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Peri-urban tree canopy assessments: Leveraging partnerships and technology for climate resilience

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Abstract

The urban tree canopy plays a crucial role in climate change mitigation and adaptation, yet peri-urban environments—transition zones between urban and rural areas—remain unexplored in urban tree canopy assessments. With rapid urbanization expected to increase the global population to two-thirds by 2050, managing peri-urban green infrastructure is essential for enhancing climate resilience. While the socio-environmental and economic benefits and services of urban and peri-urban forests are well-documented, municipalities with limited resources often lack the financial, human, or technical resources and expertise to obtain accurate data using geospatial technologies. This study evaluates cost-effective methods of urban tree canopy assessment in a peri-urban and resource-limited municipal context, aiming to improve municipal governance. Findings suggest that a low-cost point-sampling approach can enhance municipal capacity to manage forests in peri-urban environments, thus enhancing climate resiliency. Additionally, partnerships between higher-education institutions and municipalities can optimize resource sharing and facilitate integrated peri-urban forest management.

KEYWORDS
urban tree canopy, peri-urban forestry, geospatial technologies, urban forest management

Résumé

La canopée urbaine joue un rôle crucial dans l'atténuation et l'adaptation aux changements climatiques. Pourtant les environnements périurbains, zones de transition entre les zones urbaines et rurales, restent inexplorés dans les évaluations de la canopée urbaine. Avec une urbanisation rapide et la croissance de la population mondiale d'ici 2050, la gestion des infrastructures vertes périurbaines est essentielle pour améliorer la résilience climatique. Si les avantages socio-environnementaux et économiques des forêts urbaines et périurbaines sont bien documentés, les municipalités manquent souvent des ressources financières ainsi que de l'expertise technique nécessaires pour obtenir des données précises à l'aide des technologies géospatiales. Cette étude évalue des méthodes peu couteuses d'évaluation de la canopée urbaine dans un contexte périurbain, dans le but d'améliorer la gouvernance municipale. Les résultats suggèrent qu'une approche d'échantillonnage ponctuel à faible coût peut renforcer la capacité des municipalités à gérer les forêts en milieu périurbain, améliorant ainsi la résilience climatique. De plus, les partenariats entre les établissements d'enseignement supérieur et les municipalités peuvent optimiser le partage des ressources et faciliter la gestion intégrée des forêts périurbaines.

MOTS CLÉS
canopée urbaine, foresterie périurbaine, technologies géospatiales, gestion des forêts urbaines

Key messages

- Peri-urban environments are critical yet understudied in urban tree canopy assessments.
- Peri-urban and/or municipalities with limited resources often face challenges in obtaining accurate urban tree canopy data.
- Collaborations between municipalities and higher-education institutions can improve forest management.

INTRODUCTION AND BACKGROUND

Globally, cities are the most threatened by climate change, yet many are not equipped to respond to these threats (Konijnendijk, 2023). As cities continue to experience intense urbanization, urban forests have become increasingly vulnerable to climate change (Ordóñez & Trammell, 2022); thus, inventories and assessments of green infrastructure (GI) assets have become crucial (Tapsuwan et al., 2021). Urban forests are critical for enhancing climate resiliency as pressures from urbanization increase, with urban expansion being the main cause of forest loss (Galle, 2024). Urban expansion is increasingly rendering forests to city limits, such as peri-urban areas (Francini et al., 2024), underscoring the need to include these areas in municipal governance (United Nations Economic Commission for Europe, 2021). Defined as the "network comprising all woodlands, groups of trees and individual trees located in urban and peri-urban areas" (Food and Agriculture Organization [FAO], 2016, p. 2), urban forests provide environmental, economic, and social benefits and services that contribute to ecological and human well-being (Davies et al., 2017; Galle, 2024; Konijnendijk, 2023). Despite providing a nature-based solution to climate change (Davies et al., 2017), urban forests remain negatively impacted by human activities (Ordóñez & Trammell, 2022). Anthropogenic changes in temperature and precipitation patterns, for example, increase forest vulnerability to environmental stressors and disease (Ordóñez & Duinker, 2015). Further, urban forests are increasingly susceptible to wildfires, storms, and invasive species—threats expected to intensify with climate change (Konijnendijk, 2023).

Since 2010, urban forests have received significant attention, with increasing emphasis on their management and planning as critical assets for climate adaptation and mitigation (Food and Agriculture Organization, 2016; Ordóñez & Trammell, 2022; Tsegaye et al., 2019). They play a vital role in reducing stormwater runoff (Matteo et al., 2006), enhancing air quality (Ordóñez & Duinker, 2015), moderating microclimates (Tapsuwan et al., 2021), and lowering surface temperatures (Ordóñez et al., 2024). Urban forestry professionals emphasize the importance of recognizing urban forests as GI assets managed by municipal governments to ensure their long-term protection (Green Infrastructure Ontario Coalition, 2018; Tsegaye, et al., 2019). In Canada, municipalities manage urban forest green infrastructure within asset management frameworks that assess value, lifecycle costs, risks, and service levels, with individually measurable assets more easily incorporated into planning and investment decisions (Green Infrastructure Ontario Coalition, 2018). A commonly used metric for assessing urban forests is urban tree canopy (UTC) cover, which measures the spatial extent and distribution of tree cover (United States Department of Agriculture [USDA], 2019); these data are typically obtained through a UTC assessment. UTC cover assessed as a percentage of land with tree canopy is commonly used by municipalities because it is easily interpreted, supports planning targets, and requires minimal technical expertise. While pixel-based (e.g., normalized difference vegetation index) or point-based methods (e.g., airborne laser scanning) provide valuable tree asset measurements, they are often cost-prohibitive and/or require additional resources and expertise. Percent cover offers a practical, policy-relevant metric for assessing canopies.

Increasingly, municipal governments are interested in methods used to measure urban forest assets, as demonstrated by the number of assessments conducted across North America (e.g., Ordóñez & Duinker, 2013; Ordóñez et al., 2024). A UTC assessment measures tree canopy cover (%) on public and private lands, identifies planting spaces, and estimates ecosystem services using geospatial technologies, such as satellite remote sensing. These approaches are well-established in literature (e.g., Hwang & Wiseman, 2020; McGee et al., 2012; United States Department of Agriculture, 2019), and are important as resilient communities require abundant, diverse canopies to withstand environmental conditions and provide ecosystem benefits and services (Ordóñez & Duinker, 2015; Ordóñez & Trammell, 2022). Some larger municipalities—defined by Statistics Canada (2025) as those with populations of 100,000+ (e.g., Toronto, Canada)—have conducted site-specific tree inventories and assessments (Ordóñez et al., 2024); however, the approach used and levels of detail vary. Municipalities need data every five to eight years to set canopy targets and guide urban forest management plans (UFMPs) to address increasing urbanization and climate change (Larouche et al., 2021; Ordóñez et al., 2024; United States Department of Agriculture, 2019).

