustains the entity of the urban forest itself (Locke et al., 2010). Each municipality must adopt its own goals, depending on several unique factors, including local preferences, climate, environmental concerns, geography, desired ecosystem services, LULC patterns, and other factors.

Representatives from the municipality, conservation authorities, NGOs, and the broader community should identify the socio-environmental problems that can be solved using trees as nature-based solutions (e.g., stormwater runoff, heat islands, air pollution, environmental injustice). Identifying these needs locally and in smaller geographical units makes any possible modification more and pursuing the goal more feasible. The most appropriate sites for expanding the canopy coverage would be highlighted in the suitability investigation. Socio, economic, and environmental factors such as type of lands regarding permeability, ownership, land-use, legal obligations, etc. contribute to the suitability modelling (Locke et al., 2010).

In any UTC assessment using image analysis (e.g., image classification), in addition to the canopy coverage other coverages can be identified. In the definition of canopy goals, low-lying vegetation and bare soil are flagged as possible canopy (Behounek & Ayersman, 2019). Possible canopy refers to permeable lands (i.e., low-lying vegetation and bare soil) biophysically capable of supporting new trees. Using socio-economic measures, the possible tree canopy can be limited to areas with the potential for tree expansion plans. Figure 2.1 demonstrates how a potential tree canopy is implemented. The UTC assessment would be the first step in achieving a potential tree canopy. In most studies focused on prioritizing canopy goals, such as Locke et al. (2010), social, environmental, and economic criteria have been applied to determine potential canopy goals (Locke et al., 2010). The potential tree canopy will ultimately be a sustainable optimal choice that has been explicitly adopted for the study area to provide the desired ecosystem services and support a healthy tree canopy over time (Leff, 2016).

2.3.1 Canopy Goal Setting in Ontario and the Niagara Region

Unlike the USDA, which is the federal authority for delivering UTC assessments in the United States, no federal or provincial organization is responsible for policymaking and defining standards and guidelines in this regard in Canada (Kenney, 2003). In Ontario, municipal governments are responsible for urban trees. The variable sources, official capacities and priorities have obscured the effectiveness of urban tree management, especially for small cities (Barker & Kenney, 2012). Cities and towns in Ontario have adopted different strategies for assessing their urban tree canopies, making it challenging to compare their UTC assessments. In most cities in Ontario, the criterion set by official plans is considered the canopy goal (e.g., Ottawa with 30%; Toronto and Guelph with 40%). None of the reviewed canopy goals have presented comprehensive planning based on biophysical, socio-economic criteria and feasibility studies.

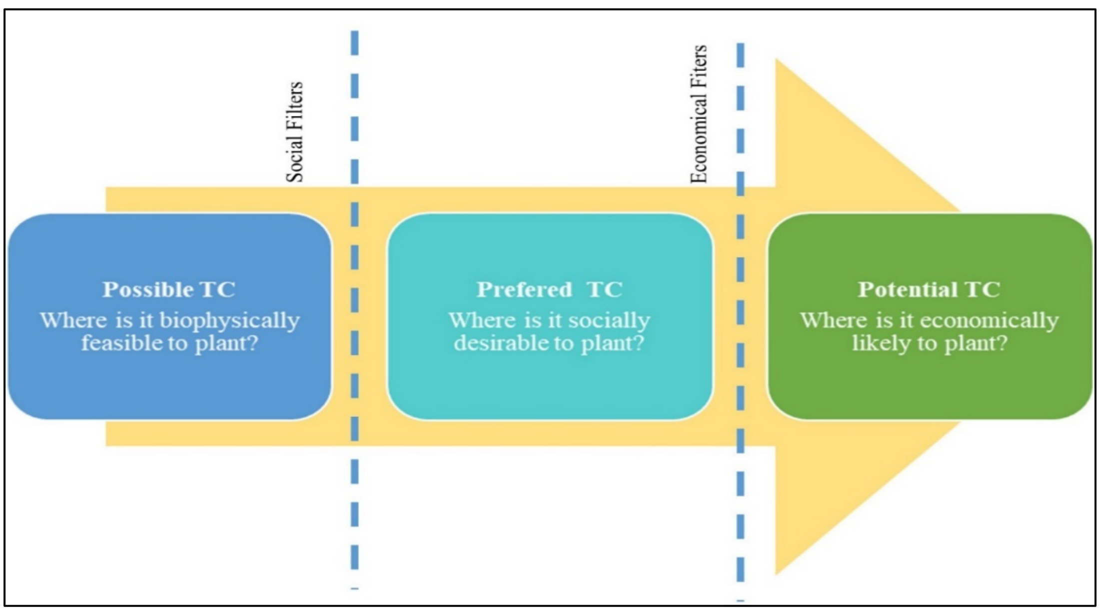

Figure 2.1
The evolutionary stages of achieving a potential tree canopy

Note. Adapted from *Behounek & Ayersman, 2019*

All available land-cover types can also be classified in UTC assessments using image classification. Identifying permeable lands as possible sites for expanding the canopy is the first step in setting canopy goals. In some cities and towns in Ontario, such as Mississauga (2014), Newmarket (2016), and Kitchener (2016), total biophysically suitable permeable sites are identified as possible planting areas (Plan-It Geo, 2014; Lake Simcoe Region Conservation Authority, 2016; O'Neil-Dunne, 2016). The optimal canopy goal has not progressed beyond identifying permeable lands with low-lying vegetation and soil coverage in the investigated cities and towns.

A minimum of 30% essential woodland cover in the Niagara Region is applied as a minimum canopy goal required for sustaining species richness and healthy aquatic systems. This criterion is extracted from the article "How much habitat is required?" by Environment Canada, which provides a series of guidelines for protecting forest, riparian, wetland, and grassland habitats (Environment Canada, 2013). According to this article, "30% forest cover at the watershed scale is the minimum forest cover threshold. This equates to a high-risk approach that may only support less than one-half of the potential species richness, and marginally healthy aquatic systems" (p. 60). Higher levels of this guideline (40% and 50%) also view forest cover from the perspective of providing better protection for species richness and aquatic systems.

To understand the extent to which this criterion can be accepted as a sustainable potential canopy goal, the Niagara Region's existing Official Plan (2014 consolidated version) and its revised and developing version (2019) were investigated (Niagara Region, 2014 & 2019). To measure the degree of conformity of the 30% index with an optimal canopy goal, it is important to initially compare the range of trees considered in this index with the standard definition of urban trees.

The Official Plan has cited two references for defining woodlands. According to the Forestry Act, 1990, woodland refers to “land with at least, (a) 1,000 trees, of any size, per hectare, (b) 750 trees, measuring over five centimeters in diameter, per hectare, (c) 500 trees, measuring over 12 centimeters in diameter, per hectare, or (d) 250 trees, measuring over 20 centimeters in diameter, per hectare” (R.S.O., 1990, Chapter F.26). Although in this study we do not have access to the structural information about the trees (e.g., trunk diameter at breast height), the point to be drawn from this definition is that it measures the forest in large patches of one hectare. The other source, ecological land classification (ELC) for southern Ontario, uses the absolute cover of trees, where woodlands are defined as treed areas that have a total cover between 35% and 60% and forests have an absolute cover of at least 60% (Lee et al., 1998). This definition fits in with land-use/land-cover classification studies since it is independent of forest biometrics.

These definitions have exempted large, wooded areas managed as economic resources (e.g., orchards and Christmas tree farms) from their definition of woodlands. In this respect, they are consistent with the UTC assessments but focus specifically on vast wooded areas and do not include street trees and areas with low tree density. In addition to the difference in attitudes toward trees between urban tree canopy studies and what is found in the official plan and its supporting sources, tree conservation and management goals are also different. In urban forestry, the goal is to use the environmental, social, and economic benefits of trees to increase sustainability and equity for human beings and other creatures (Leff, 2016). The use of trees as green infrastructure has attracted particular attention regarding climate change impact mitigation. In 2013, Environment Canada explicitly indicated that “the defined criteria are considered to provide the ecological health of the ecosystems and do not have an urban context" (Environment Canada, 2013, p. 11).

2.4 Chapter Summary

This chapter presented the critical findings of a literature review that was conducted to find the resources that could adequately answer the research questions and achieve the three objectives of the study. The next chapter provides a detailed discussion of the data and methods used to assess the UTC using two different geospatial approaches followed by accuracy assessments.

3. Data and Methodology

3.1 Introduction

The purpose of this research study is to assess the tree canopy in the Town of Lincoln, Ontario, using geospatial technologies. The first approach used to determine the canopy cover using a top-down approach to classify an image based on the spectral characteristics of pixels in the image. The second approach is a visual analysis and interpretation of random sample points on remote-sensing imagery available via Google Maps using the i-Tree Canopy web-based application. From now on, the second approach is referred to as “i-Tree Canopy” in this study.

The image classification approach is considered to be the main approach in this study. It covers all shade and ornamental trees intentionally planted, naturally occurring, and/or accidentally seeded on public and private lands. Therefore, the canopy in question mainly includes a canopy of shade trees, ornamental trees, and large non-crop shrubs identified in terms of size in the WorldView-2 image with 2 m spatial resolution. Fruit trees, crop shrubs, trees located in nurseries (e.g., christmas trees) present in the study area are subtracted from the assessment in the post-classification process. Using the second approach (i-Tree Canopy), all trees, including fruit trees, are counted while excluding agricultural shrubs (e.g., vines) within the Town of Lincoln.

3.2 Data Collection

In this study, a WorldView-2 satellite image acquired over the Town of Lincoln on July 10, 2018, was used to perform land-cover image classification (WorldView-2 Scene, 2018). This multispectral image included four spectral bands covering the blue, green, red, and near-infrared (NIR) parts of the electromagnetic spectrum (EMS). The near-infrared is an important part of the EMS for identification of vegetation, especially in agricultural areas where vegetation may be sporadic in some areas (newly sprouted fields).The visible bands (i.e., the blue, green, and red) alone do not provide enough spectral distinction from other cover types, such as soil. This can case misclassificadtion of these pixels. The near-infrared band, however, increases the spectral separability between classes with spectral similarities in the visible bands. The 2 m spatial resolution of the imagery was most suitable for investigating urban trees.

In addition to the WorldView-2 image, other geospatial datasets, including shapefiles and geodatabases related to land-use types, municipal boundaries, and topographic data, were obtained from the Brock University Maps, Data, and GIS Library for use in this study.

In the canopy assessment using i-Tree Canopy, the identification and interpretation of sample points were undertaken using the Google Maps interface. Google Maps images are not integrated and consist of mosaicked images acquired by different satellites with different spatial resolutions. Coincidentally, at the time of this UTC assessment for the Town of Lincoln, the baseline satellite dataset used by Google Maps for most locations within the Niagara Region dated back to July 2018. It is important to note that the image uploaded to the i-Tree Canopy software was displayed in true colour; therefore, visual interpretation of image features was reliant on the analyst’s interpretation of image features in true colour only.

3.3 Data Pre-processing Operations

Raw remotely sensed data contain geometric and radiometric distortions (Richards, 2012); these compromise the accuracy of information products derived from these data (e.g., land-use and land-cover maps). Pre-processing operations provide opportunities to correct these distortions to ensure that subsequent data analyses are based on geometrically and radiometrically corrected data. The WorldView-2 satellite image used in this study was an orthoimage (i.e., it was purchased with geometrical corrections applied to it). There was also zero percent cloud cover at the time of image acquisition; therefore, there were no concerns about removing radiometric distortions (e.g., errors caused by energy interactions in the atmosphere) from these data. All data analyses subsequently performed on these pre-processed data were conducted using the Environment for Visualizing Images (ENVI, version 5.6, Harris Geospatial Solutions, Colorado, USA).

When possible, all spatial data obtained from library sources (e.g., urban areas boundary data or classified maps used for accuracy assessments) were selected from the periods close to WorldView-2 image acquisition time (i.e., July 2018). Since there was no recent, precise data on vineyards and orchards' location in the study area, the areas devoted to these two land uses were created from scratch in ArcMap.

3.4 Approaches to UTC Assessment

Two main approaches to UTC assessment were examined in this study. The workflow below (Figure3.1) shows the sequence of processes required to estimate the canopy using the image classification approach. Using the Environment for Visualizing Images (ENVI, version 5.6), a leading software package frequently used to process and analyze remote-sensing data, different land-cover types within the study area, including the tree canopy, were classified. After creating the land-cover map, it was possible to determine the type and distribution of each of these covers within individual geographical units (e.g., neighbourhood, census units, municipal wards).

