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Mapping tree canopies in urban environments using airborne laser scanning (ALS): a Vancouver case study

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Abstract

Background: The distribution of forest vegetation within urban environments is critically important as it influences urban environmental conditions and the energy exchange through the absorption of solar radiation and modulation of evapotranspiration. It also plays an important role filtering urban water systems and reducing storm water runoff.

Methods: We investigate the capacity of ALS data to individually detect, map and characterize large (taller than 15 m) trees within the City of Vancouver. Large trees are critical for the function and character of Vancouver's urban forest. We used an object-based approach for individual tree detection and segmentation to determine tree locations (position of the stem), to delineate the shape of the crowns and to categorize the latter either as coniferous or deciduous.

Results: Results indicate a detection rate of 76.6% for trees > 15 m with a positioning error of 2.11 m (stem location). Extracted tree heights possessed a RMSE of 2.60 m and a bias of − 1.87 m, whereas crown diameter was derived with a RMSE of 3.85 m and a bias of − 2.06 m. Missed trees are principally a result of undetected treetops occurring in dense, overlapping canopies with more accurate detection and delineation of trees in open areas.

Conclusion: By identifying key structural trees across Vancouver's urban forests, we can better understand their role in providing ecosystem goods and services for city residents.

Keywords: Urban forest, Large trees, Light detection and ranging, Airborne laser scanning

Background

The past decades have seen unprecedented global population growth and urbanization with over 50% of the Earth's population living within cities (Small 2001; Weng 2014). Canada is at the leading edge of the curve, with 80% of Canadians now living in cities (Statistics Canada 2017). This places enormous pressures on the planning and management of urban regions to ensure their sustainability, with particular importance on natural urban environments. As a result, a comprehensive understanding of the urban environment is fundamental to ensure sustainable and adaptive urban ecosystems (Williams et al. 2018). The spatial-temporal distribution of vegetation within an urban environment is known as "greenspace", and is a fundamental component of the urban environment. Greenspace has a critical role: it influences urban environmental conditions and energy exchange through the absorption of solar radiation and modulation of evapotranspiration, and plays an important role filtering urban water systems and reducing storm water runoff (Oke 1982; Nowak and Dwyer 2007). Studies have also indicated the significant social (Grahn and Stigsdotter 2003; Westphal 2003), economic (Tyrväinen et al. 2005), and aesthetic values (Tyrväinen et al. 2005; Jim and Chen 2006) associated with urban vegetation (Liu et al. 2017). For example, Kleinman and Geiger (2002) estimated that 100 trees absorb up to 5 tons of CO_2 per year from the atmosphere and 450 kg of pollutants including ozone and particulates. Therefore, within an urban context, greenspaces are the primary means of

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maintaining intact natural ecosystems, capturing and storing carbon, and preserving biodiversity.

Traditionally, information about urban forest canopy has been obtained from field sampling, manual interpretation of aerial photography and, more recently, using technologies such as Google Street View (Liu et al. 2017; Li et al. 2015). In addition, many cities utilize inventory systems to collate tree location, species and condition information for street and park trees. However, these methods are expensive, labor-intensive, and time-consuming, and a lack of complete coverage (Alonzo et al. 2014). Remote sensing offers a unique and efficient approach for understanding and mapping urban landscapes providing synoptic views over large areas. Inclusion of remote sensing data provides spatial layers upon which relationships can be developed between urban greenspace and social issues such as access to parks and recreation areas and provides a platform for extrapolation and expanded assessment into broader contexts nationally and internationally (Sutton and Costanza 2002).