Geospatial technologies, like remote sensing and geographic information systems (GIS), enable more effective UTC assessment (e.g., Neyns & Canters, 2022), but resource-limited municipalities often lack the financial, human, or technical resources and expertise required to obtain geospatial information about their UTC and adjacent land use and land cover (LULC) (McGee et al., 2012). While ground-based measurements represent an alternative, they are costly, time-consuming, and often incomplete, especially for trees on private lands (Klobucar et al., 2021). Trees on private lands can account for 50–70% of a municipality's urban forest (Hutt-Taylor and Ziter, 2022); yet these remain largely unmonitored. Ideally, both ground-based and satellite-derived UTC data would be available to municipalities permitting evidence-based decision making regarding setting UTC and GI goals, enhancing tree policies and urban planning, and the development or implementation of UFMPs (Ordóñez & Duinker, 2013). However, obtaining geospatial information presents a major challenge for peri-urban and/or resource-limited municipalities.

Peri-urban areas are defined as the “transition zone, or interaction zone, where urban and rural activities are juxtaposed, and landscape features are subject to rapid modifications, induced by human activities” (Douglas, 2005, p. 18). Often neglected by both rural and urban administrations, these are important transitional areas of LULC change; however, their blended landscapes create unique challenges for mapping, managing, and sustaining the UTC. While few peri-UTC assessments are published in academic literature, there are ongoing efforts expanding this work—e.g., Toronto's Ravine Strategy—given the potential of these areas to enhance climate resilience. They also provide urban forest restoration and replanting opportunities (Francini et al., 2024). Another distinct challenge for resource-limited municipalities is that they face institutional and financial limitations (e.g., constrained staffing, funding, and/or technical expertise) that affects their ability to conduct UTC assessments or implement urban forest management. To date, UTC research and implementation efforts have largely focused on the actions of well-resourced municipalities (e.g., Ottawa and Toronto, Canada). Recently, the provincial government of Ontario mandated municipal asset management planning, requiring municipalities to implement comprehensive asset plans by 2025, explore cost-saving measures like GI, and establish desired service levels considering climate change. In 2023, municipalities were also mandated to perform UTC inventories within their boundaries to determine canopy cover, along with other natural assets. The ability of resource-limited municipalities to meet these mandates with minimal information or involvement from upper-level government continues to be a longstanding challenge (e.g., Barker & Kenney, 2012).

Within this context, partnerships between higher education institutions (HEIs) and the community involving university researchers, students, municipal staff, community residents, and/or not-for-profits offer an alternative approach to obtaining UTC information, especially for resource-limited municipalities confronting urbanization and climate change. These partnerships leverage resources by providing financial support, including access to research, funding, human resources, hardware/software (including geospatial data and technologies), and opportunities to evaluate partnership success (e.g., Plummer et al., 2021). Partnerships provide resources such as UTC mapping, private tree identification, assessment of tree condition, co-development of UFMPs, as well as the monitoring and evaluation of project outcomes. This permits tracking of progress toward municipal goals (Kenney et al., 2011; Matasci et al., 2018); it also provides opportunities to establish new or enhance existing urban forest bylaws (e.g., private tree bylaws) and policies, mobilize knowledge, and report outcomes related to provincial mandates.

Through an HEI-community partnership with the Town of Lincoln, Ontario (the Brock-Lincoln Living Lab), the main goal of this study was to develop improved, cost-effective, and rapid geospatial methods of assessing the UTC in a peri-urban and resource-limited municipality at a scale necessary to inform urban forest governance. To achieve this goal, three objectives were identified:

1) To identify, describe, and document the current capabilities of remote sensing technologies to obtain critical information about the UTC;
2) To evaluate and compare methods for estimating tree canopy cover in a peri-urban municipality, using remote sensing image classification and low-cost point-sampling; and
3) To determine the extent to which the web-based tool, i-Tree Canopy, can be used for rapid UTC assessment.

LITERATURE REVIEW

A literature review on remote sensing was conducted to identify its capabilities in obtaining critical information about the UTC in urban and peri-urban environments. Extensive documentation exists on the use of remote sensing in assessing, monitoring, and managing urban vegetation (Neyns & Canters, 2022; Shahtahmassebi et al., 2021). Further, UTC assessments using remote sensing data analysis methods, such as image classification, have been used extensively and are well-established in literature (e.g., Hwang & Wiseman, 2020; Li et al., 2019; Matasci et al., 2018; Timilsina et al., 2019; United States Department of Agriculture, 2019). Several remote sensing studies have compared devices and platforms, data analysis techniques, outcomes, and accuracies achieved in UTC assessments (e.g., Li et al., 2019; Matasci et al., 2018;

McGee et al., 2012); others have assessed UTC change over time (e.g., Locke et al., 2023; Roman et al., 2021). To date, the maximum likelihood classification (MLC) method has been frequently used in these studies (Alshari & Gawali, 2021). MLC is a pixel-based method that calculates the probability that any given pixel in an image belongs to a specific LULC type, assuming that the statistical values for each LULC across each band of remote sensing data are normally distributed (Jensen, 2016; Thompson, 2012). More recently, object-based and other classification methods have been tested using sophisticated remote sensing data (e.g., Timilsina et al., 2019); however, the costs of acquiring and analyzing such data are often prohibitive for resource-constrained municipal governments.

i-Tree Canopy, a web application designed by the USDA, uses a random point method to sample LULC within an area beneath a series of points overlaid on Google Maps basemap imagery which includes a combination of aerial photography and commercial satellite data sources. It is a rapid form of UTC assessment, where minimal expertise is required, costs are low, and accuracies are acceptable. Although this tool has been available since 2011 (Nowak, 2021), few studies (e.g., Wiseman et al., 2023; Hwang & Wiseman, 2020; Klobucar et al., 2021; Parmehr et al., 2016) have reported on this assessment approach. Parmehr et al.'s (2016) study compared i-Tree Canopy's performance to a classification of fused Light Detection and Ranging (LiDAR) and satellite data. While accurate, this approach may not be financially viable for resource-limited municipalities as it is often seen as producing data that exceeds the requirements for standard UTC assessment. Unlike the current study, the Hwang and Wiseman (2020) study was conducted in an entirely urban area. In evaluating i-Tree Canopy, they employed two methods: i-Tree Landscape and unsupervised classification on a 1 m spatial resolution multispectral image. Findings indicated that the mixed nature of vegetation cover in agricultural areas diminished the performance of unsupervised methods.