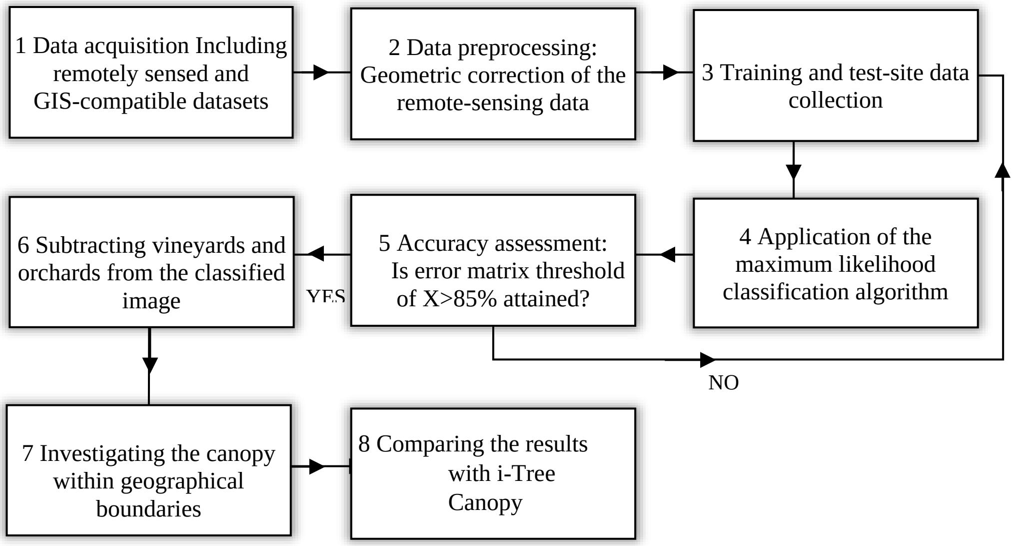

Figure 3.1
Procecess used to perform image classification in this study

The second approach applied the interpretation of random points in i-Tree Canopy software to estimate the canopy and other available covers. Designed by the United States Department of Agriculture (USDA), i-Tree Canopy is primarily used in forestry, landscape, and ecological studies. Although assessing the UTC using i-Tree Canopy has fewer complexities than the data-analysis techniques used in image classification (e.g., the maximum-likelihood classification algorithm); it only estimates land covers and does not produce any map output products. The

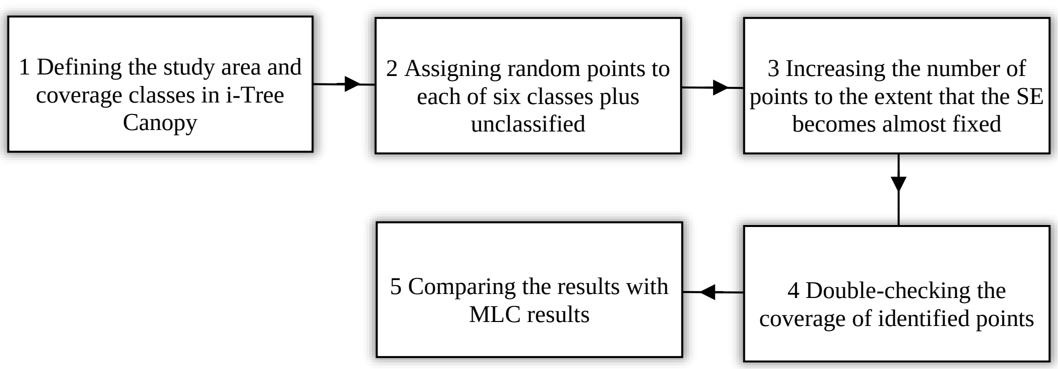

Figure 3.2
Procecess used to perform to assess the canopy using image interpretation

flowchart below (Figure 3.2) shows the process of assessing the canopy using image interpretation.

3.4.1 Image Classification Approach

The maximum-likelihood classification (MLC) method is one of the most commonly used algorithms for performing LULC classification on remote-sensing data. In this study, analyst-defined classes were identified and used in a pixel-based classification approach where the output result contained one coverage class per pixel. Using this algorithm, each pixel in the image was also assigned to a predefined threshold with the maximum likelihood of that threshold. Pixels were labelled as “unclassified” if the probability values were below the user’s threshold. The maximum-likelihood classifier assumes that the statistics for each coverage class in each band are normally distributed; it measures the probability that a given unknown pixel in an image belongs to a specific coverage class (Richards, 2012). Before performing the MLC, the study area was classified using unsupervised classification to decide the number and type of classes available and better understand the study area and existing land cover types. The computer uses the unsupervised classification approach to determine which pixels are related and groups them into classes based on their statistical characteristics (Jensen, 2004).

Training data play an essential role in the supervised classification process whereby the image analyst selects statistically representative sample pixels of each LULC class to be identified in a study area. A supervised image classification algorithm (e.g., MLC) subsequently uses this statistical information to classify an entire remote-sensing image. The quality of the training data used in the classification process can significantly influence the accuracy of the results; thus, selecting these data requires knowledge of the study area and expertise on the part of the image analyst (Lillesand et al., 2015).

This study selected training data to represent six different landcover classes identified for the Town of Lincoln, including trees/shrubs, low-lying vegetation, impervious (buildings), impervious (roads), soil, and water. A description of each land cover class and the number of pixels considered as training samples for each class are included in Table 3.1. The number of pixels in each training set (i.e., all the training pixels selected for each coverage class) varies slightly. Statistically, representative sample sizes were determined based on the accepted theory of using a minimum of $10n$ – $100n$ pixels, where n is the number of bands (i.e., three) used in the classification procedure (Richards, 2012).

Table 3.1
Description of the Land Cover Classes

Class name	Class description	Training pixel count
Trees/Shrubs	Including all shade and ornamental trees and non-crop shrubs distinguishable in the satellite imagery	5,967
Low-lying Vegetation	Including croplands, lawns, meadows, reeds and floating-leaved plants	5,533
Impervious Buildings	Including all residential and commercial buildings and greenhouses	5,086
Impervious Roads	Including highways, rods, driveways, sidewalks and parking areas covered with asphalt	5,342
Soil	Including bare soil, mineral resource extraction areas, fallow lands and newly harvested areas with no coverage, and unpaved roads	5,558
Water	Including all hydrological features like streams, canals, lakes, reservoirs, bays and ponds	5,355

Individual pixel training-data samples were selected (mainly in polygons) from different homogeneous regions of the image, wherever possible, to capture the full range of spectral variability within each cover class in the study area (Figure 3.2). Further, spectrally pure pixels (i.e., those that contained only one land-cover type) were selected since the quality of these training data impacts the accuracy of the classification result (Lillesand et al., 2015). Whenever separability analysis showed a low possibility of spectrally separating training data of different classes, these data were reviewed and modified. Given the image acquisition date (July 10, 2018) and considering agriculture as the dominant land-use type in this area, most of the study area had agricultural cover (orchards, vineyards, and croplands). Areas containing agricultural vegetation were mixed with understory in some areas, making it challenging to capture pure pixel samples.

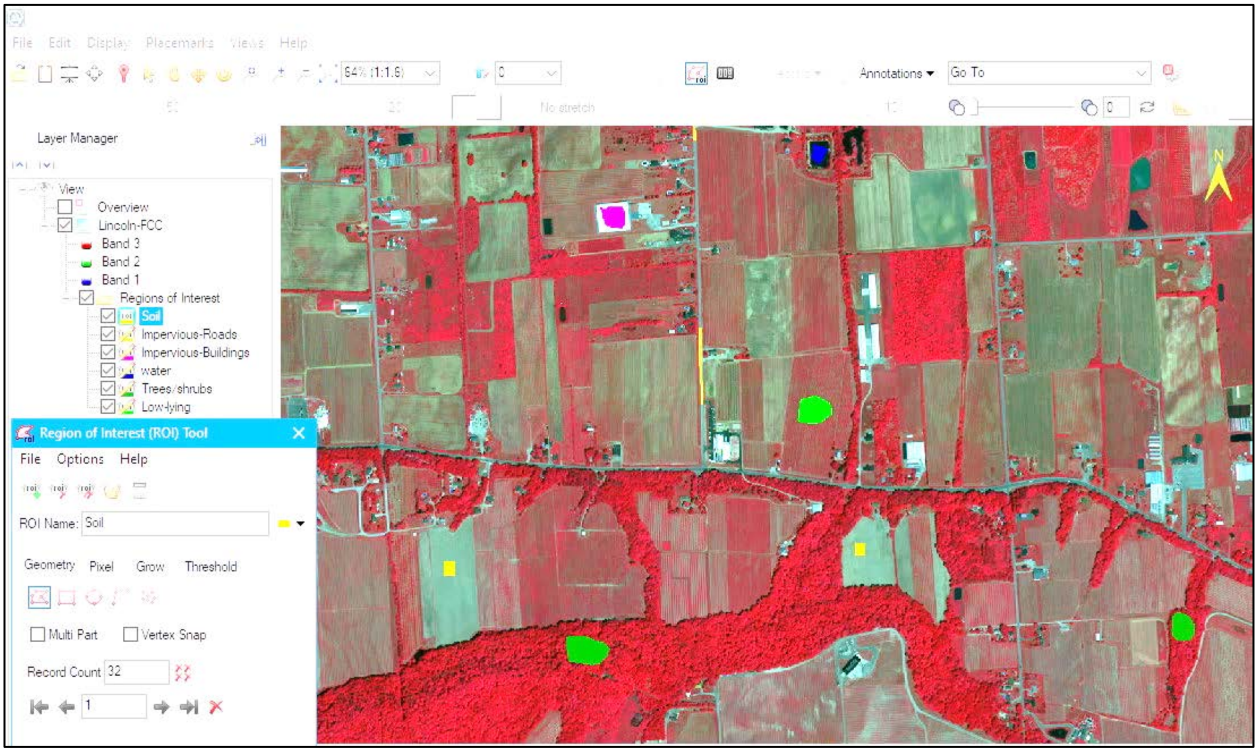

Figure 3.3
A screenshot of training-site data collection in ENVI

The spectral bands used in the land-cover classification were the green, red, and near-infrared bands because classes had spectral similarities in the blue part of the spectrum that increased the misclassification of pixels. For example, the spectral difference between impervious roads and the soil class in the near-infrared was more significant than the other three bands. Water and low-lying vegetation were also more distinguishable in the green, red, and near-infrared.

Existing studies of UTC assessment using geospatial technologies have mainly been implemented in urban contexts, and in these areas, the presence of crops has not been a common issue. Of the few UTC assessments conducted in rural areas, some have recommended eliminating fruit trees and shrubs from the canopy assessment (e.g., Davies et al., 2017; Graça et al., 2018). The contribution of urban trees providing some ecosystems services (e.g., pollution removal, rainfall interception) are directly related to their canopy size and location (i.e., vicinity to human settlements, land use, and land ownership). Small fruit trees and shrubs fall short of providing many environmental benefits due to their small canopy size and locating far from urban areas (Davies, 2017).

Distinguishing fruit trees and vines from other non-crop trees is technically challenging using the MLC. In many cases, fruit trees are spectrally categorized into a tree/shrub class, while vines (due to their small foliage) are more likely to be misclassified as low-lying vegetation or, in some cases, soil. Figure 3.3a represents a top-down view of a vineyard in the study area. The land cover between every row of vines was either planted (e.g., inter-row vegetation – see left side of image) or bare soil (see right side of the image). Figure 3.3b covers the same geographic area as image ‘a’ (although slightly zoomed out) and is a classified image (i.e., a land-cover map) of the same vineyard. Despite what is expected (i.e., rows of dark green representing the trees/shrubs class); shrubs are misclassified as low-lying vegetation (bright green) and soil (yellow). Since vineyards occupy about 12% of the study area, their presence in the classification may significantly interfere with identifying low-lying vegetation and soil. Although the focus of this study is on canopy coverage, knowledge of both low-lying vegetation and soil cover is essential for setting future canopy goals.