Classification of urban imagery at various spatial resolutions has been a major theme in urban landscape studies (i.e., Schneider 2012; Frolking et al. 2013; Castrence et al. 2014; Lin et al. 2014; Chen et al. 2015; Williams et al. 2018). Previous studies have applied fine spatial resolution imagery (e.g., Benz et al. 2004), hyperspectral data (e.g. Roberts et al. 1998; Heiden et al. 2007), and aerial photography (e.g., Hodgson et al. 2003) all of which offer a high degree of spatial or spectral detail and allow derivation of urban land cover information which in turn is important for inferring land-use, mapping ecosystem services, or modelling of more complex processes like air quality, hydrology, or carbon stocks and flows. Likewise, land cover and its change over time may also help with urban metabolism and ecological footprint studies (Kellett et al. 2013). With respect to mapping tree cover in urban environments optical data from very high spatial resolution satellites such as those of the Worldview and GeoEye series can provide imagery with a pixel size < 0.5 m and as a result have markedly increased the potential to map and classify tree species within complex urban environments (Novack et al. 2011; Richardson and Moskal 2014). In addition, new methods such as intelligent image segmentation and object-based classification techniques are also highly applicable for urban remote sensing applications (Myint et al. 2011).

Optical sensor-derived data, such as aerial photography and Landsat satellite imagery, however, are generally poor when characterizing the vertical structure of urban vegetation (Plowright et al. 2016). The dimensions and vertical architecture of trees reflect their productivity, age, overall health and vigor (Schomaker et al. 2007). A large, dense crown is an indicator of optimal tree growth, while less dense crowns can be indicative of poor health and stress (Zarnoch et al. 2004; Plowright et al. 2016). Although some vertical tree metrics can be estimated through indirect relationships with optical bands (Cohen and Spies 1992), additional three-dimensional data on tree condition is critically important.

Airborne laser scanning (ALS), also known as light detection and ranging (LiDAR), offers a means to directly measure the three-dimensional structure of vegetation. An ALS instrument emits pulses of light that are reflected off trees, ground surfaces, and other terrestrial features and can penetrate through gaps in the foliage, enabling ALS to directly measure the vertical aspects of tree crowns and forest canopies (Plowright et al. 2016; Coops et al. 2007). A key benefit of ALS is the capacity to reliably obtain high-precision, three-dimensional measurements of buildings and trees over broad spatial scales which, as a result, has attracted significant interest among urban and natural resource managers (Hudak et al. 2009; Williams et al. 2018). ALS has been shown to be highly accurate for estimating a range of vegetation parameters such as tree height, biomass, stand density, basal area, volume, and Leaf Area Index (LAI) (Liu et al. 2017; Riaño et al. 2004; Hudak et al. 2006; Næsset 2007; Edson and Wing 2011). Kim et al. (2009) and Kim et al. (2011) used intensity values and structure variables including standard deviations (SD) of heights, percentiles, and crown ratios derived from leaf-on and leaf-off data, for tree species differentiation. In urban environments Liu et al. (2017) evaluated the potential of ALS to map 15 common urban tree species using a Random Forest (RF) classifier in the City of Surrey, British Columbia, Canada. Results indicate an overall accuracy of 51.1%, 61.0% and 70.0% using hyperspectral, ALS and the combined data respectively. The overall accuracy for the two most important and iconic native coniferous species improved markedly from 78% up to 91% using the combined data. The results of this research highlight that variables derived from ALS data contributed more to the accurate prediction of species than hyperspectral features (Liu et al. 2017).

Large, mature trees are valued for a number of reasons by city dwellers and managers. Larger, older trees have consistently been shown to store more carbon (Stephenson et al. 2014), and support a diversity of bird taxa. The values are difficult, and in some cases impossible, to replicate with large numbers of smaller trees (Le Roux et al. 2015). This is because large older trees provide critical structural complexity that is beneficial to a variety of bird species, particularly habitat specialists that have co-evolved with mature forests (e.g., cavity nesters) (Lindenmayer and Laurance 2016). Older trees can also benefit surrounding trees by fostering a higher diversity of mycorrhizal fungi, which can facilitate nutrient transfer among trees of different age classes and species (Simard and Durall 2004; Twieg et al. 2007). For the general population as well these larger trees provide a range of ecosystem services, with large trees having high cultural and emotional value associated with them (Lindenmayer et al. 2014; Pearce et al. 2015). With large, old trees predicted to decline in urban landscapes (Le Roux et al. 2014) it is increasingly critical to identify, map and characterize (in terms of type, height and size) large trees over the city's land base.