While technological advancements have improved UTC assessments over time, studies conducted in peri-urban municipalities are underrepresented in literature (Barker & Kenney, 2012; Kenney & Idziak, 2000). In peri-urban municipalities with limited resources, distinguishing between LULC types is challenging, particularly when relying on lower spatial resolution in low-cost or "free" imagery (e.g., Google Maps). Evaluating the feasibility and accuracy of i-Tree Canopy in measuring the UTC and adjacent LULC types in this context, compared to standard approaches, represents a major need for resource-limited municipalities, where consultant fees to obtain this information are cost-prohibitive.

MATERIALS AND METHODS

Site selection and rationale

Many municipalities along the Great Lakes shorelines, such as Lincoln, Ontario, are confronting major climate-related challenges such as floods (see Edwards, 2017). Thus, the Town of Lincoln has significant interest in measuring and enhancing the UTC within their municipal boundaries (Figure 1) to support climate resiliency (Konijnendijk, 2023). The town of roughly 25,000 residents covers approximately 163 km^2 of land and is comprised of seven built-up areas (Statistics Canada, 2022). The LULC types within Lincoln's borders are predominately agricultural (including orchards and vineyards), wetland, and forest areas (DigitalGlobe Inc., 2018). The Town of Lincoln has identified sustainable peri-urban forests as a goal in GI asset management and planning; however, it lacks sufficient human, financial, and other resources needed to realize this goal.

Lincoln, the fastest-growing municipality in the Niagara Region, was selected for further study given its lack of resources for obtaining UTC information, its vulnerability to climate change, and its willingness to establish a formalized partnership with an HEI (Brock University) to achieve its goal of becoming a climate-resilient municipality. As a municipality that can be characterized as both peri-urban and resource-limited, Lincoln provides a representative case for exploring how these intersecting challenges influence the feasibility of UTC assessment approaches. It is anticipated that the methods used in this study can be adapted to other municipalities also required to meet provincial mandates by 2025.

This study enabled the Town of Lincoln to independently assess its UTC using existing resources and minimal expertise. Unlike typical UTC assessments focused solely on urban areas, this study considered all trees contributing to Lincoln's socio-environmental well-being. Given the proximity of forested areas along the Niagara Escarpment to peri-urban areas within the municipality's boundaries, and their ecological interactions, these trees were included in the peri-UTC assessment. Despite orchards and vineyards contributing to the town's vegetation cover and positively impacting human well-being (Galle, 2024), they were subtracted from the MLC method for five reasons. First, this study aimed to support the development of a UFMP in a peri-urban and resource-limited municipality. Second, the approach aligned with standard practices in larger urban centres, where agricultural lands are typically excluded from canopy targets. Third, the purpose and scope of this study prioritized larger, canopy-forming trees because urban canopy resilience benefits are closely related to canopy size and proximity to urban areas (Galle, 2024), as demonstrated by Davies et al. (2017), Inkiläinen (2013), and Konijnendijk (2023). Fourth, orchards and vineyards typically occur in narrow rows or patches and are often misclassified as low-lying vegetation, reducing classification accuracy. Finally, this study was conducted in collaboration with a municipality assessing its tree canopy across public and private lands, and orchards and vineyards typically fall outside municpal jurisdication and regulatory frameworks, making them less feasible to include in UFMPs.

FIGURE 1 Study area map showing the municipal boundary of Lincoln, Ontario, Canada. *Source:* Esri (2023).

Although UTC assessments typically prioritize urban trees, it is essential to identify other LULC types in these assessments. This valuable information informs management and planning activities, such as identifying planting spaces (Francini et al., 2024; McGee et al. 2012; United States Department of Agriculture, 2019). Consequently, this study also identified other significant LULC types within the town's borders.

WorldView-2 satellite data and other geospatial datasets

Remote sensing data were derived from WorldView-2 satellite imagery on 10 July 2018 (DigitalGlobe Inc., 2018). These data were purchased as orthoimages, indicating prior geometric corrections. With 0% cloud cover during acquisition, there were no concerns about radiometric distortions. Four bands of data covered the blue (450–510 nm), green (510–580 nm), red (630–690 nm), and near infrared (NIR) (770–895 nm) portions of the electromagnetic spectrum (EMS), with 2 m spatial resolution. This resolution is suitable for studying mature trees. The NIR is crucial for vegetation identification, especially in areas with sparse vegetation. Visible bands alone lack sufficient spectral distinction, leading to potential misclassification, while the use of NIR enhances spectral separability between LULC types. Data analyses were conducted on all four bands using the Environment for Visualizing Images (ENVI 5.6). Other geospatial datasets were used in this study, including municipal boundary data, Google Maps basemaps, and LULC datasets—such as the Southern Ontario Land Resource Information System (SOLRIS) (Ontario Ministry of Natural Resources and Forestry, 2019) and the Canada Land Inventory dataset (Agriculture and Agri-Food Canada, 2019). These datasets were used for ground truthing and validating LULC classifications and delineating municipal boundaries.

i-Tree Canopy data

The study investigated the viability of using i-Tree Canopy and data from Google Maps for peri-UTC assessment (i-Tree, 2020). These data were obtained within the same timeframe as the WorldView-2 data and covered only the visible portions of the EMS. While the systematic grid-based sampling method employed by i-Tree Canopy ensures that samples are representative and unbiased across the study area, the accuracy relies on the spatial and spectral resolution of the imagery (Richardson & Moskal, 2014) and the ability of the analyst to identify features correctly (Parmehr et al., 2016). Experiments were undertaken using 1,000 to 6,000 random point samples to determine optimal sample size for accurate peri-UTC assessment. The standard error (SE), a means of estimating uncertainty, decreases as the number of sample points increases (Parmehr et al., 2016), further discussed below.

Image classification using WorldView-2 satellite data

Image classification refers to any data reduction technique that attempts to place features with similar spectral characteristics into either computer- or analyst-defined classes (Jensen, 2016). The overall goal is to automatically extract thematic information from image data. Before performing the MLC, the study area was first classified using an unsupervised classification approach, namely the iterative self-organizing data analysis technique (ISODATA), to determine the number and type of LULC types in the study area. Using this technique, a computer determined which pixels were related and grouped them into classes based on their statistical characteristics (Jensen, 2016). Classification parameters were varied until satisfactory results (e.g., accuracies over 85%) were obtained.

In this study, the MLC algorithm was applied to four bands of WorldView-2 data. MLC is a standard remote-sensing approach used in UTC assessment. It provides a standard estimate of the peri-UTC and adjacent LULC. Using this approach, the image analyst supervised automatic classification of unknown pixels within imagery by providing the MLC algorithm a numerical description (i.e., spectral signature) of the LULC types in the study area. Training areas representing LULC types (Table 1) were chosen as representative samples from a population assumed to be normally distributed. For this purpose, a total of $10n$–$100n$ (where n is the number of bands used) samples were selected to represent each LULC type. Training and test-site data were then used to both calibrate and validate the classification method (Lillesand et al., 2015).