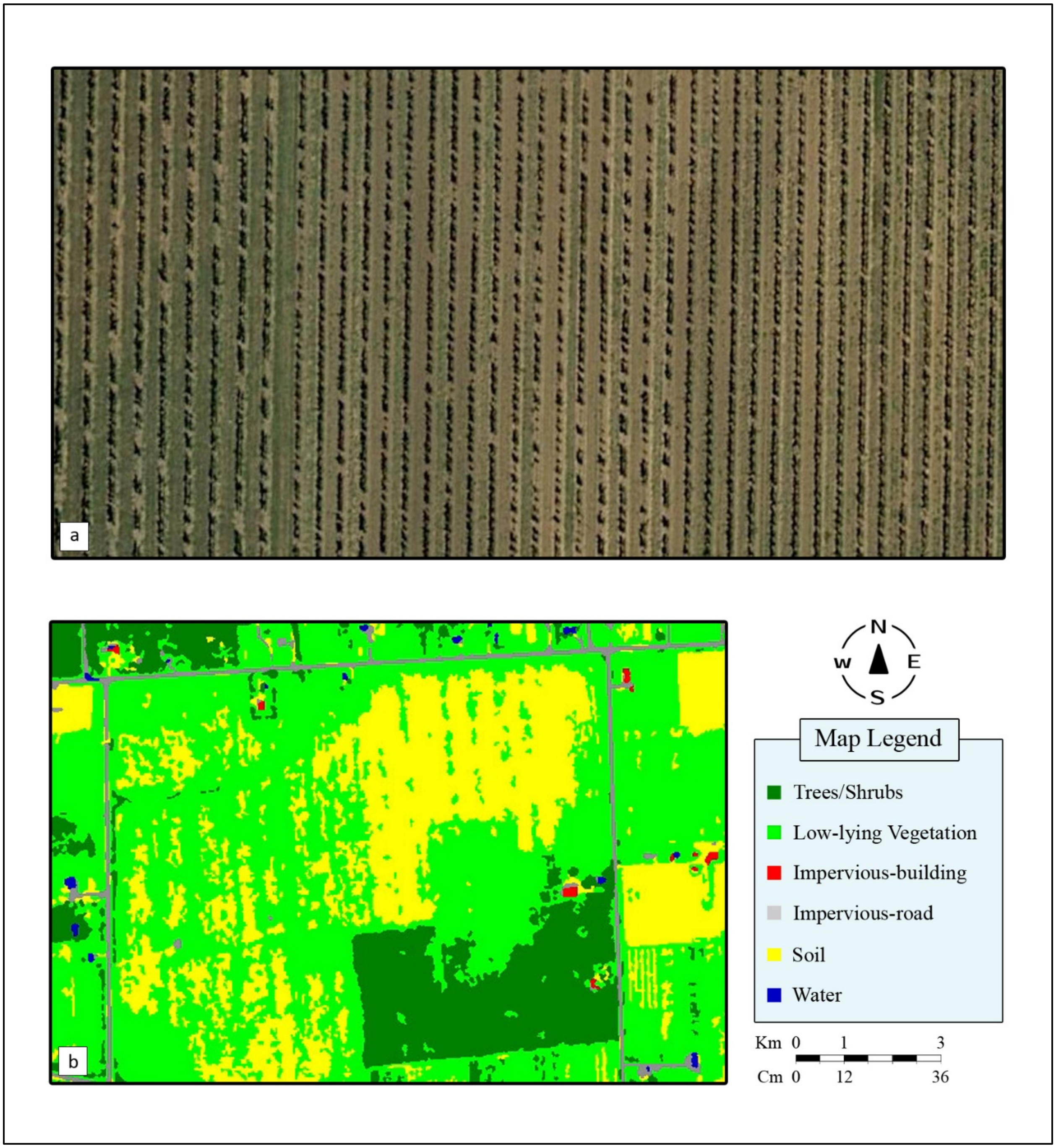

Figure 3.4
Misclassification of vines and small fruit trees as low-lying vegetation and soil

To focus on shade and ornamental trees and prevent overestimation in other classes, after performing the classification and achieving a desirable accuracy, using GIS data, the areas devoted to orchards and vineyards were subtracted from the UTC assessment. By removing agricultural items from the canopy of urban trees in a post-assessment process, most of the shrubs in the study area are removed from the assessment. Ornamental shrubs are small and are not visible on the satellite image, so they were not a concern in this study. Due to the presence of nondominant large shrubs with large canopies, the canopy class is named “trees/shrubs” in the land-cover classification. Large shrubs are usually located on the edge of forested areas or river banks.

3.4.2 Image Interpretation Approach (i-Tree Canopy)

Since 2006 the USDA Forest Service, in collaboration with scientific institutes and academic institutions, has been developing desktop and web-based applications focusing on forestry and quantifying ecosystem services (e.g., i-Tree Canopy, i-Tree Eco, i-Tree Landscape). i-Tree Canopy is a tool designed to enable users to estimate tree and other cover classes quickly and precisely within a study area. Although the results obtained from this method entirely depend on the analyst’s ability to interpret earth surface features correctly, it does not require particular expertise and substantive background knowledge.

The analyst determines the cover classes required based on knowledge of the study area and assigns every sample point to one of these classes (Figure 3.4). It is essential to ensure that all required classes are determined before starting the interpretation. It will not be possible to add or remove new classes during the assessment process. Since an MLC was selected as the main approach in this study and for better comparison of the two approaches, the same classes were set in i-Tree Canopy. The program generates the assessment results considering that independent, random samples from a normally distributed population generate a random mean (Thompson, 2012). A total of 500-1,000 random points is the minimum sample size recommended by the software developers to obtain an acceptable level of accuracy in UTC assessment. i-Tree Canopy provides land-cover assessment in both percentage and area. In percent cover, the values are normalized by the size of the site. As a result, the size of the area does not affect the number of random points. In contrast, the size of the study area directly impacts the number of random sample points in the estimation of the area occupied by each land cover type. Therefore, a higher number of random points helps to ensure the accuracy of area estimates in more extensive areas (Parmehr et al., 2016).

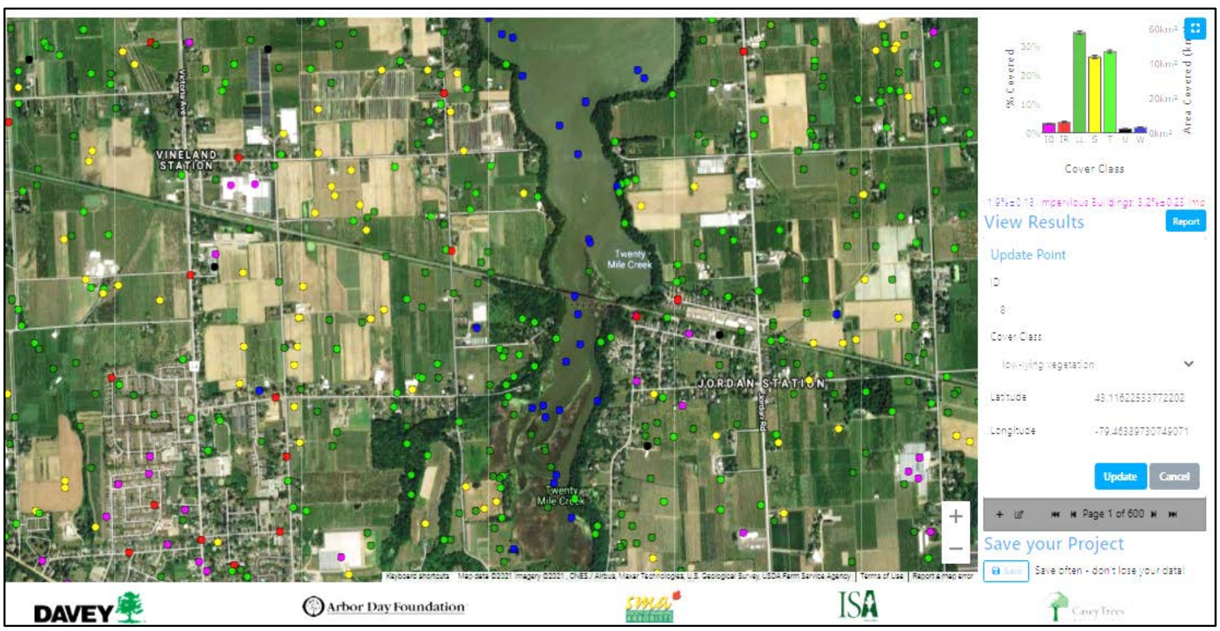

Figure 3.5
A screenshot of interpreting sample points in i-Tree Canopy

In this study, the interpretation started with 1,000 points and gradually reached 6,000 to reduce the standard error for classes and to obtain an accurate result within a 95% confidence interval. By assigning randomly generated sample points to the same LULC classes identified in the MLC method, comparisons between these two approaches became possible. The canopy identification was made with high accuracy since canopies usually create a homogeneous, continuous, and dense cover with minimum interference from understory.

Distinguishing heterogeneous, mixed, and/or sparse coverage (e.g., croplands or vineyards with sparse coverage) in i-Tree Canopy can be challenging. When the cross sign indicating the location of a random point is situated on these types of lands, it becomes difficult for the analyst to make a definite decision. This challenge may not be as problematic in urbanized communities with no agricultural land uses (e.g., Parmehr et al., 2016). Nevertheless, the ability to identify homogeneous cover types (e.g., canopy) was not compromised. If there was any doubt about the land-cover type and the point was located near main roads, the coverage was checked using Google Street View. If the entity of a point was utterly ambiguous, the random point was assigned to an “unclassified” class. This class mainly included shaded points, small vine canopies, and points located on the border of two different cover types. To eliminate any human error in visual interpretation using i-Tree Canopy, all random points were checked twice.

In addition to examining the suitability of the i-Tree Canopy as a UTC assessment tool, its functionality for quick studies was also examined. For this purpose, the coverage estimation and the standard error for the three important land-cover types (including trees/shrubs, low-lying vegetation and soil) were examined after adding every 1,000 new random points.

3.5 Accuracy Assessment

Accuracy assessment is an essential part of any classification process. It compares the classified image to another reference data source considered to be accurate. The accurate, reliable data can be collected in the field and obtained from interpreting high-resolution imagery, existing classified imagery, or GIS data layers (Lillesand et al., 2015). The most popular technique to assess a classified map's accuracy is to build a set of random points from field data and compare that to the classified data in a confusion matrix. A confusion matrix is a table designed to explain the performance of a classification algorithm on a set of test data for which the valid values are recognized (Foody, 2009). In this N*N matrix (N is the number of classes), the columns typically represent the reference points (i.e., test-site data), and the rows represent the final image-classification result (Table 3.2). The diagonal cells of the matrix (marked in yellow) contain the number of correctly identified test-site pixels. The classification's overall accuracy (%) can be determined by dividing the sum of correctly identified pixels by the total number of test-site pixels. The standard overall accuracy result for LULC maps is between 85% (Anderson et al., 1976) and 90% (Lins & Kleckner, 1996). If the accuracy assessment is less than the standard 85%, the training data should be reviewed and modified until the classified image is accurate.

Table 3.2
Example of a Confusion Matrix Using Test-site Pixels

		Test-site pixels			
		A	B	C	Total
Classified Image	a	37	3	7	∑a=47
	b	9	25	5	∑b=39
	c	11	2	43	∑c=56
Total		∑A=57	∑B=30	∑C=55	N=142

Assessing the accuracy of a classification result requires investigating the available errors besides the overall accuracy. Errors of omission or Type II error refers to pixels of one class that have been classified incorrectly as another class. Errors of omission represent false negatives. For class *a* in Table 3.2, omission errors are highlighted in blue. Dividing the absolute value of class omission (it equals 10 for class *a*) by the total number of pixels classified into class *a* (47) yields a relative omission error (≈ 0.2 for the class *a*) (Lillesand et al., 2015). For any class, when a classifier assigns pixels to a particular class that does not belong to it, the commission errors or Type I error occurs. Errors of commission represent false positives (Richards, 2012). The commission errors for class A (≈ 0.4) are shown in green. Other measures, including “producer’s accuracy” and “user’s accuracy”, are often calculated and used to indicate if a value in a given class was classified correctly and that a value predicted to be in a specific class is that class, respectively (Lillesand et al., 2015). The Kappa Coefficient of Agreement is another measure of classification accuracy. It represents agreement between the classification result and pixels of known value. Kappa values range between zero and one, where 1 represents a perfect agreement, and 0 means no agreement (Lillesand et al., 2015).