The City of Vancouver, British Columbia, Canada, developed an Urban Forest Strategy in 2014 with a specific target of planting 150,000 new trees by 2020 (City of Vancouver 2014). The plan includes policies and by-laws to protect existing trees, plant trees to increase urban forest canopy, and to manage a healthy, resilient urban forest for future generations of the city. Its goal is to plant 150,000 new trees between 2010 and 2020, and increase the urban forest canopy from 18% to 22% by 2050 (City of Vancouver 2014). Key to the strategy is to protect and maintain current trees, especially those which are mature and large. To detect, map and characterize these large trees we develop and apply an object-based approach for individual tree detection and segmentation designed to both determine tree locations (position of the stem) and to delineate the shape of the crowns. We then extract attributes of interest such as tree height and crown diameter. Subsequently, using a series of ALS metrics we examine the capacity of ALS data to predict if crowns are deciduous or coniferous. We compare the predictions with both existing databases of tree locations and new field data collections. In this paper we investigate the capacity of ALS data to individually detect, map and characterize large (taller than 15 m) trees within the City of Vancouver, recognising the additional cultural and ecological importance these trees have compared to the overall urban forest canopy.

Study area

Home to over 600,00 residents, the City of Vancouver, BC is the third largest city in Canada (Statistics Canada 2017). The city is bounded by the Coast Mountains and Burrard Inlet to the north and the Fraser River to the south, which flows into the Strait of Georgia in the west (Williams et al. 2018). Landuse and landcover includes densely built-up areas, extensive areas of lower-density single-family homes as well as varied greenspaces ranging from small parks less than 0.5 ha, to golf courses and the 405 ha Stanley Park (Vancouver Board of Parks and Recreation 2016). Most of Vancouver's native forest vegetation was removed during early settlement and forest harvesting between 1860 and 1910. Remnant areas of temperate rain forest remain in Stanley Park and other large parks and is dominated by large evergreens: western hemlock (*Tsuga heterophylla* (Raf.) Sarg.), western red cedar (*Thuja plicata* Donn ex D.Don), and Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco). Exotic tree species are common as park and street trees with dominant species including maples and cherries (over 50% of all street trees), but also including ashes, lindens, oaks, magnolias, hornbeams, and beeches.

Recent estimates from ALS data indicate that the City of Vancouver has about 18% urban forest cover, with about 61% on public lands (streets and parks), and 39% on private lands (City of Vancouver 2018). Forest cover measurements indicate a minor decline in overall forest cover from 19% in 1995 to 18% in 2015. Most of the tree loss is associated with urban densification, including the loss of large, mature trees.

Data

The ALS data used in this study was acquired in February 2013 over the boundaries of the City of Vancouver. The discrete-return dataset was provided in 168 non-overlapping tiles in LAS format with a point density > 12 points·m^{-2}. The vertical and horizontal accuracies are 0.18 and 0.36 m (95% confidence interval), respectively. An example of a typical point cloud acquired over an urban area is shown in Fig. 1 and shows a profile of ALS returns.

To validate the tree detection, delineation, characterization and species determination, individual tree data within the city was compiled from three different sources. The first was a geodatabase which provides an extensive inventory of trees located in the public parks of the City of Vancouver. It has been collected by a combination of photo-interpretation and field visits. This dataset was used as a base layer providing the spatial coordinates for 22,211 trees. For a subset of 18,146 of these trees, the tree type (deciduous or coniferous) was specified. No height data is available in this existing database. A second dataset with tree height measurements for large significant trees obtained by laser rangefinder and species identification was available for Stanley Park and Kerrisdale area. To complement these datasets, an additional field campaign was completed in four city parks: Queen Elizabeth Park, Memorial West Park, Musqueam Park and Locarno Park. A Vertex ultrasound hypsometer was used to determine the height of identified crowns and the average of two tape measurements on perpendicular axes constituted the recorded value for crown diameter. The compiled dataset presented a total of 74 trees with height and type information, 51 of which with a crown diameter value.