Estimates of Lincoln's canopy of trees and shrubs providing maximum benefits and services to the municipality (including shade trees, ornamental trees, and large non-crop shrubs), and adjacent LULC types were determined after completing the MLC. As noted above, orchards and vineyards can result in canopy over-estimations so they were subtracted from further study. Future studies of the peri-UTC will not be impacted by this approach since agricultural areas are not considered in canopy planning. Results of applying the MLC to the entire study area were subsequently used as a reference for making comparisons to results from i-Tree Canopy as it does not support mathematical formulas on imagery.

Accuracy assessment: MLC

Accuracy assessment is an essential part of supervised image classification, such as MLC. It is used to compare the classified image to credible and accurate reference data. These data can be collected in the field or derived from high-resolution imagery, existing classified imagery, or GIS data layers (Lillesand et al., 2015). In this study, 600 random pixels, independent of the training data, were generated to reduce bias in the analyst's knowledge of the study area (Richards, 2012). The number of training data ensured that accuracies could be calculated with an SE of no greater than 0.05 (Stehman, 2001). In this study, classification accuracy was evaluated using a confusion matrix, a standard approach in remote sensing (Jensen, 2016). Each pixel in the classified LULC image was compared to the corresponding class in reference or ground-truthed data sources. The overall accuracy of a classification result is determined by dividing the sum of correctly identified pixels by the total number of reference pixels (test-site pixels). The standard overall accuracy result for LULC maps is over 85% (Anderson et al., 1976; Lins & Kleckner, 1996). Accuracy assessment was conducted on the classified image with subtracted orchards and vineyards with no test pixels drawn from these areas. After acceptable accuracy was achieved, the classification result was deemed to be the final estimate of canopy cover within Lincoln.

Random point sampling using i-Tree Canopy

In i-Tree Canopy, the same LULC types (Table 1) were selected to determine its ability to estimate peri-UTC and adjacent LULC types identified using the MLC. Using this approach, some smaller cover types were more challenging to identify; however, their texture and shape suggested they were vines, agricultural shrubs, or small fruit trees growing in rows across the landscape. In this study, these features were labelled as "unclassified." Larger fruit trees,

TABLE 1 Land use and land cover classification scheme used in this study.

Land use and land cover types	Class description
1) Trees/shrubs	Shade and ornamental trees and non-cropland shrubs distinguishable in satellite imagery
2) Low-lying Vegetation	Croplands, grass, and vegetation in wetlands
3) Impervious Surfaces	Buildings, greenhouses, highways, roads, driveways, sidewalks, and parking areas paved with concrete/asphalt
4) Soil	Bare soil, mineral resource extraction areas, fallow lands, newly harvested areas without vegetation cover, and unpaved roads
5) Water	Hydrological features including streams, creeks, lakes, and ponds

however, were identified as "trees/shrubs" due to their larger canopy and distinctive shape. A total of 6,000 random points were generated, and their type was interpreted and assigned to predetermined LULC types. The i-Tree Canopy estimate aligned with the MLC that encompassed the entire study area since all the features present in the i-Tree Canopy assessment were also present in the MLC result.

Accuracy assessment: i-Tree Canopy

In i-Tree Canopy, accuracy assessment relies on the analyst's ability to correctly identify random points, which is influenced by the spatial and spectral resolution of the image data. Increasing the number of random points improves precision as the SE decreases. The SE indicates how close the mean of any given sample from that population is likely to be, compared to the population mean. A low SE shows that the sample means are closely distributed around the population mean (Thompson, 2012). To increase precision in this study, the number of random points increased stepwise in thousands of units. Each unit significantly reduced the SE compared to the previous one. This process ended after 6,000 points, as it no longer resulted in appreciable changes to the SE. To assess the accuracy of this method, a subset of identified points was randomly selected, and their LULC type was compared with the SOLRIS map using a confusion matrix.

Approach used in rapid UTC assessment

The i-Tree Canopy method offers a time-efficient, cost-effective alternative to traditional UTC assessments by reducing the time and effort for data acquisition, processing, and interpretation (Parmehr et al., 2016). This approach estimates LULC types using random points, making it ideal for peri-urban forest governance, especially for interim evaluations between comprehensive assessments. It supports canopy cover monitoring and helps assess the effectiveness of bylaws and UFMP targets. This study evaluated the suitability of i-Tree Canopy for rapid assessments with limited random points, by comparing cover estimates and SEs across different groups of 1,000 to 6,000 random points for three cover types: trees/shrubs, low-lying vegetation, and soil.

Cost-benefit analysis

Cost-benefit analysis was subsequently conducted using a detailed description of project tasks, timing, and costs to compare traditional image classification to the point-based method. Remote sensing data were acquired at a reduced cost through an HEI-community partnership. Direct costs for remote sensing data typically include image acquisition, computers and software licenses, personnel costs, and ancillary data collection. The quality and characteristics of imagery— e.g., spatial and spectral resolutions—are critical factors that significantly impact the accuracy of the analysis and cost of image acquisition.

RESULTS

Image classification

The outcome of the ISODATA approach was used to determine the number and types of LULC in the study area. Classification parameters were varied, with satisfactory results being obtained using this approach. Based on these results, along with the collection of field data, a total of six LULC types were defined for the study area (Table 1). Using the MLC approach, estimates of the peri-UTC and adjacent LULC types were made (Table 2). The two approaches used in this study (remote sensing image classification and i-Tree Canopy) were compared using the pre-subtraction results. Accuracy assessment of the MLC was performed on the classification result obtained after the subtraction of orchards and vineyards, yielding a classification accuracy of 88.2% and a Kappa coefficient of 0.86. Figure 2a illustrates the spatial distribution of all LULC types using the MLC approach while Figure 2b depicts a comprehensive map showing the spatial distribution of priority, resilience-focused trees within Lincoln's municipal boundaries.

i-Tree Canopy

Calculations relative to i-Tree Canopy were based on statistical methods and observations of the number of random points from each LULC relative to the total number of random points (Table 3). The precision of this approach was expressed as an SE for each LULC type. LULC

TABLE 2 Summary of the types of land use and land cover identified using maximum likelihood classification. *Data source*: DigitalGlobe Inc. (2018). © CNES 2018, Distribution AIRBUS DS via Land Info LLC.