For some studies, field-data collection for accuracy assessment may not be possible due to difficulties accessing the study area (e.g., terrain conditions, war, or other accessibility challenges). In such cases, alternative methods and reference data are good alternatives for assessing accuracy (Ismail & Jusoff, 2008). The initial design for assessing the accuracy was selecting test sites in the field and comparing those to the classified map result. Field-data collection was scheduled for July 2020 to be most similar to the land-cover types present in the July 2018 WorldView-2 image. With the advent of COVID-19, field-based data collection was not possible. Following the COVID-19 safety protocols, available reference data (e.g., previous classified maps, GIS datasets, Google Earth imagery) were used to identify test-site pixels to examine the accuracy of the canopy assessment.

To identify the test-site pixels, a total of 600 random pixels were generated and were independent of the training data to reduce bias in the analyst’s knowledge of the study area (Richards, 2012). Several remote-sensing experts have recommended that an average of 30-50 sample points per class be identified for test sites (e.g., Wulder et al., 2006). A sample size of

100 points per class is believed to ensure that accuracy can be calculated with a standard error of no greater than 0.05 (Stehman, 2001). Two reference datasets including the Southern Ontario Land Resource Information System (SOLRIS) and Canada Land Inventory (CLI) were used to verify the test-site data. The randomly generated pixels were exported to an ArcMap environment and overlaid on the reference data to determine the coverage of each pixel. For final assurance, since the reference data (i.e., available classified maps) were last updated and revised before 2010, all test-site data were also verified in Google Earth.

In i-Tree Canopy, the accuracy of the assessment depends upon the ability of the analyst to identify random points correctly. Increasing the number of random points enhances the assessment's accuracy as the standard error (SE) decreases. The standard error indicates the population's similarity to the sample mean (Thompson, 2012). To illustrate, assume 1,000 points have been interpreted as either "tree" or "non-tree," with 330 and 670 points, respectively. To calculate percent tree cover and SE, let:

N = total number of sampled points (i.e., 1,000)

n = total number of pixels classified as tree (i.e., 330), and

p = n/N (i.e., 330/1,000 = 0.3)

q = 1 – p (i.e., 1 - 0.33 = 0.67)

SE = $\sqrt{}$ (pq/N) (i.e., $\sqrt{}$ (0.33 x 0.67 / 1,000) = 0.0148*100=1.5%)

Thus, in this example, tree cover in the city is estimated at 33%, with a SE of 1.5%. Another important factor in image interpretation that must be discussed is the confidence interval. The confidence interval presents a range of values that are likely to include a population value (in this case, area, or percentage) with a certain degree of confidence. An interval at 95% or higher confidence is ideal in statistics (Thompson, 2012). In the example above: a 95%

confidence interval = SE*1.96 (z-score[1]) = 0.0148*1.96 = 0.029. This figure must be added to and subtracted from the estimate (i.e., 0.3) to obtain the confidence interval. So, with 95% confidence the canopy cover estimation would be between 27% -32%.

3.6 Calculating the Canopy Distribution and Area

Although total canopy cover provides an indication of the presence of trees, it is not always practical for different types of urban, environmental, and social planning (e.g., canopy goal setting, increasing environmental equity, confronting impacts of climate change), so it is better to investigate the canopy within smaller, targeted, geographical areas. Depending on geographical scale, urban trees can be categorized into isolated trees, rows of trees, clusters of trees, and urban forests (Davies et al., 2017). The significant environmental benefits derived from urban trees comes from the urban forests, and vast clusters of trees (e.g., carbon sequestration, rainwater rain interception), but benefits related to social life can also be derived from isolated trees or rows of trees (e.g., the impacts of trees on reducing the crime rate, increasing property value). Since the focus of this study was on the benefits of trees related to confronting the negative impacts of climate change and increasing sustainability, canopy coverage was studied in the geographical areas of the two Niagara Escarpment Plans, the Greenbelt Plan, and the seven urban areas within the Town of Lincoln.

After ensuring the accuracy of the classification, the relevant data were transferred to an ArcMap environment (version 10.7.1) to address the distribution and calculate the area covered by the canopy. Geographic datasets in ArcMap are displayed in layers. An output coverage layer can be produced for any geographical unit by overlaying the canopy layer on any layer representing an area (e.g., urban areas, Niagara Escarpment, or Greenbelt boundaries) and using

1 A z-score shows the position of a score in terms of its distance from the mean, when measured in units of standard deviation (Thompson, 2012).

intersect tool in ArcMap. This layer contains portions of canopy that intersect the desired area. The share of each geographical area of the total canopy can be determined by “calculate geometry” tool.

3.7 Chapter Summary

This chapter discussed the methodological approaches used to achieve objectives one and two of this study. It began by describing the acquisition and pre-processing of WorldView-2 image provided a detailed explanation of the two geospatial approaches implemented to assess the urban tree canopy for the Town of Lincoln. The rationale behind MLC use, the number of training data used, and the challenges in selecting representative samples in a peri-urban region with mixed covers were discussed. This chapter provided explanations on how i-Tree Canopy can estimate the UTC and the challenges an analyst may encounter when using this software. This chapter concluded with discussions on the accuracy assessment of both approaches.

4. UTC Assessment Results

4.1 Introduction

The image classification (maximum-likelihood classification) and the image interpretation (i-Tree Canopy) approaches were used to assess tree canopy cover within the Town of Lincoln. In this chapter, the results of these two approaches, along with an assessment of their accuracy, will be presented.

4.2 UTC Assessment Results Using the Image Classification Approach

The maximum-likelihood classifier (MLC) is a pixel-based approach to classify remotely sensed data. It categorizes pixels into pre-determined classes based on their probability of belonging (Lillesand et al., 2015). The WorldView-2 image data used in this study were acquired July 10, 2018, when most of the study area was covered by different types of vegetation. The dominant land-use type in the area is agriculture. Since one of the objectives of this study is to calculate the overall tree cover, an attempt was made to separate trees from crops.

The training data were revised and modified several times to enhance spectral signature separability. A spectral signature is the variation in the reflectance or emittance of an object to incoming solar energy (Richards, 2012). Increasing the spectral separability of the training-site data improves the chances of unknown pixels being correctly assigned to the LULC class in which they belong during the image classification process (Lillesand et al., 2015). Figure 4.1 illustrates the mean spectral values across all three bands used in the supervised image classification process. The mean training data values of trees/shrubs and low-lying vegetation in all three spectral bands were spectrally close, showing a higher possibility of misclassification between these two classes. Using the NIR band reduced the probability of misclassification between low-lying vegetation and water as well as the impervious roads and soil classes. This distinction is crucial as identifying bare/exposed soil may help determine suitable locations for developing the tree canopy in the future, considering other factors (e.g., existing land use, needs assessment).

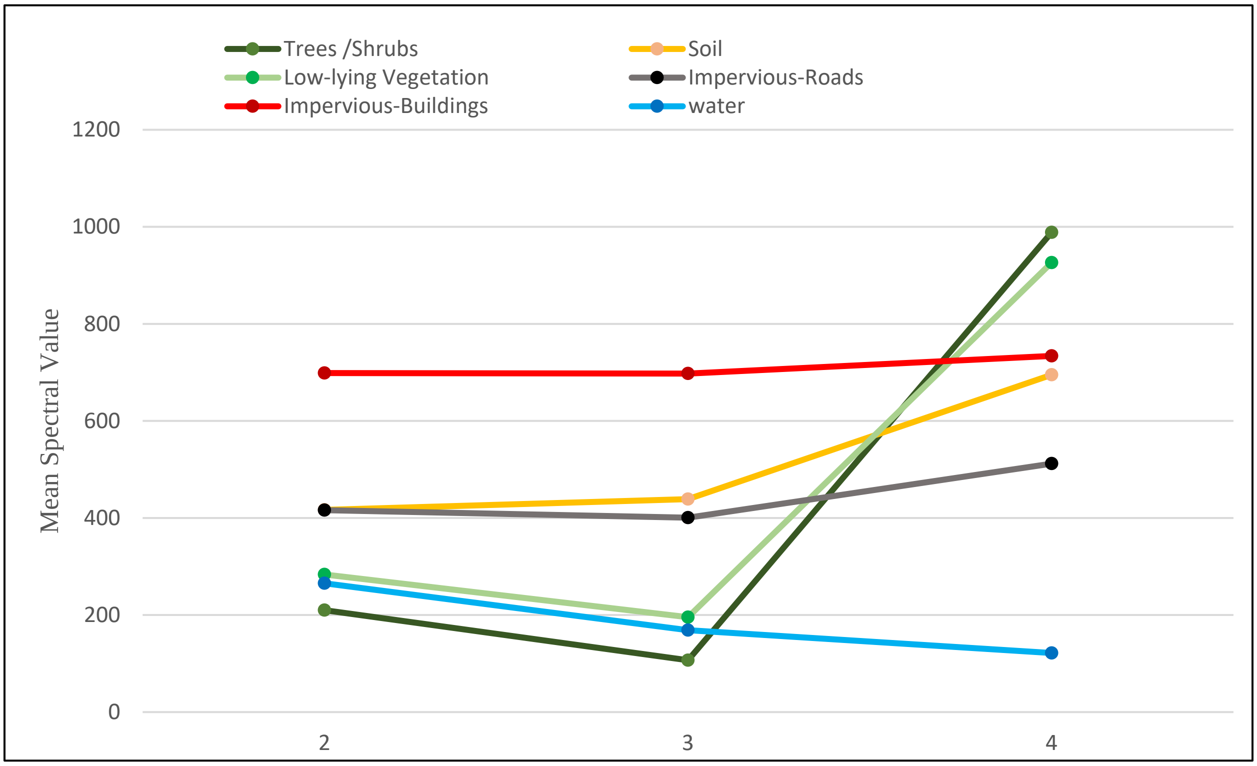

Figure 4.1
Average spectral values of training data in three bands

The spectral separability of all possible combinations of the training data pairs was calculated using the Jeffries-Matusita separability measure (Table 4.1). These separability values ranged from 0 to 2. Values above 1.9 represented the pairs with good separability (Richards, 2012). For most pairs, the separability value was within the standard range. Separability was slightly below the maximum separability value for the first five class pairs in the table. While Two classes can be combined if separability values fall below one (Harris Geospatial Solutions, 2020); that did not occur in this study.

Table 4.1
Jeffries-Matusita Separability Values Between Class Pairs

Pair Separation (least to most)	Separability Value
Impervious-Roads and Soil	1.611
Impervious-Buildings and Impervious-Roads	1.709
Low-lying and Trees/shrubs	1.739
Impervious-Buildings and Soil	1.792
Water and Impervious-Buildings	1.872
Water and Impervious-Roads	1.942
Low-lying and Soil	1.944
Trees/shrubs and Soil	1.983
Water and Soil	1.996
Trees/shrubs and Impervious-Roads	1.997
Trees/shrubs and Water	1.998
Trees/shrubs and Impervious-Buildings	1.999
Low-lying and Impervious-Buildings	1.999
Low-lying and Water	1.999

Note. Values in this table are based on the Jeffries-Matusita separability measure applied to the training-site data selected in this study.

As mentioned in the methods chapter, this study aimed to assess the canopy of urban trees (i.e., all shade and ornamental trees identifiable in the WorldView-2 image with pixel sizes of 2 m) without the presence of crop trees and shrubs. Also, the spectral similarities between small fruit trees and grapevines with inter-row vegetation, along with their relatively small canopy size within each pixel, may have led to some misidentification of fruit trees and vines as low-lying vegetation or soil. Due to the similarity of fruit tree species and shrubs with other trees, it was impossible to differentiate them spectrally. After completing the classification process and achieving an acceptable level of accuracy (i.e., 85%), using the available GIS data layers, the area occupied by orchards and vineyards was excluded in the final LULC map (Figure 4.2).