Methods

The developed workflow for detecting the large trees in this study is detailed below and consists of three key

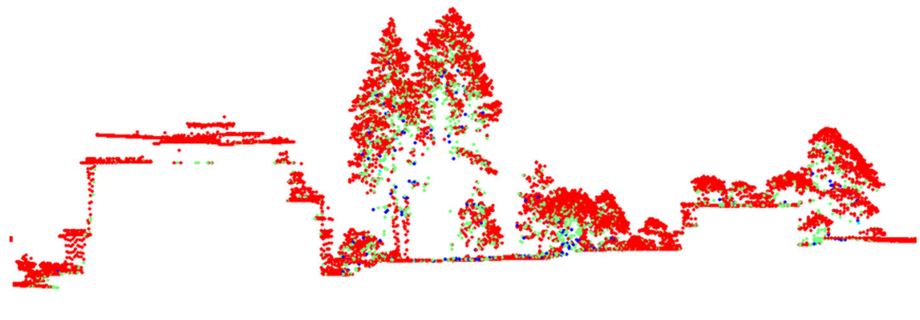

Fig. 1 Example of an ALS point cloud across a small section of the urban environment. Point colored by return type with red corresponding to first returns and other colors second or third returns. Urban structures and ground are typified by a single (first) return whereas vegetation is characterized by a set of multiple return types

steps. First, using the raw point clouds of the LAS files, a canopy height model (CHM) for the study area was derived. Second, a segmentation of the tree crowns took place and tree attributes were extracted. Third, each crown was classified into coniferous/deciduous based on ALS point cloud metrics.

Canopy height model production

The ALS point clouds were first normalized by extracting the height above the ground of each point. From these normalized point clouds a 0.3-m Digital Surface Model (DSM) was derived providing the height above the ground of each pixel. To do so, the pit-free DSM algorithm (Khosravipour et al. 2016) was used. Finally, a mask was generated to remove buildings and other urban structures as well as low vegetation from the surface resulting in a clean CHM representing only high vegetation.

Tree crown segmentation and attribute extraction

For the automatic delineation of tree crowns, the CHM was filtered and smoothed using a moving window applying median and mean filters to attenuate abrupt changes in height. The peaks corresponding to the treetops were then identified as the local maxima of the smoothed surface, with the condition that they were separated by a minimum distance of at least 2.4 m (8 pixels). We then applied a marker-controlled segmentation with the compact watershed algorithm (Soille and Ansoult 1990; Neubert and Protzel 2014) with compactness parameter set to 1 to encourage more regular segments. During this step, the local maxima were used as the markers, i.e., the starting points for the region growing process to delineate each segment. Then, for each crown the height of the treetop (based on the original, unsmoothed CHM), the X and Y coordinates of the stem location (as the polygon centroid), and the crown diameter (as the diameter of a circle of equal area) were extracted. As the focus of the paper is on the characterization of big trees, the results were then filtered to include only trees that were higher than 15 m.

Coniferous vs. deciduous classification

In the final phase, each detected tree was classified as coniferous or deciduous using a Random Forest (RF) classifier (Breiman 2001) based on 27 predictive features derived from a series of ALS metrics (Table 1). Some of the raw ALS metrics were normalized by the 99th percentile of height (closely approximating the height of the tree) in order to avoid scale difference in the final features caused by different tree heights (see description).

The ground truth data providing the reference labels "coniferous" or "deciduous" came from the park trees geodatabase. The reference tree found to be the closest to the segment centroid assigned the ground truth label to the segment. In total, the dataset used to train and validate the model included 1809 coniferous and 4183 deciduous trees. A random 70%/30% training/validation split was adopted, resulting in 4178 trees in the training set and 1814 in the validation set. A RF classifier with 1000 trees was then trained and applied to the data to label each segment in the area of interest.