Class Summary	Pre-subtraction Percent (%)	Area (km^2)	Post-subtraction[a] Percent (%)	Area (km2)	Accuracy (%)
Trees/shrubs	23	38	21.3	35.4	94
Low-lying Vegetation	41.1	68.2	26	43.1	67
Impervious Surfaces	7	11.6	6.8	11.4	84
Soil	26.6	44.1	22.9	38	90
Water	2.4	5.2	2.4	4	93

[a]The total area that was subtracted as orchards and vineyards was about 34 km^2 which covered 21% of the study area.

estimates using i-Tree Canopy were compared with the pre-subtraction MLC results to assess its use in estimating peri-UTC cover, an important objective of this study (see Table 2). Figure 3 illustrates a comparison between these methods in the estimation of the three main LULC types (by percent cover), which are crucial for urban forest governance.

Rapid UTC assessment

i-Tree Canopy's suitability for rapid peri-UTC assessment was also explored in this study. Results from adding thousands of random points to assess i-Tree Canopy's suitability are depicted in Figure 4, illustrating how the SE of the estimates decreased as points increased from 1,000 to 6,000. This trend indicated a reduction in uncertainty by adding points, resulting in narrower confidence intervals. Percent cover calculations for the three main LULC types also changed with increasing points (Figure 5), showing significant decreases in SE values of over 59% for low-lying vegetation and the trees/shrubs classes, and 57% for the soil class. SE values were influenced by the proportion of interpreted random points compared to the total number of points.

A comparison of time and cost

A main advantage of i-Tree Canopy is its low cost compared to traditional image classification. For an LULC study, traditional UTC assessments typically range between \$20,000 and \$70,000, depending on factors like geographic location, spatial extent, and data characteristics. Using i-Tree Canopy for rapid assessment (1,000 points) costs approximately \$175. Given Ontario's 2025 minimum hourly wage of \$17.60, the cost remains under \$200, including initial setup expenses. The process is cost-effective, as a non-specialist can analyze 100 points per hour. Additionally, it requires minimal expertise, and almost anyone with basic training can interpret random point coverage.

DISCUSSION

Comparing methods for estimating peri-UTC cover

As municipalities continue to experience rapid urbanization, peri-urban forests are increasingly vulnerable to climate change, including extreme weather events (Ordóñez & Trammell, 2022). Despite increasing interest in improved urban forest governance at municipal levels in Canada (Ordóñez et al., 2024), an extensive literature review revealed a gap in UTC assessments for peri-urban municipalities. This study extends the application of pixel-based canopy assessment and i-Tree Canopy to peri-urban environments, highlighting the limitations and practical scope of each method.

A major challenge in assessing peri-UTC and adjacent LULC is the prevalence of mixed LULC types. This complexity makes it difficult to accurately evaluate canopy cover and distinguish permeable surfaces, such as soil and low-lying vegetation, both essential for setting future canopy goals. Small features, including immature trees, add to this challenge by blending into mixed covers, making them harder to detect and map. This issue affects both assessment methods, as features smaller than the image's 2-m pixel size are also difficult to capture using MLC.

This study aimed to conduct peri-UTC assessment in Lincoln using two methods: remote sensing image classification (i.e., MLC) and random point sampling (i.e., i-Tree Canopy). The MLC method has been widely used in larger municipalities and was therefore an

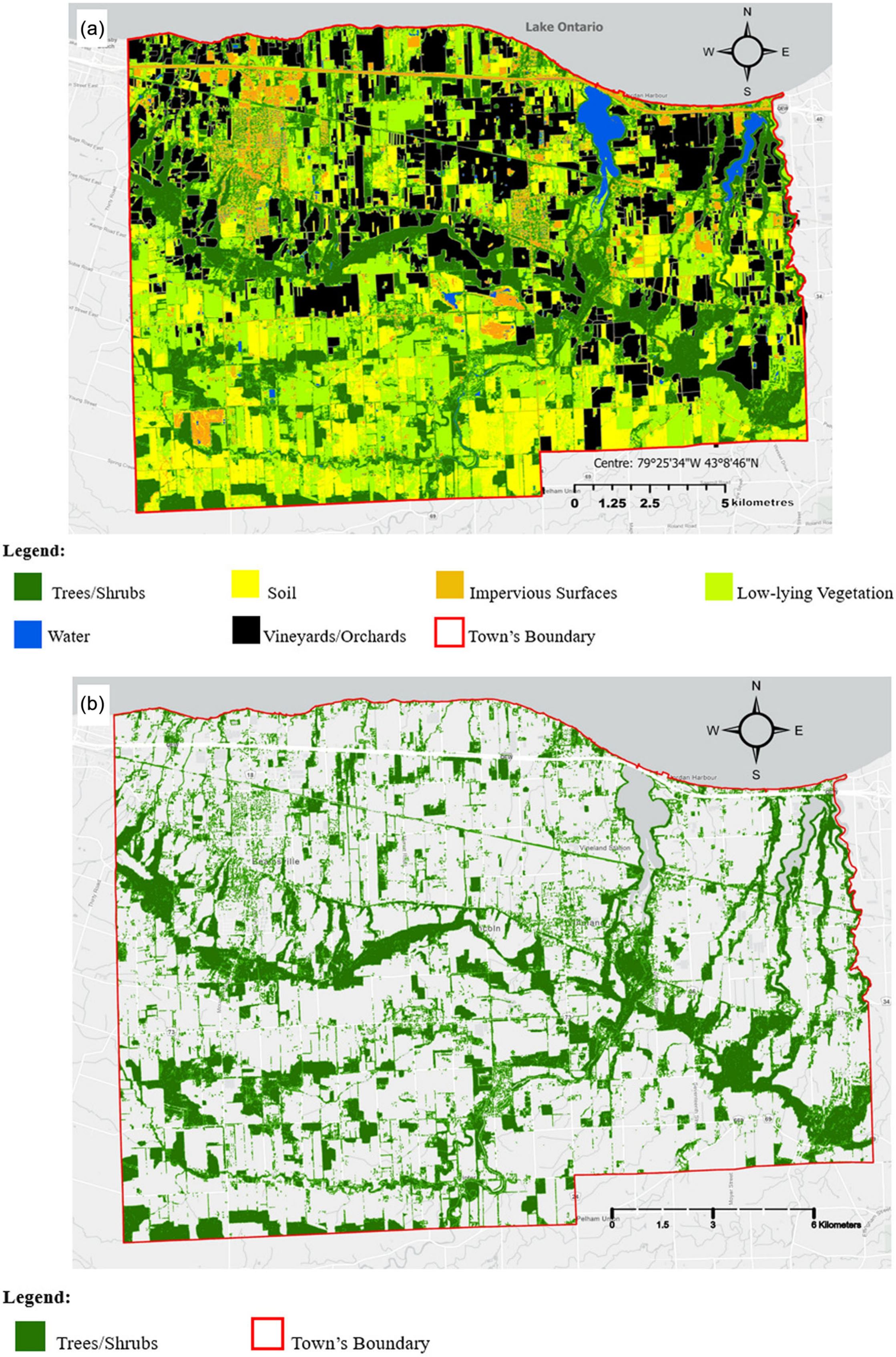

FIGURE 2 (a) Spatial distribution of land use and land cover in Lincoln mapped using the maximum likelihood approach. (b) Spatial distribution of priority, resilience-based trees within Lincoln's municipal boundaries. *Data source*: DigitalGlobe Inc. (2018). © CNES 2018, Distribution AIRBUS DS via Land Info LLC.