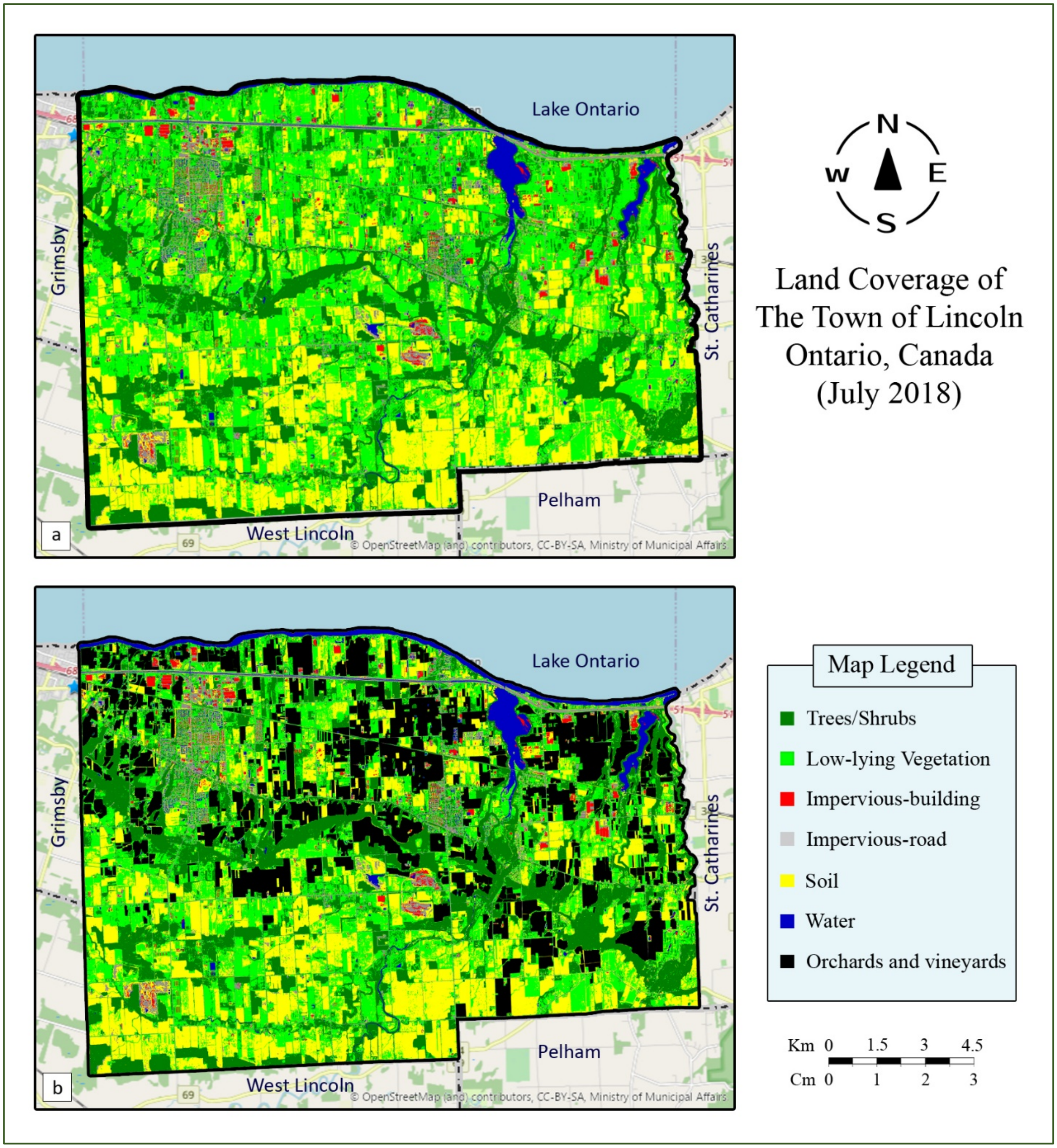

Figure 4.2
UTC assessment map of the Town Lincoln using the MLC approach

Note: *Image(a) shows all the land covers in the Town of Lincoln. To focus on urban trees, in Image(b) areas with crop trees and shrubs have been removed using GIS datasets.*

The number of pixels counted for each class, the percentage cover of classes, and their total area before and after subtraction are shown in Table 4.2. The total area that was subtracted as orchards and vineyards was about 34 km^2 which covered 21% of the Town of Lincoln.

Table 4.2
Summary of the Types of Land Covers Identified Using MLC

	Pre-subtraction			Post-subtraction		
Class Summary	Pixel Count	Percent (%)	Area (km^2)	Pixel Count	Percent (%)	Area (km^2)
Trees/Shrubs	9,497,318	23	38	8,838,326	21.3	35.4
Low-lying Vegetation	17,049,537	41.1	68.2	10,786,190	26	43.1
Impervious-Buildings	700,692	1.7	2.8	681,140	1.6	2.7
Impervious-Roads	2,203,967	5.3	8.8	2,166,664	5.2	8.7
Soil	11,016,239	26.6	44.1	9,488,734	22.9	38
Water	1,001,631	2.4	5.2	998,899	2.4	4

After assessing urban trees, it is possible to examine the canopy and its spatial distribution across urban boundaries within the Town of Lincoln. This process is typically undertaken to detect canopy goals, examine environmental justice, and to determine the benefits of ecosystem services to confront climate change. In this study, the spatial distribution of the tree canopy was investigated within the seven urban areas of the Town of Lincoln and the two Greenbelt and Niagara Escarpment Plans boundaries.

Table 4.3
The Distribution of Tree/Shrubs within Urban Areas

Urban Area	Area (km^2)	Trees/shrubs Cover (km^2)	Trees/shrubs Cover (%)
Beamsville	6.6	1	15.1
Campden	0.5	0.1	20
Jordan	0.4	0.1	25
Jordan Station	0.4	0.1	25
Prudhommes	0.5	0.2	40
Vineland	1.4	0.3	21.4
Vineland South	0.2	0.04	20
Total	10	1.8	18

Of the 165.5 km^2 total area occupied by the Town of Lincoln[2], only a small portion of land is devoted to dense settlements or urban areas. Approximately 18% of total urban areas (10 km^2) are covered by trees/shrubs. Trees identified in urban areas mainly included single trees, lines of trees (e.g., street trees), and tree clusters (e.g., parklands) and did not include extensive woodlands.

Most of the study area is located within the boundaries of the two Niagara Escarpment and Greenbelt plans, in which continuous forests are located. Therefore, the contribution of each of these two plans in the total canopy coverage of urban trees was also examined. The south-central to the southwest region is the only area of the Town located in neither of these two plans, mainly including croplands and accounts for 22% of the total canopy cover. From the total 35.4 km^2 of canopy cover, 77.2% (27.3 km^2) is within Lincoln's Greenbelt boundary. A total of

[2] According to the 2016 census profile, Lincoln's land area is 162.81 km^2. Since the available GIS data considers 165.5 km^2 as the area of the Town, the latter figure was used in all calculations in this study.

28.3% of the Town is devoted to the Niagara Escarpment Plan, in which trees cover 15.2 km^2 of the area.

4.3 UTC Assessment Results Using Image Interpretation (i-Tree Canopy)

The i-Tree Canopy approach was implemented by defining the same classes as the MLC to examine the reconciliation of two measures and judge the suitability of i-Tree Canopy as a UTC assessment measure in small communities, especially where there are lands with mixed covers (Table 4.4). The number of random sample points interpreted reached a total of 6,000 points. The standard errors (SE) related to any of the cover classes are mentioned to show the extent to which the sampling results can represent the total land cover.

Table 4.4
Summary of the Land Cover Types Identified using i-Tree Canopy

Class Summary	Points	Percent (%) ± SE	Area (km^2) ± SE
Trees/Shrubs (orchards included)	1,405	23.4 ± 0.6	38.8 ± 0.9
Low-lying vegetation	2,062	34.4 ± 0.6	56.9 ± 1
Impervious-Buildings	190	3.2 ± 0.2	5.3 ± 0.4
Impervious-Roads	231	3.9 ± 0.3	6.4 ± 0.4
Soil	1,536	26.6 ± 0.6	42.4 ± 1
Water	114	1.9 ± 0.2	3.6 ± 0.2
Unclassified	462	7.7 ± 0.3	12.8 ± 0.6

Part of the second objective of this study was to evaluate the suitability of i-Tree Canopy for assessing urban canopies compared to the image classification method. To compare the results of these two methods, the target coverages in their calculations must be the same. Since post-classification processes (i.e., subtracting undesirable areas) were impossible in i-Tee Canopy, all random points on vines were classified as “unclassified.” Given the 2 m spatial resolution of the imagery, the vines were not classified as “trees/shrubs” using the image classification method. Therefore, the image classification results (before subtraction) and the i-Tree Canopy results were considered equivalent (Figure 4.3).

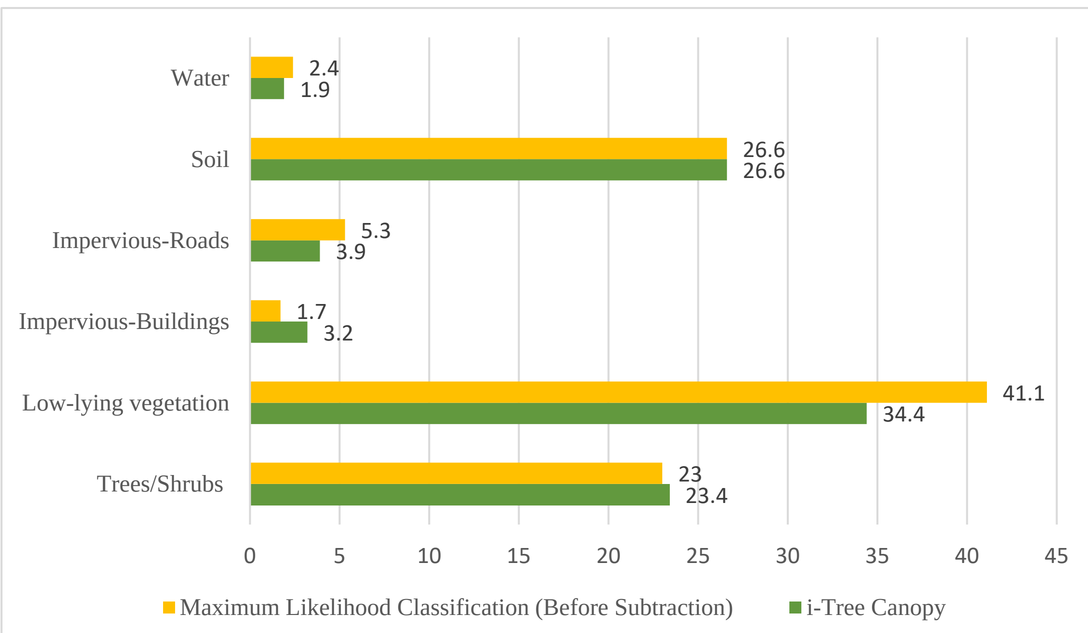

Figure 4.3
Comparison of the results obtained from MLC and i-Tree Canopy

This study's final land cover estimation was based on the interpretation of 6,000 random points. To evaluate the suitability of i-Tree Canopy for quick studies, the assessment results (Figure 4.4) and standard errors (Figure 4.5) were compared for each batch of 1,000 added new random points.