Assessment protocol for tree detection and attribute extraction

The first step in assessing the accuracy of the tree delineation and associated extracted attributes consisted of linking each segmented crown to a given reference tree. To do so, the reference trees were subset to focus on those > 15 m, based on a direct height extraction from the canopy model. If a single reference tree was found within an ALS-derived segment, a direct match was established and the tree was added to the list of matched trees. If more than one reference tree was found inside a single segment, the closest tree to the centroid was considered a match and added to the list. The remaining trees were added to the list of unmatched trees. The

Table 1 List of the 27 features derived from the ALS metrics extracted for each segment

Feature name	Description
Normalized average height	Average height of all returns above 2 m, normalized by the 99th percentile of height.
Normalized standard deviation of height	Standard deviation of height of all returns above 2 m, normalized by the 99th percentile of height.
Normalized average square height	Average of the square of the height of all returns above 2 m, normalized by the 99th percentile of height.
Skewness of height	Skewness of the height of all returns above 2 m.
Kurtosis of height	Kurtosis of the height of all returns above 2 m.
Canopy cover from first returns	Fraction of first returns above the 2 m threshold (number of first returns above 2 m divided by the total number of first returns)
Canopy cover from all returns	Fraction of all returns above the 2 m threshold (number of all returns above 2 m divided by the total number of all returns)
Normalized percentiles of height: $p = 10, 20, 30, 40, 50, 60, 70, 80, 90, 95$	Percentiles of height (height below which p % of points lay), normalized by the 99th percentile of height.
Bicentiles of height: $b = 10, 20, 30, 40, 50, 60, 70, 80, 90, 95$	Percentage of the points whose height is below b % of the 99th percentile of height.

reference trees that were found to be outside any segment were also appended to this list.

The list of matched trees is considered to contain the True Positives (TP), i.e., the correctly detected trees, whereas the list of unmatched trees is considered to contain the False Negatives (FN), i.e., the missed reference trees. The TP rate is then computed as TP / (TP + FN). The reference dataset being a presence-only dataset (not an exhaustive list of all tree locations), it was not possible to compute a False Positives rate, i.e., the number of trees incorrectly detected by the algorithm at locations where no trees are present. For the TP, the average horizontal distance (in meters) between reference tree and the matched tree was computed. Additionally, the treetop height and/or crown diameter, if measured in the field, were compared to the ALS estimates and Root Mean Square Error (RMSE) and bias (both in meters) were computed. The accuracy of the coniferous/deciduous classification was assessed based on the independent validation set, with measures such as Overall Accuracy (OA) and F1-scores (harmonic mean of user's and producer's accuracy) derived from the confusion matrix.

Results

The tree delineation procedure had a TP rate of 76.6% for trees > 15 m ($n = 5710$). Examining the 4375 correctly detected trees, the average positioning error of the stem location was 2.11 m. Based on the 68 correctly detected trees having coinciding reference height measurements, the RMSE and bias were equal to 2.60 m and – 1.87 m, respectively. Crown diameter was estimated with a RMSE of 3.85 m and a bias of – 2.06 m using the crown diameter measurements of 45 correctly detected reference trees.

The confusion matrix for the coniferous/deciduous classification is reported in Table 2. The OA was 86.9%, with F1-scores of 0.79 and 0.91 for the coniferous and deciduous classes, respectively. A subset of the developed spatial coverage of large trees (< 15 m) across the city is shown in Fig. 2.

The results indicate the fully automated tree detection and crown delineation approach performs well. The TP rate is consistent with other studies, especially if taking into account that the reference trees were principally located in parks and therefore were often located in high density clusters. The missed trees account for less than 25% of the reference trees and are principally a result of undetected treetops occurring in dense canopies. Detection and delineation of trees in open areas was in general more accurate. The tree height RMSE and the associated bias suggests the workflow underestimates the height of tall trees, which is a typical of ALS -based estimates of height, as the laser return is unlikely to intersect with the exact apex of the tree. However, field measurement error is also likely, given difficulties in measuring the height of tall trees in the field (all the trees that were measured are > 30 m).