TABLE 3 Summary of the land use and land cover types identified using i-Tree Canopy. *Data source*: i-Tree, 2020.

Class Summary	Points	Percent (%) ± SE	Area (km^2) ± SE
Trees/shrubs	1,405	23.4 ± 0.6	38.8 ± 0.9
Low-lying Vegetation	2,062	34.4 ± 0.6	56.9 ± 1
Impervious Surfaces	421	3.5± 0.4	5.8± 0.4
Soil	1,536	26.6 ± 0.6	42.4 ± 1
Water	114	1.9 ± 0.2	3.6 ± 0.2
Unclassified (including vineyards)	462	7.7 ± 0.3	12.8 ± 0.6

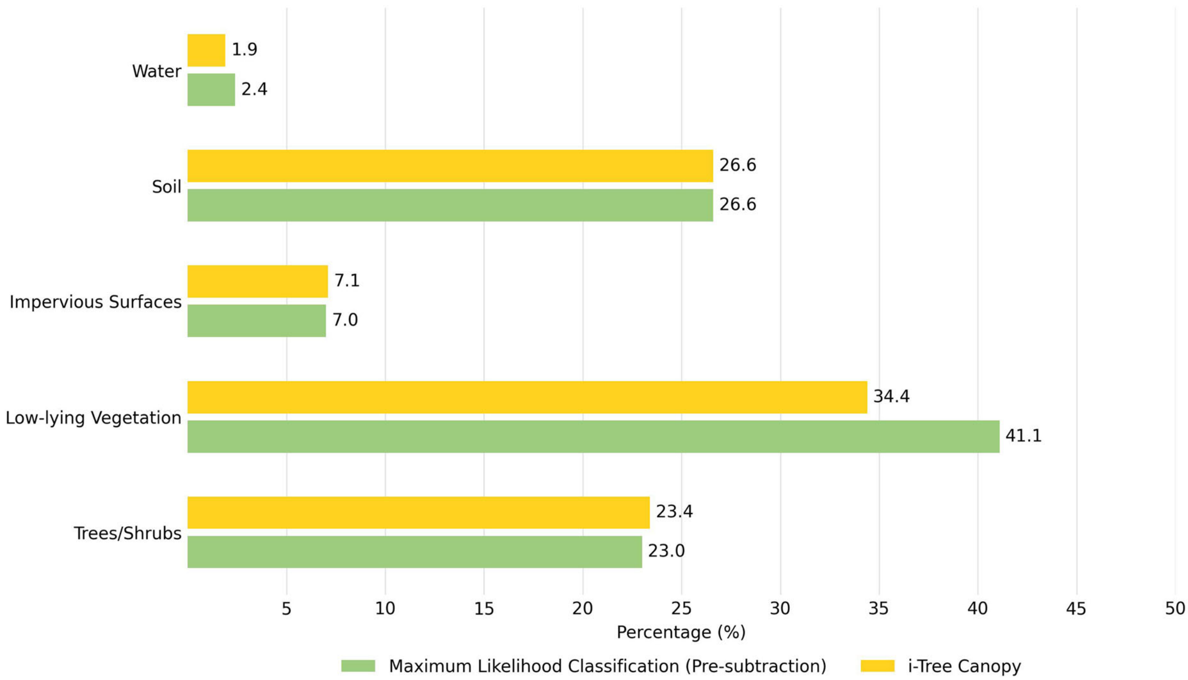

FIGURE 3 Comparison of the estimated land use and land cover coverage (%) using i-Tree Canopy versus maximum likelihood classification. *Data source*: DigitalGlobe Inc. (2018). © CNES 2018, Distribution AIRBUS DS via Land Info LLC.

appropriate standard against which i-Tree Canopy could be compared. Similar to findings by Wiseman et al. (2023) and Hwang and Wiseman (2020), our study confirms that i-Tree Canopy is particularly beneficial for municipalities with limited financial and technical resources. However, for higher levels of decision making (e.g., canopy goal setting), the use of other ancillary statistical and spatial data may be necessary.

Results indicated that both methods yield similar results with canopy estimates of 23% (MLC) and 23.4% (i-Tree Canopy), respectively. When orchards and vineyards were subtracted from the MLC, canopy cover was estimated at 21.3%. While these were encouraging results, several limitations and strengths of these technologies were revealed in this study, like those found in comparable studies (e.g., Parmehr et al., 2016). The performance and accuracy of the MLC approach may have been adversely impacted by two factors: the pixel size (2 m) in comparison to the size of the features under investigation such as immature trees (Powell et al., 2007), and the spectral similarity between LULC types in the study area. Similar challenges were identified in other studies (Jensen, 2016; Tewkesbury et al., 2015). These challenges were avoided by increasing LULC signature separability using reflectance data from the NIR part of the EMS. The possibility of misclassified orchards and vineyards, with their small size as low-lying vegetation, was prevented by excluding them from further processing. Excluding orchards and vineyards from the assessment permitted concentration on trees with larger canopies, which offer greater ecosystem benefits and services (Galle, 2024).

The overall classification accuracy of the MLC method (>85% at 88.2%) was deemed acceptable based on existing standards (Anderson et al., 1976). The 94% accuracy obtained for the trees/shrubs class, which was the focus of this study, emphasized the reliability of this method