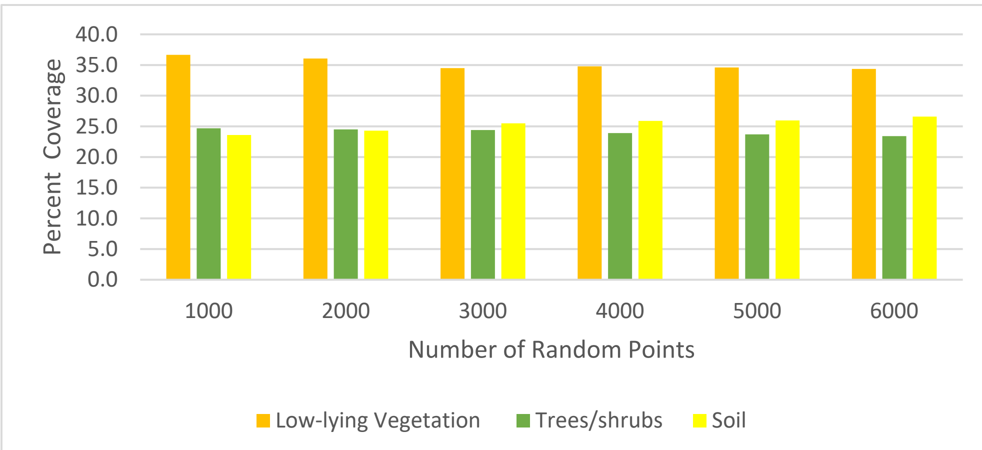

Figure 4.4
Estimation of main land coverages for each accumulative batches of

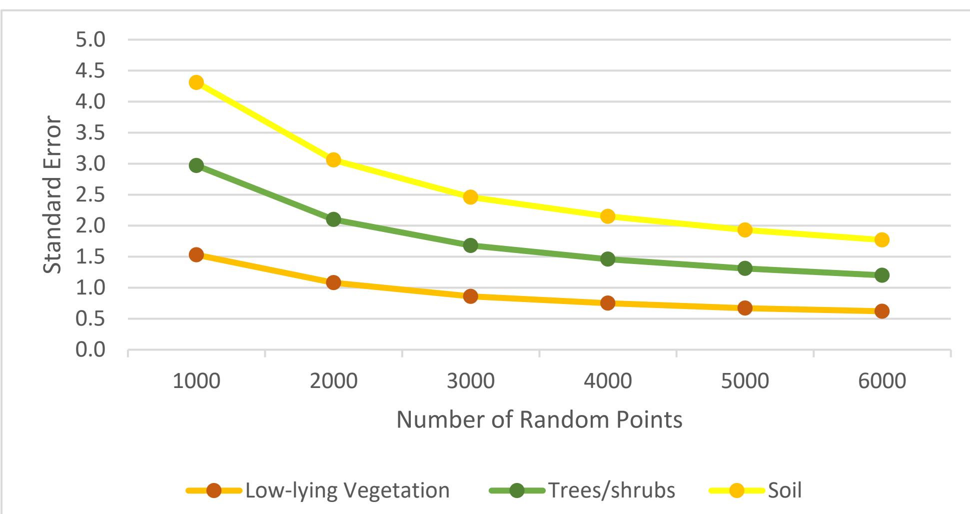

Figure 4.5
The standard error for each accumulative batches of random points

4.4 Accuracy Assessment of the Maximum Likelihood Classification Approach

As indicated in the methods chapter, an accuracy assessment was performed on the classification resulting from applying the MLC algorithm to three bands of the WorldView-2 data. According to Table 4.5, the overall accuracy of the classification, which is defined as the total number of correctly classified pixels by the total number of reference points, was 85% (512/600). Since the overall standard accuracy for LULC maps was set between 85% (Anderson et al., 1976) and 90% (Lins & Kleckner, 1996), the results obtained from the MLC approach were considered as the final accurate LULC map for the Town of Lincoln.

Table 4.5
Confusion Matrix of the Land Cover Classification Map

		Reference Data						
	Land Cover Class	Low-lying Vegetation	Trees/shrubs	Impervious buildings	Soil	Water	Impervious roads	Total
Classified Image	Unclassified	4	1	0	1	3	0	9
	Low-lying Vegetation	67	4	1	0	0	2	74
	Trees/shrubs	0	94	0	0	0	1	95
	Impervious buildings	1	0	78	3	4	1	87
	Soil	27	1	0	90	0	3	121
	Water	0	0	14	0	93	3	110
	Impervious roads	1	0	7	6	0	90	104
	Total number of test-site data	100	100	100	100	100	100	600

In addition to the overall accuracy, the class accuracies can be obtained from the confusion matrix to understand how each class performed in the supervised classification procedure. The “trees/shrubs” class resulted in the highest accuracy (94%), followed by “water” (93%) and both “soil” and “impervious-roads” with 90%. Two other classes resulted in much lower results, with 78% and 67% for impervious buildings and low-lying vegetation, respectively.

The Kappa coefficient for this map result was 0.8245, demonstrating relatively high agreement (82%) between the classified map and reference data. In addition to the diagonal figures representing the correctly classified pixels, the classification errors in the off-diagonal cells of the confusion matrix also provide valuable information about the classification results. In Table 4.5 above, the error of omission for each class is presented in the row before or after the main diagonal. The error of commission for each class is shown in column cells of the class above and below the main diagonal. The errors of omission and commission are connected to two other measures of accuracy: user’s accuracy (the number of the correctly identified pixels of a class) and producer’s accuracy (the number of correctly identified pixels divided by the total number of pixels in the reference image). The results of these measures that are presented in Table 4.6.

Table 4.6
Classification Errors for the Maximum-Likelihood Classification Algorithm

Cover Class	User's Accuracy (%)	Producer's accuracy (%)
Trees/shrubs	98.9	94
Low-lying Vegetation	90.5	67
Impervious buildings	89.7	78
Impervious roads	86.5	90
Soil	74.4	90
Water	84.6	93

4.5 Accuracy of UTC Assessment in Image Interpretation (i-Tree Canopy)

The accuracy assessments for each class in an image interpretation method depends on the total number of the random samples and the total number of points classified as that specific class (Thompson, 2012). In i-Tree Canopy, the sample identification started with 1,000 points gradually increased to 6,000 points to reduce the standard error as much as possible. The standard error of class cover (%), area ($km^{2)}$ and the number of points assigned to each class with a sample of 6,000 random points are illustrated in Table 4.4. The 95% confidence interval[3] is used to measure accuracy in i-Tree Canopy (Table 4.7). This means that for the trees/shrubs class assessed in i-Tree Canopy with 95% confidence, the cover percentage would be 22.3 to 24.5%. At least 7% of the random points were assigned to the unclassified category that was mainly related to vines, points located in shadowed areas, or points located between two different classes.

[3] The z-score or standard score for 95% confidence interval equals 1.96.

Table 4.7
Summary of the Land Cover Types With a 95% Confidence Interval in i-Tree Canopy

Class Summary	Cover Within a 95% Confidence Interval	
	Percent (%)	Area (km^2)
Trees/Shrubs (orchards included)	22.3 - 24.5	37 - 40.6
Low-lying vegetation	33.2 - 35.6	54.9 - 58.9
Impervious-Buildings	2.7 - 3.6	4.5 - 6
Impervious-Roads	3.4 - 4.3	5.6 - 7.2
Soil	25.5 - 27.7	40.6 - 44.2
Water	1.6 - 2.3	2.6 - 3.7
Unclassified	7 - 8.4	11.6 - 13.9

4.6 Chapter Summary

This chapter presents quantitative results obtained from the use of geospatial technologies in assessing the UTC with two different approaches. Initially, this chapter provided results obtained from the image classification (i.e., MLC) approach. Training-site data were described with the average spectral values and spectral separability values presented. This chapter also contained the results of land cover classification using the image classification and image interpretation (i.e., i-Tree) approaches. Accuracy assessment results were presented using a confusion matrix. Other measures, including the Kappa coefficient of agreement, errors of omission and commission, producer’s and user’s accuracy were also provided. The accuracy of the i-Tree Canopy was calculated for each class separately within a 95% confidence interval. The following chapter will present a detailed analysis and discussion of the results obtained.

5. Discussion

5.1 Introduction

This chapter provides an interpretation of the results and reflects on why the results matter and how they answered the questions posed in this research study. The assessment of urban trees in the Town of Lincoln was technically conducted in two phases. In the first phase, an image classification approach using the supervised classification of the total land cover based on the spectral characteristics of the pixels was performed. The second phase classified the entire study area by creating random points and assigning each point to one of the predefined cover classes using an image interpretation method. Implementing the land-cover classification using these methods satisfied the first two objectives of this study.

5.2 Interpretation and Analysis of the UTC Assessment Results

In assessing different land cover types within the Town of Lincoln using the image classification method, a 21.3% tree canopy cover was identified. This figure included all shade and ornamental trees in large, forested areas, isolated and small groups of trees located in urban parks and trees on private or public properties. Considering the size of shrubs relative to pixel sizes in the WorldView-2 image (i.e., 2 m), medium and small-sized shrubs were unlikely to be identified in the trees/shrubs class. As seen in the classified map result (Figure 4.2), these same shrubs (including vines), were predominantly misclassified as low-lying vegetation or soil, so they do not impact the canopy cover results.

Most land covers in the study area were related to low-lying vegetation (with 26% coverage post-subtraction), and in second place was the soil class with 23% coverage. The relatively lower accuracy of these two classes caused by fruit trees and vines can justify the removal of orchards and vineyards from the assessment. Excluding orchards and vineyards from the study did not affect the trees/shrubs class and only reduced it by 1.6%, which was related to mature fruit trees. By removing these two, in addition to avoiding overestimation in both low-lying vegetation and soil classes, other secondary objectives critical for enhancing sustainability and confronting climate change using trees as nature-based solutions were pursued.

First, examining trees from an urban perspective focusing on mitigating the negative impacts of climate change, green infrastructure, and achieving environmental sustainability, the efficiency of trees becomes very important (Davies et al., 2017). On average, height and canopy size of fruit trees are below the criteria for providing significant ecosystem services. Reducing stormwater runoff, regulating air temperature, reducing air pollution, and producing oxygen, are among the services related to these structural characteristics of trees (Alonso et al., 2011; Handley et al., 2007; Tyrväinen et al., 2003). By removing fruit trees and vines the UTC assessment would be more focused on trees capable of providing services and benefits in an urban context.

Second, in addition to the structural features of trees that affect their ecosystem services, the location and proximity of trees to human settlements are also considered important (e.g., flood reduction is more effective if woodland is located upslope of urban areas). Some of the benefits of trees, such as regulating temperature or reducing air and noise pollution, have greater value in the vicinity of human settlements (Inkiläinen et al., 2013; McPherson, 1994; Tyrväinen et al., 2003). In terms of location, orchards are usually located outside of urban areas and may have less efficiency in mitigating the impacts of climate change.

Finally, agricultural lands are not ideal sites for expanding tree canopies, although they are biophysically capable of supporting trees. Since most of the study area is located within the Greenbelt Plan and this plan focuses on protecting agricultural land (Ministry of Municipal

Affairs, 2017), identifying orchards and vineyards can assist in planning for prioritizing canopy goals in the future.

5.2.1 The Distribution of Urban Trees (Based on the Image Classification Approach)

The current and potential urban tree canopy can be investigated within different geographical boundaries, from watersheds to neighbourhoods and even small property parcels (O'Neil-Dunne, 2014). Parcel datasets may contain helpful information such as ownership and land-use types, which are very useful for achieving canopy goals in the future. The spatial distribution of trees at this scale was not part of the study's objectives; instead, the spatial distribution of the tree canopy is discussed based on the geographical boundaries of Lincoln's seven urban areas and two Niagara Escarpment and Greenbelt plans.

Considering trees as urban amenities, by evaluating their spatial distribution, it is possible to discuss environmental equity in urban areas. Environmental equity is part of the social pillar of sustainability and can be connected to income, property price, type of homeownership, and other socio-economic factors (Landry & Chakraborty, 2009). None of the urban areas embrace the vast continuous forests. Their canopy comprises street trees and small and/or medium-sized groups of trees located in public and private properties. Overall, Prudhommes has the highest density of canopy cover between seven urban areas. Although Beamsville has the largest area of tree cover, its canopy density is less than any other urban area in Lincoln. The canopy coverage of this area mainly comes from isolated trees and rows of street trees. Urban areas with higher canopy coverage (e.g., Prudhommes) benefit from small and medium-sized clusters of trees.

Most of the canopy cover in the study area is part of one of two provincial Greenbelt and Niagara Escarpment Plans. The Greenbelt and Niagara Escarpment Plans are essential in policymaking for any development activities in Ontario and the Niagara Region. Therefore, the presence of trees in these two plans was also examined. The Greenbelt Plan occupies 79.8% of the study area and provides permanent protection of the agricultural land and the ecological features and functions occurring within its boundaries (Ministry of Municipal Affairs, 2017). The Niagara Escarpment Plan aims to protect the geologic feature of the Niagara Escarpment and lands in its vicinity as a continuous natural environment with limited possibility for compatible development (Ministry of Natural Resources and Forestry, 2017). Most of the large continuous woodlands identified in this UTC assessment are located in the Niagara Escarpment Plan and are known as Escarpment Protection Areas. Escarpment Protection Areas are visually prominent and environmentally significant, especially regarding increasing resilience to climate change (Ministry of Natural Resources and Forestry, 2017).