Across the City of Vancouver clear differences in the number and height of large trees is apparent (Fig. 3). The urban forest of Stanley Park on the peninsula adjacent to downtown has a number of large mature trees which are dominant in terms of the number, height and

Table 2 Confusion matrix for the coniferous/deciduous classification of the delineated segments

	Predicted	
Actual	Deciduous	Coniferous
Deciduous	1137	111
Coniferous	127	439

Fig. 2 Detail of the tree crown map (coniferous in green, deciduous in yellow) in a subset of the City of Vancouver with an orthophoto as a background and the 5 reference trees located in the area (pink dots)

crown size. Generally however there is an East – West gradient with postal codes west in the city generally being dominated by taller, coniferous trees, whereas in the east the tree height is lower and stands have generally dominated by deciduous trees. The only exception to this is Killarney in the south east which has values dominated by the mature forest in the Fraserview Golf Course.

Figure 4 shows summaries of the distribution of average tree height (> 15 m), density of tall trees per ha, average crown diameter and percentage of conifer by postcode across the city. The results mirror those in Fig. 3 with an increase in the density and height of trees from east to west (with the exception of the Fraserview Golf Course). Tall trees are more associated with conifer compared to deciduous tree species with larger conifers such as western hemlock, western red cedar, and Douglas-fir dominating on the western side of the city.

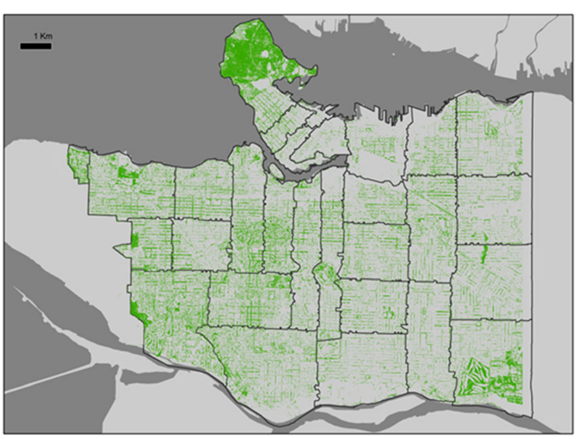

Fig. 3 Mapped locations of all detected trees > 15 m across the City of Vancouver

Discussion

Results presented in the case study demonstrate that individual large tree canopies can be mapped from ALS point clouds-derived rasters and with an object-based workflow. The use of the high-density ALS data also proved potential in the fully-automatic classification of trees as either coniferous or deciduous. While the deciduous/coniferous tree classification was accurate in this study, the tree crown attributes for deciduous trees are likely to present errors due to the lack of a complete vegetated crown at the time of ALS acquisition in February. Crown diameter was also underestimated (on average by 2 m) mainly due to overlapping crowns in dense canopies. In open areas, isolated trees were well delineated. Part of the height and crown diameter mismatch may be attributed to the four year lag between the ALS acquisitions (in 2013) and the field data collection (mainly in 2017), an interval during which some of the younger trees have grown.

The ALS data acquired for this study was acquired principally for the purposes of developing high quality digital terrain information across the city. The leaf-off ALS acquisition may have hampered the results in the detection/delineation of deciduous trees, lowering thus the overall TP rate. It is not uncommon that leaf-off collections are undertaken in order to obtain precise DEM's with a focus on urban structures, hydrology and urban water movement. Leaf-off collections can result in sparse point clouds for deciduous stands because of the large number of laser pulses penetrating the canopy. Improved delineation of the crowns for deciduous trees enabled by a leaf-on acquisition may result in the extraction of more meaningful ALS-based features, in turn potentially enhancing the classification results.