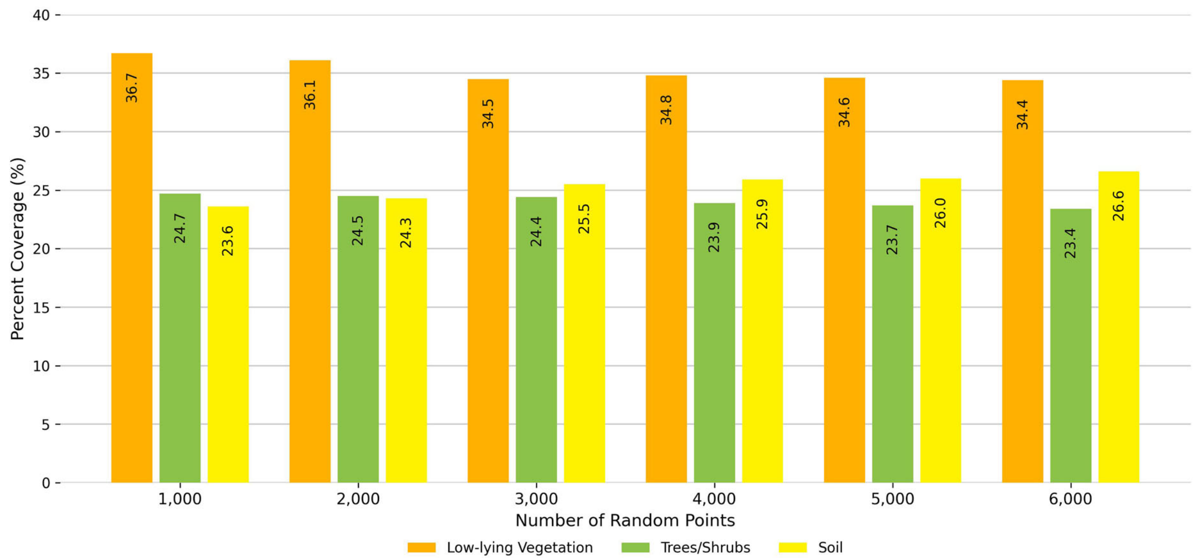

FIGURE 4 Percent cover of low-lying vegetation, trees/shrubs, and soil cover based on the number of random sample points. *Data source*: i-Tree, 2020.

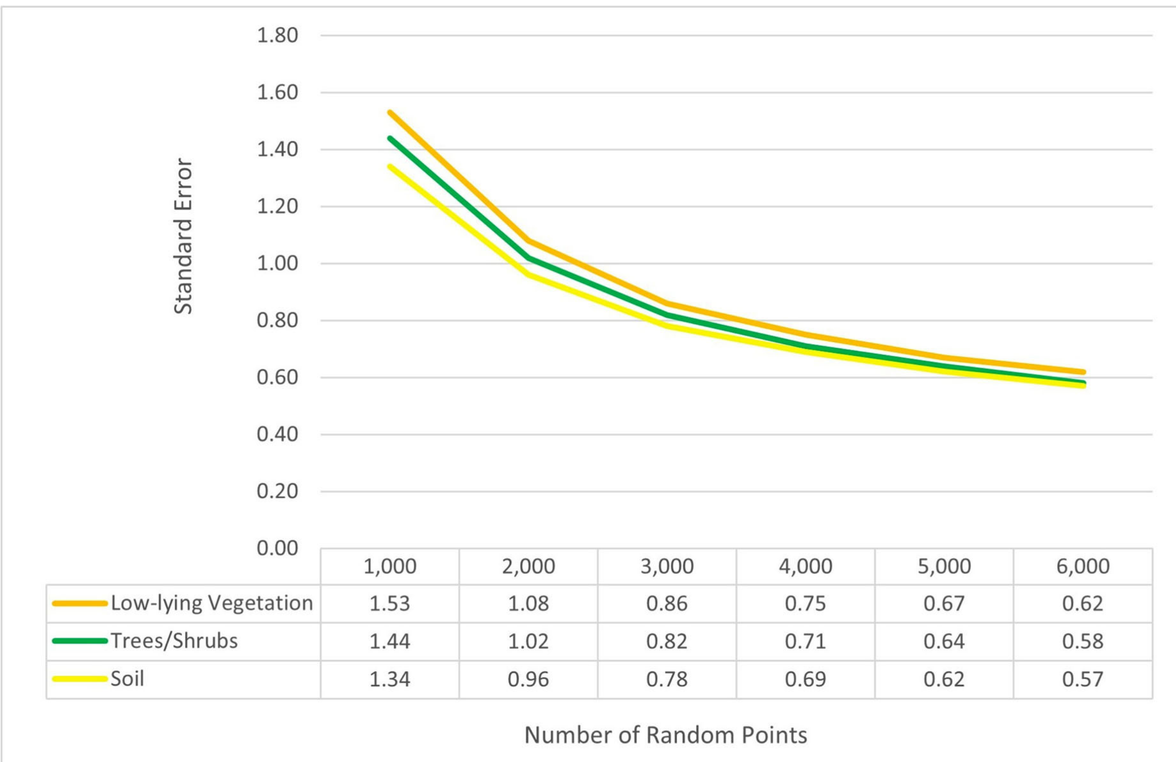

FIGURE 5 Changes in standard error as the number of random points increases from 1,000 to 6,000 points for the three main LULC types considered in this study. *Data source*: i-Tree, 2020.

for peri-UTC assessment. Similarly, classification accuracies for other homogeneous land covers (e.g., soil and water) were also deemed acceptable. The performance of i-Tree Canopy to assess the peri-UTC and other LULC types important to developing an effective UFMP were evaluated using the MLC assessment results (including orchards and vineyards). After the interpretation of 6,000 random points, the results obtained from i-Tree Canopy largely resembled the MLC results. Since the canopy creates homogeneous cover, identification of trees/shrubs was associated with high certainty, with 23% cover estimated by MLC before excluding orchards and vineyards. Homogeneity also extends to the soil class. i-Tree Canopy reliably estimated soil cover (26.6%), aligning precisely with the MLC results.

Due to mixed pixels and sparse cover in some areas (e.g., croplands), challenges emerged in identifying low-lying vegetation using both methods, resulting in significant differences in assessment results. These discrepancies stemmed from the use of the NIR band in the MLC, which increased the likelihood of detecting herbaceous species in the landscape. Therefore, more low-lying vegetation pixels were detected using MLC; comparable results were obtained by Locke et al. (2016), and Pourpeikari Heris et al. (2022). Secondly, when the crosshairs for random points in i-Tree Canopy covered a mix of LULC types, low-lying vegetation could not be distinguished from soil, resulting in inaccurate identification of these points. Using the MLC method, these challenges were overcome as other spatial data can be integrated to better identify LULC in these areas; however, this capability is not available using i-Tree Canopy.