Knowledge of tree canopy within the Niagara Escarpment and Greenbelt plans is of great importance in policymaking, maintaining the integrity and protecting forests in these two provincial programs. Extended forested areas provide important ecological services such as watershed protection, prevention of soil erosion and mitigation of the impacts of climate change. By assigning the information of this study as the 2018 tree canopy, any changes in tree coverage within these two tree areas can be examined over time.

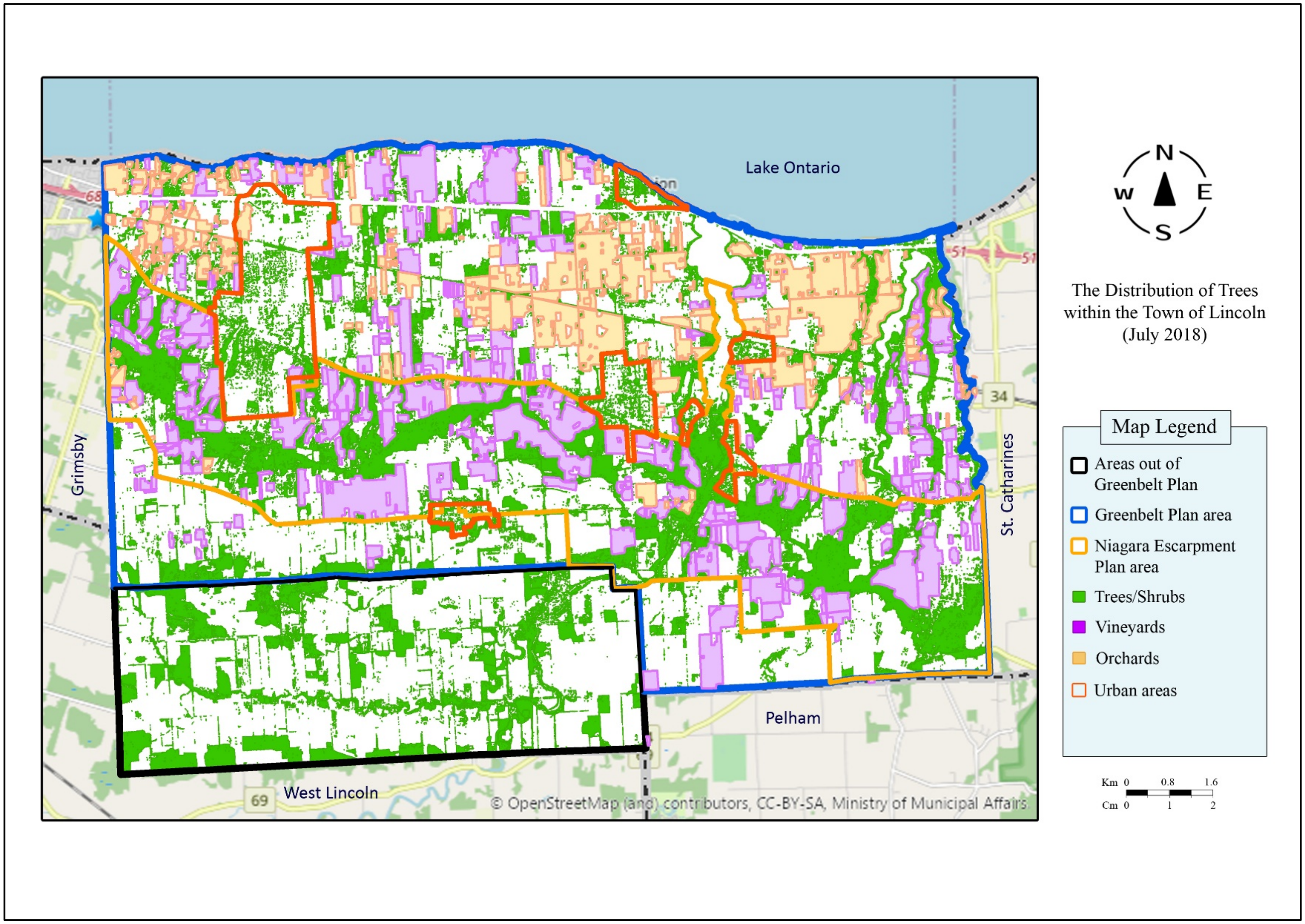

Figure 5.1
The distribution of tree canopy within the Greenbelt and Niagara Escarpment

5.2.2 The i-Tree Canopy's Compatibility With the Image Classification Approach

Fundamentally, the two canopy assessment approaches were different from each other. Using image classification (i.e., the MLC algorithm), the spectral characteristics of the image pixels were used to classify different types of land cover. At the same time, in i-Tree Canopy, random points were interpreted and assigned to land-cover classes. Since the overall classification accuracy (i.e., the probability that an individual pixel will be correctly classified) and the trees/shrubs class accuracies were within the acceptable standard (85% and 94%), the MLC results were considered to be an appropriate standard to evaluate the suitability of i-Tree Canopy.

The land-cover estimation using the i-Tree Canopy software is represented in numerical data, and it does not produce a map output result. Thus, the spatial distribution of LULC types cannot be compared. Due to its non-spatial nature, it was impossible to subtract fruit trees from the total canopy estimation in i-Tree Canopy. So, comparing the identified classes in i-Tree Canopy was made with the MLC results before subtraction of orchards and vineyards. In image classification using the WorldView-2 image, the foliage of vines and other small-sized shrubs were not categorized as trees/shrubs. Since in i-Tree Canopy, all vines were assigned to the unclassified category, the image classification's results before subtracting orchards can be considered equivalent to image interpretation results for the comparison. As illustrated in Figure 4-3, the estimations of the canopy in both approaches for most classes were quite close. The figure shows that in cases where random points are located on pure cover types (e.g., trees/shrubs, bare soil, or water), i-Tree Canopy results are similar to those obtained using the MLC approach. The difference between the output of the two approaches on low-lying vegetation can be explained by the fact that the MLC approach used the information in the near-infrared part of the electromagnetic spectrum. Unlike i-Tree Canopy analysis implemented on data available in the visible part of the spectrum (i.e., the visible blue, green, and red bands), using a near-infrared band makes the weak presence of herbaceous species detectable. Therefore, more low-lying vegetation has been detected using the MLC.

For evaluating the suitability of this method for quick studies with limited random points, the estimation of coverages and their standard errors for each 1,000 added points were compared (Figures 4.4 and 4.5). The results showed that the estimated land coverages, even at 1,000 random points, are significantly close to the estimation at 6,000. The standard error was significantly reduced by adding the first two batches of 1,000 (at 2,000 and 3,000 points) and then continued to decrease with a gentle, non-prominent slope. This shows that appropriate assessments can be achieved with a wider confidence interval and lower accuracy, even with fewer random points.

Although the implementation of UTC assessment using i-Tree Canopy software is associated with technical limitations, the slight difference between the results obtained from this approach and the image classification (i.e., MLC) approach shows that these differences depend on the goal, time, and budget available for such a study may be negligible.

5.2.3 Advantages and Disadvantages of the i-Tree Canopy Approach

i-Tree Canopy is used to assess urban trees, whether in large cities, small communities, or rapid studies. The deficiencies of this software are being reviewed, and its performance is constantly being improved by the USDA. One of the most important advantages of i-Tree Canopy is its low cost compared to image classification methods. For a LULC study, depending upon geographic location, spatial extent and available data, a canopy assessment cost may vary between $6,000 to $50,000 CDN. Considering interpretation in i-tree Canopy as a non-specialist job (with a minimum hourly wage of $14.25 CDN in Ontario as of 2021) and interpreting 100 points per hour, the cost of a study with a thousand points would be approximately $143 CDN. Including the initial setup expenses, the final cost of this assessment would not exceed $160 CDN. In addition to not requiring expensive remote-sensing data and associated commercially available software, training of the image analyst can be performed more quickly regardless of background technical knowledge.

There are four notable limitations of i-Tree Canopy assessing land-cover types, including urban tree canopies. First, as the name implies, any UTC assessment must provide an estimation of the canopy that is fulfilled in i-Tree Canopy. The need for implementing a UTC assessment may not extend beyond the numerical value estimated by i-Tree Canopy (e.g., policymaking, tracking overall change in the canopy, and/or using it as primary data for other planning purposes). But when UTC assessment is considered as the first stage of a complete urban forestry strategic plan, where spatial information about existing trees and suitable places to expand the canopy is required, i-Tree Canopy falls short of meeting those needs.

Second, land cover misclassification is common when identifying points within sparsely covered areas, shadow areas, or boundaries between two different cover types. Such errors are more likely to occur if the image accessed via Google Maps does not have high spatial resolution or was taken on a cloudy day. When selecting i-Tree Canopy for assessing urban trees, the spatial resolution of satellite imagery available for specific geographic locations must be investigated first. Since the spatial resolution of the Google Maps imageries varies by location and low-quality images can result in inaccurate canopy assessments, i-Tree Canopy may not be a suitable substitute for image classification in all areas.

Third, Google Maps uses mosaicked sets of images with various technical specifications (including spatial resolution). It is possible that a single study area could be composed of multiple mosaicked images acquired in different seasons. This becomes problematic for UTC assessments when leaf-off images (i.e., trees with no foliage) represent some parts of the study area. Finally, a land cover survey in i-tree Canopy will be done in predefined dimensions and geographical boundaries. The resulting data cannot be generalized at other required scales later.

5.3 Best Approaches for UTC Assessment in Small Communities

Trees as natural assets and nature-based solutions are relatively inexpensive solutions for many environmental and socio-economic problems such as managing stormwater, increasing environmental justice, mitigating air pollution, and reducing energy consumption (Mullaney et al., 2015). Many of these services are provided by trees, and the optimal use requires knowledge of the tree canopy. The high cost, technical problems, and lack of expertise to evaluate tree canopies should not prevent small communities from accessing this essential urban and regional planning tool.

The UTC assessment is a process that must be repeated every few years (the USDA recommends 5-8 years) to investigate the gains and losses in the canopy and the progress towards set canopy goals. Therefore, considering UTC assessment as a recurrent process, it is essential to adopt an approach that imposes minimal financial burdens, has fewer complexities, is feasible using available human resources, and at the same time is reliable and accurate.

UTC assessment is not limited to the percentage and the coverage area of the canopy. Although the numerical value is very important, it does not support canopy goals and prioritizing goals completely. For rapid analysis of large geographic areas (e.g., preliminary strategic planning or benchmarking of land cover changes) where the percentage of tree canopy cover relative to other land cover types is required, i-Tree Canopy is a good choice. More sophisticated image processing methods (e.g., image classification using an MLC approach) will be needed when comprehensive and detailed information about the tree canopy is needed (e.g., conservation purposes, canopy goal setting, and policymaking).

A portion of the cost of performing a UTC assessment using geospatial technologies is related to acquiring satellite imagery. Coarse spatial resolution images (e.g., ≥ 30 m pixel sizes) can cause canopy underestimations by up to 28% (Greenfield et al., 2009). Such images should not be used in the UTC assessment on the pretext of being financially viable as they will result in inaccurate canopy estimates. If it is impossible to obtain high-resolution data, images with spatial resolutions of 10 to 15 m can still be used to assess the canopy with acceptable accuracies (Leff, 2016). In this regard, these types of images may be a good option for smaller communities with limited budgets.

In UTC assessments, the number of studies that draw upon open-source remote-sensing data is increasing (Tilahun & Teferie, 2015; Li et al., 2020). Downloadable images from Google Earth with suitable resolutions for locations across North America can substitute expensive high-resolution imagery for small communities. Also, in terms of analyzing software for LULC classification and other spatial data analyses, free, open-source options (e.g., QGIS) can be a reasonable replacement for expensive software (e.g., ArcMap or ENVI).

Suppose the community conducting the UTC assessment intends to use this study for long-term and secondary purposes such as conservation objectives, determining the canopy goal, and prioritizing suitable areas for planting new trees. In that case, it is worthwhile to make this assessment once with remote-sensing methods. If an i-Tree Canopy assessment is performed simultaneously, it can be used as a possible alternative for numerical change detection and periodic studies in future (Konijnendijk et al., 2005).