With relation to the choice of extracting trees taller than 15 m, a comparison of tree delineation methods by Jakubowski et al. (2013) suggested that ALS data with an average of around 2 points·m^{-2} was sufficient for detecting large individual trees. In general, attempts to extract individual tree attributes have relied on higher densities. Point densities > 9 points·m^{-2} were used to accurately extract tree height, base height, crown diameter, and crown volume as well as perform segmentation of individual trees directly from the raw LiDAR point cloud (Zhang et al. 2015). Smaller trees might require even higher density. In terms of the accuracy assessment, to effectively optimize the parameters of the automatic

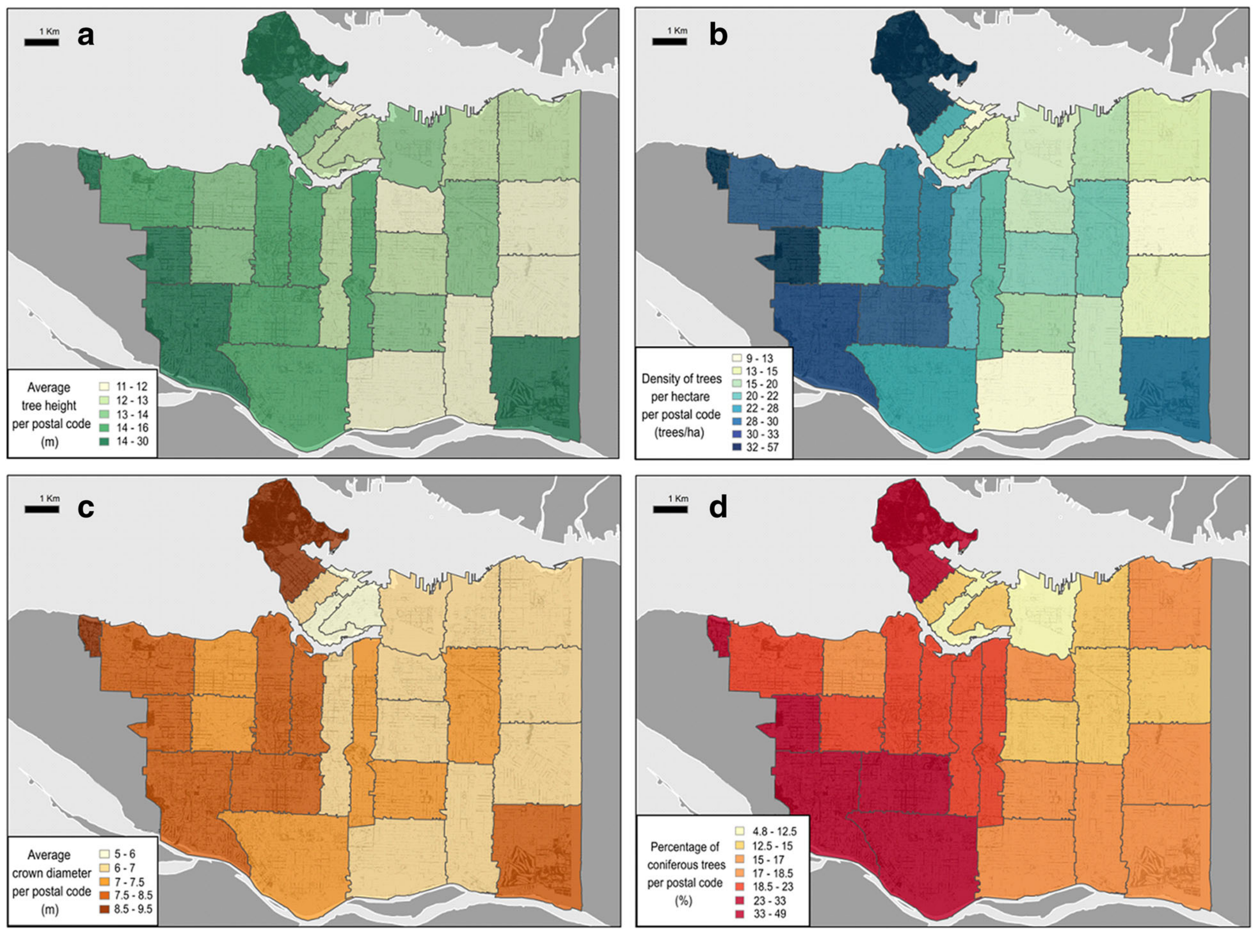

Fig. 4 Summary of detected tree attributes by postcode (**a**) Height, (**b**) Density, (**c**) Crown diameter and (**d**) % conifer

workflow, a comprehensive validation dataset is required. In addition future work could focus on the extraction of other tree attributes besides tree location and crown size. For example, individual crown structure can be examined using ALS as filled and open volumes within a canopy (Lefsky et al. 1999). The approach involves superimposing a grid over individual canopies composed of 0.1 m^3 voxels up to the level of the highest LiDAR return. These cells are classified as either "filled" or "empty" volume depending on whether a return was recorded within the voxel and as either "euphotic" zone, if the cell is located within the uppermost 65% of all filled volumes, or as "oligophotic" zone if it is located below this point in the profile. Coops et al. (2007) found that the overall canopy surface structure of Douglas-fir stands in coastal British Columbia, Canada, were characterized by the total amount of the "open gap" canopy volume profile class with dense, shorter stands showing an even upper canopy surface, while the mixed, more variable crown structures, have a significantly higher amount of open gaps, which are indicative of increased total canopy surface.

A small field campaign was conducted for this study to acquire height and crown diameter for a small set of sample trees. However, a complete census of tree locations over a test area may be desirable to assess and compare the delineation assumptions which should rely not only on TP rate but also on the False Positive rate (reporting on false alarms, i.e., segments that do not correspond to any actual tree). Manual crown delineation as done by a photo-interpreter based on an orthophoto could also be useful, even though overlapping crowns may be hard to correctly digitize.