The MLC method accurately assessed existing tree canopy at 21.3% cover with 94% accuracy. It performed well in homogeneous LULC types like soil and water by enhancing class separability using NIR data. However, accuracy was lower for low-lying vegetation due to spectral mixing with soil. Employing higher-resolution imagery is unlikely to improve low-lying vegetation detection due to size limitations. However, object-based classification methods may be more effective by using spatial and spectral properties (Sibaruddin et al., 2018).

i-Tree Canopy performed well for peri-UTC and was consistent with MLC for most LULC types except low-lying vegetation, where both had lower accuracies. This study does not recommend using i-Tree Canopy for assessing classes with small-scale features, sparse distribution, and intermixing with other LULC types. Because i-Tree Canopy only outputs numeric results, it cannot support spatially informed planning, such as equity assessments or canopy goal setting, a key limitation noted by Parmehr et al. (2016).

i-Tree Canopy offers a cost-effective alternative to traditional remote sensing methods for UTC assessment. It uses free imagery, simplified analyses, and a straightforward interface for non-specialist users; thus, it addresses he financial and technical challenges for resource-limited municipalities. A 6,000 random point interpretation can cost $1,200 taking a non-specialist's time—this amount is negligible compared to that of MLC and more sophisticated methods. While it cannot replicate methods like MLC, i-Tree Canopy meets the needs of municipalities seeking UTC information. Although designed for accessibility, the tool still requires users to visually classify LULC from imagery, which introduces subjectivity. A training module reviewing LULC definitions and sample point interpretation using the Google Maps basemap interface could minimize this subjectively. Training could improve consistency and allow non-specialist users to distinguish similar LULC types, such as trees, low-lying vegetation, and impervious surfaces.

Overall, the advantages of i-Tree Canopy outweigh its limitations, making it a useful tool in peri-urban contexts. Further research is needed to understand its performance in similar contexts. However, it has several limitations that merit consideration. First, it relies on freely available Google Maps basemaps, which vary in image resolution across regions. This can lead to misclassification of certain LULC types, which may result in over- or under-estimation of canopy cover. Second, i-Tree Canopy does not support spatially explicit outputs, limiting its usefulness for applications such as equity-based canopy planning and/or identifying planting opportunities. Lastly, the method depends on the user's interpretation of imagery, which may introduce classification bias, particularly when evaluating mixed pixels. Despite these limitations, it remains a practical and cost-effective tool for municipalities with limited resources and can serve as a useful interim approach between comprehensive UTC assessments.

Rapid UTC assessment

In terms of i-Tree Canopy's performance for rapid UTC studies, the data from three main LULC classes across six thresholds showed that reasonable estimates can be achieved with fewer than 6,000 points. As illustrated in Figure 4, none of the three LULC classes had significant changes in percent cover from one to six thousand points. What justifies the interpretation of more random points is the need for higher precision in the study, which is not typically a consideration in rapid studies (Locke et al., 2016). Although cover estimates for these three classes did not significantly change with increased points, precision increased. A reduction in SE allows the data to be presented in a smaller and more reliable confidence interval. As seen in Figure 5, the reduction of the SE from 1,000 random points to 3,000 for all three classes was more significant than the next three thresholds and for rapid study, a slightly higher precision can be overlooked for the sake of higher operating speed by interpreting 3,000 random points.

Urban forest governance

Municipalities in Canada seeking to achieve climate resiliency can benefit from the outcomes of this study in combination with current research on developing effective UFMPs (e.g., Ordóñez et al., 2024), including studies that consider other aspects of forest management such as equitable urban forest governance (e.g., Grant et al., 2024; Pike et al., 2024). For example, Ordóñez et al. (2024) noted that municipalities in Canada have largely focused on increasing tree abundance without careful consideration of issues related to biodiversity, climate change vulnerability, and community stewardship. Further, while equitable access to tree canopy was not the focus of this study, the MLC results revealed variations in canopy between 15% and 41% for the seven built-up areas in the town. Collectively, these research outcomes support further consideration of equitable urban forest governance as part of developing an UFMP for Lincoln.

Outcomes and future recommendations

The outcomes of this study make important contributions to the field of urban and peri-urban forestry. First, the study makes a valuable contribution to the urban and peri-urban forest literature by addressing the challenges of UTC assessment in peri-urban environments, particularly those with limited resources. Second, it illustrates the benefits of collaboration in HEI-community partnerships. Third, the study contributes to the development and implementation of an UFMP in Lincoln. Recently, the Town established a working group to review municipal tree policies and practices with the goal of developing an UFMP. They have also undertaken focus group meetings with stakeholders including academic institutions, interest groups, and residents of Lincoln. This HEI-community partnership continues to provide expertise on UFMP development, informed by tree canopy and LULC estimates and best practices from the literature (e.g., Ordóñez et al., 2024; Roman et al., 2021). Lastly, our research outcomes have potential to support the United Nation's Sustainable Development Goals in both Lincoln and beyond—including those relating to good health and well-being (#3), sustainable cities and communities (#11), climate action (#13), and life on land (#15) (Dean et al., 2024; Gupta et al., 2024).

In future, the use of i-Tree Canopy to assess and monitor the UTC in peri-urban environments is recommended while more detailed assessments should be conducted every five to eight years. Leveraging the resources of HEI-community partnerships, such as the Brock-Lincoln Living Lab partnership, is also recommended for municipalities with limited resources, given the success of these partnerships as assessed by Plummer et al. (2021). These types of partnerships should be strongly encouraged because they positively contribute to many challenges faced by municipalities working toward sustainable forest management.

Overall, this study provides valuable insights into peri-UTC assessment; however, the 2-m spatial resolution of the WorldView-2 imagery, while effective for mature tree canopy estimation, may not have captured low-lying vegetation or newly planted trees accurately. Similarly, i-Tree Canopy's reliance on Google Maps imagery limits the precision of LULC classification in areas with mixed vegetation. The spectral resolution and image quality varies by location, with higher-resolution data often available in larger municipalities while peri-urban environments generally have lower-quality imagery. These inconsistencies impact UTC assessment accuracies, especially in areas where vegetation cover is diverse or fragmented. Further, i-Tree Canopy's point-sampling approach depends on the analyst's ability to correctly interpret LULC types, introducing potential subjectivity and classification errors.

CONCLUSION

Leveraging an HEI–community partnership, this study compared two geospatial technologies in Lincoln, Ontario, for UTC assessment in a peri-urban municipality with limited resources for improved urban forest governance. It focused on assessing i-Tree Canopy's performance, aiming to identify its advantages, disadvantages, and suitability for municipal use while minimizing resource demands. Results indicated that both methods yield similar results with estimates of tree canopy cover of 23% (MLC) and 23.4% (i-Tree Canopy), respectively. When orchards and vineyards were removed from the MLC results, tree canopy cover was estimated at 21.3% for the entire municipality with 94% accuracy.

This study highlighted the critical importance of UTC assessments in peri-urban municipalities for effective urban forest governance. Findings also underscore the value of low-cost geospatial tools, like i-Tree Canopy, for peri-urban municipalities with limited resources, while emphasizing the need for more advanced approaches, such as MLC, over longer timeframes.

Outcomes from this study contribute to addressing gaps in the peri-urban forestry literature, while highlighting sustainable urban forest practices, and supporting equitable forest governance. By leveraging an HEI-community partnership, peri-urban and resource-limited municipalities can effectively develop UFMPs and achieve their sustainability goals, including climate resilience. Future research should focus on refining these methods while also fostering community engagement for impactful peri-urban forest management.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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