5.4 The Compatibility of Niagara Official Plan's Canopy Goal as an Optimal Canopy

Forests have always been protected not only because of their intrinsic values but because other natural functions and ecosystems depend on their functionality and health (Ramakrishna & Woodwell, 1993). One of the conservation goals of forests is to preserve aquatic systems and watersheds that have been adopted widely by municipalities and urban and regional management systems (Furniss, 2010). In the Niagara Region, as in many other regions and cities in Ontario, the official plan's "minimum canopy cover" (i.e., 30%) defined by Environment Canada has been set to conserve watersheds, aquatic systems, and sustain species richness (Niagara Region, 2019, p. 112). The benefits of trees in urban environments are not limited to providing a well-balanced water system. Although more research is needed on the extent to which the 30% goal defined by Environment Canada can meet the socio-environmental needs of urban environments as a canopy goal, there are a few points about this index that need to be considered.

To begin with, the article explicitly states that it predominantly has a non-urban context (Environment Canada, 2013, p. 11). Although implementing the guideline will generate ecological benefits (Environment Canada, 2013, p. 3), socio-economic criteria must also be considered in any UTC goal. In addition, two sources have been used to define woodlands in Niagara's Official Plan. The Forest Act defines woodlands based on their number and diameter (Niagara Region, 2019, p. 112) and the Ecological Land Classification for southern Ontario based on absolute canopy cover. Trees are defined as large, wooded units in both sources and not individually, while for urban tree management and goal setting, all single trees located on public and private lands count and are valued.

Furthermore, with the availability of higher spatial resolution imagery, the tendency to implement the UTC assessments and define canopy goals by smaller geographical units has increased. Some cities use ward, neighbourhood, or even small property parcels to classify potential planting areas (O'Neil-Dunne, 2014). In urban planning, the study area may be a relatively small part of a larger watershed, and its specific features may be undermined if observed from a watershed perspective. It is best to plan for the canopy goal within the city under investigation.

In conclusion, the optimal canopy goal is not a numerical value that increases the overall canopy cover of the study area. If an optimal canopy goal is designed to promote sustainability, new trees are not just planted to achieve the planned canopy goal. New trees should be located in places that need a particular ecosystem service (Leff, 2016). In terms of adapting to the impacts of climate change and mitigating its effects, the canopy goal is fully operational when trees are situated in an appropriate geographic location. For example, trees are more effective in reducing stormwater runoff when they are located upslope of urban areas (Matteo et al., 2006); or to reduce the electricity costs, trees are best placed to the west aspect of the building to provide efficient shade (Hwang et al., 2015).

5.5 Chapter Summary

This chapter presented the interpretation of the results achieved from the remote-sensing (MLC) and i-Tree Canopy approaches. The results of these two approaches were compared to assess the possibility of using i-Tree Canopy as an affordable method, especially for small communities. The most suitable options for small communities, which usually face technical and financial barriers to conduct a UTC assessment, were examined. Although some of these options may not have the highest standard in LULC assessment, they can assist small communities in utilizing such a tool in urban tree management, mitigating climate change impacts, and achieving sustainability. Finally, the compatibility of the Niagara Official Plan’s criteria as an optimal canopy goal was examined.

6. Conclusions

This study aimed to assess current urban tree canopy cover using geospatial technologies within the Town of Lincoln, Ontario. This study used image classification technologies and image interpretation to estimate land covers, including the tree canopy. Since maximum likelihood classification is a standard method with a long history in LULC studies, it was considered the main approach used in this study. In addition to investigating the functionality of the image interpretation (i-Tree Canopy), cost-effective, accurate approaches with fewer complexities were introduced for UTC assessments in small communities. Unless a study on the optimal canopy goal for the Town of Lincoln is undertaken, it is impossible to state with certainty to what extent the 30% percent canopy goal referenced in the Official Plan can serve as a canopy goal. A standard canopy goal has some characteristics that the canopy provided by the Official Plan was examined in that format.

6.1 Summary

Based on the maximum likelihood classification, tree canopy cover was estimated to be 21.3% of the Town's area. This figure has been calculated based on the familiar concept of the urban canopy and does not include agricultural trees and shrubs. The first two dominant land cover types were low-lying vegetation (26%) and soil (22.9%), which were entirely predictable due to the extent of agricultural activity in this area.

The estimated tree canopy obtained from i-Tree Canopy (23.4%) was close to the MLC results. Since it was impossible to distinguish fruit trees from urban trees using this method, comparing the results obtained from the MLC could be made before subtracting orchards and vineyards (22.9%). One of the study's research questions was whether an image classification approach could be replaced by an image interpretation method. The efficiency of this method depends on the type of cover studied, the purpose of the study, and the required information to be obtained from an UTC assessment. The image interpretation method (e.g., using i-Tree Canopy) is suitable for examining homogeneous land-cover types. Distinguishing mixed vegetation and soil covers may be more complicated than the MLC approach given the exclusion of the near-infrared band of satellite imagery uploaded to Google Maps. In areas where mature trees have large canopies, combined with other homogeneous land covers, i-Tree Canopy will provide near-realistic numerical estimates as it did in this study.

Table 6.1
Summary of the UTC Assessment Using two Approaches

	MLC Classification Before Subtraction (%)	i-Tree Canopy Classification (%)
Low-lying Vegetation	41.1	34.4
Trees/Shrubs	22.9	23.4
Water	2.4	1.9
Impervious Buildings	1.7	3.2
Impervious Roads	5.3	3.9
Soil	26.6	26.6

Without any particular prerequisites, i-Tree Canopy can be implemented as an initial assessment for decision-making and any projects requiring land cover knowledge. i-Tree Canopy can present land cover numerically but does not highlight the spatial data related to each cover. Therefore, it cannot be used to decide the appropriate sites for tree expansion plans. A suitable UTC classifier should provide data that can be integrated with other spatial and non-spatial data (e.g., demographic, land-use data); in this regard, i-Tree Canopy is flawed. By performing this assessment in specific periods (preferably between 5 to 8 years), the overall numerical number of changes in land cover can be obtained. However, spatial information indicating where these changes have occurred is not provided. If the goal is to achieve a UTC assessment with the maximum capabilities of such a study and there are budgetary constraints, an image classification approach using suitable medium spatial-resolution data (e.g., Google Earth images, if applicable) with open-source software (e.g., QGIS) will be the most comprehensive option.

Concluding whether the 30% woodland coverage criteria set in the Niagara Region's Official Plan can be considered a canopy goal, it is essential to assume that it is recommended to protect water resources and species richness. Although it may meet other urban needs regarding using trees as a nature-based solution, it falls short of the standards for an optimal canopy goal. This index deals with extensive woodlands, and most of the urban trees isolated or in small groups are not counted in this index. The most important point about this index consistency with an standard canopy goal is that feasibility studies identify the best places for tree expansion in an optimal canopy goal that has not been seen in the Niagara Region's Official Plan.

6.2 Limitations of Research

While every effort was made to obtain accurate results and to achieve a UTC assessment according to current standards, there were limitations to this study that must be mentioned. First, the purpose of this study was to assess the tree canopy accurately; however, the inclusion of shrubs (especially those that resembled trees) in the results was inevitable.

Second, the Town of Lincoln is predominantly an agricultural area, and fruit trees are socially and economically important in the Town. The primary objective of this study was to assess the total tree canopy with and without fruit trees, considering the importance of agriculture in this community from a sustainability point of view. Due to the resolution of the satellite image (i.e., 2 m) and the small size of most fruit trees, misclassification of these trees was expected within orchards. By examining how fruit trees were identified in these areas, it was detected that most sections of orchards were identified as low-lying vegetation, except for large fruit trees. Since identifying fruit trees was not successful, they were excluded from the UTC assessment. Others have also adopted this approach in similar studies (Alonso et al., 2011; Handley et al., 2007).

Third, due to the coincidence of COVID-19 with the timing of this research study, and the requirement to follow Public Health and Brock's safety protocols, ground-based data collection (including the selection of test-site data), was done using the expert knowledge of the study area and existing ancillary data such as Google Earth imagery and reliable previously classified data (e.g., SOLRIS datasets).

6.3 Recommendations for Future Research

The first proposed study is the canopy goal-setting prioritizing the best locations to expand the tree canopy. By setting the study unit on property boundaries, the parcels with the biophysical and socio-economic potential to support new trees would be introduced. This study identifies the areas in greatest need of trees as infrastructure or solutions to environmental injustice. Partnerships, such as Niagara Adapts, for example, can be very effective in identifying vulnerable locations in terms of climate change. Once finalized, the canopy goal would be based on suitability and needs assessment, promoting equity and sustainability for all the community, especially those areas in greatest need.

Second, now that this research study has been completed as a baseline study, many other studies requiring tree canopy spatial data can be formed on this basis, including studying the relationship between canopy cover and property prices, living conditions, households' income, or energy consumption.

Third, an ecosystem services monetization study is recommended for the urban trees within the Town of Lincoln to assess the importance and role of ecosystem services provided by trees. This study can compare the expenses of establishing nature-based solutions with traditional infrastructure.

The fourth research suggestion would be conducting an inventory of the available trees within the study area. Although implementing inventories is a very resource-intensive process, this information (e.g., species, height, age, canopy area) can be used to precisely evaluate the ecosystem services provided by trees. UTC assessments based on geospatial approaches are not as functional as inventories in this regard since they view the canopy as a whole, not as a collection of trees that have different roles in providing ecosystem services based on their characteristics (McGee et al., 2012). This field-based inventory can also include spatial and non-spatial data. Many urban forest management activities and geospatial data analyses are possible using the geographical coordinates of individual trees and their non-spatial attributes (e.g., species type). Fortunately, the Niagara Region has had the opportunity to benefit from a crowd-sourcing program named tree-o-code Niagara, designed jointly by Geospatial Niagara and Public Service Request Inc. This initiative provides valuable information on the ecosystem services provided by urban trees (e.g., energy conserved, stormwater filtered, carbon dioxide removed, etc.). In addition, this software can highlight potential tree planting sites or gaps in the tree canopy. The development of this inventory in the Town of Lincoln is entirely new and, if completed, will help advance the goals of sustainable urban forestry.

Finally, regularly monitoring canopy changes is recommended after each tree canopy assessment. Repeating this assessment is a good indicator of how trees are managed. It also provides information about the extent to which the canopy goal has been realized.

6.4 Summary

This study comprehensively evaluated the urban tree canopy in a municipality in the Niagara Region using geospatial technologies. This is the first study of its kind in this Region. This study aimed to quantify tree canopy cover and explore low-cost options for using reliable geospatial tools for assessing and managing tree canopies in small communities such as the Town of Lincoln. As part of the Brock-Lincoln Living Lab partnership, the Town can use technical and academic resources to assess its UTC. This information allows for monitoring canopy changes over time and making policies to conserve and expand urban trees. This study can guide other cities and towns with similar environmental, social and geographical conditions, especially within the Niagara Region, to know the challenges and opportunities ahead in preparing their UTC assessments.

As a frontline facing climate change, small communities need to adopt appropriate measures and strategies to deal with these effects. Trees are effective in both increasing adaptability to climate change and mitigating its impacts. In small communities, especially at a lower cost than establishing and maintaining traditional infrastructure, trees as nature-based solutions that help to solve environmental challenges. This particular study area, located along the shoreline of Lake Ontario, is struggling with a number of these negative impacts. Spatial information on the existing tree canopy serves as crucial information for maintaining or increasing vital ecosystem services and targeting areas where they are most needed (e.g., shoreline areas affected by erosion and flooding). Conducting an urban tree canopy assessment for the Town of Lincoln provided an opportunity to obtain this information.

In general, the results of this research showed that small communities could also benefit from the canopy assessment of urban trees by using alternative, uncomplicated, cost-effective, and at the same time, accurate methods. Compared to other engineered strategies, the availability of trees will be the best incentive for stakeholders and decision-makers to think more seriously about the canopy goals. This study can be used at the management level for policymaking and protecting existing trees, determining the canopy goal and potential sites for planting new trees and tracking changes in the canopy. Sustainable urban forestry cannot be achieved without an urban tree canopy assessment. Urbanization and environmental problems, especially climate change, demonstrate the necessity for this assessment, regardless of whether the desired area is a large city or a small town.

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