Across the study we demonstrate that although there is variation in the number and size of trees across the city, Vancouver is still very green. This agrees with previous studies which demonstrate that only approximately 22% of the larger Metro Vancouver is urban land cover (Williams et al. 2018). The City of Vancouver had previously estimated its canopy cover from ALS data to be 18%, comparable to the cities of Victoria, BC (18%) and Seattle, WA (23%) (City of Vancouver 2014). However, our results are consistent with Williams et al. (2018) who found that broadleaf and coniferous trees cover about 19% and 6% of Vancouver's area, respectively, which they found was an increase of 7% on the previous estimate for a total canopy cover of about 25%. Similarly, Li et al. (2015) and Seiferling et al. (2017) using Google Street view imagery to estimate street-level canopy cover in Vancouver and estimated a median 25.9% street-level canopy cover for the City.

Conclusion

We presented a case study relating on an effort to map large trees in the city of Vancouver, BC, Canada. The methodology we detailed herein revolves around an object-based image analysis applied on ALS data to detect tall trees locations and to extract attributes of interest, including tree height, crown diameter and coniferous/deciduous class. By identifying large trees in Vancouver, this study adds to previous information gathered about canopy cover in Vancouver by identifying structural keystones (Le Roux et al. 2015) in Vancouver's urban forests. Because large trees are so valuable due to their form and function, their identification is critical for a comprehensive understanding of the urban forest.

Abbreviations

ALS: Airborne laser scanning; DSM: Digital Surface Model; FP: False Positives; LiDAR: Light Detection and Ranging; OA: Overall Accuracy; RMSE: Root Mean Square Error; TP: True Positives

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Availability of data and materials

LiDAR data for the Vancouver region is available at http://data.vancouver.ca/datacatalogue/LiDAR2013.htm

Authors' contributions

All authors conceived the study. GM and DW undertook the image analysis, GM, DW and NC undertook statistical analysis. All authors contributed the writing. All authors read and approved the final manuscript.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

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