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Utilizing LiDAR data to map tree canopy for urban ecosystem extent and condition accounts in Oslo

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ABSTRACT

LiDAR-based segmentation of urban tree canopies and their physical properties (canopy height, canopy diameter, 3D surface and volume) is a replicable, complementary and useful information source for urban ecosystem condition accounts, and an important basis for ecosystem service modeling and valuation. However, using available LiDAR data collected for municipal purposes other than vegetation mapping (such as for example engineering) entails a level of accuracy which may limit the usefulness of the data for change detection in ecosystem accounts. To account for changes in the urban tree canopy of Oslo (capital city of Norway) between 2011 and 2017, a segmentation model was developed based on available airborne LiDAR data scanned for general purposes. The results from the entire built-up area of Oslo indicate a general increase in the number of tall trees (>15 m) and a moderate increase in the number of small trees (<15 m), with the exception of trees between 6 and 10 m which seem to have a relatively constant development over the given period. The total tree canopy area within the built-up area increased by 17.15%, with a corresponding 21.35% increase in the tree canopy volume. The results for the Small House plan area, a policy focus area subject to urban densification and special regulations for felling of large trees, indicate a large increase in small trees (<10 m) and a moderate decrease in tall trees (>10 m). The total tree canopy area within the Small House plan area decreased by 1.04%, with a corresponding 2.13% decrease in the tree canopy volume. With respect to the segmentation accuracy, the changes in aggregate tree canopy cover are too small to determine canopy change with confidence. This study demonstrates the potential for identifying ecosystem condition indicators as well as the limitations of using general purpose LiDAR data to improve the precision of urban ecosystem accounting. For future ecosystem service accounting in urban environments, we recommend that municipalities implement data acquisition programs that combine concurrent field data sampling and LiDAR campaigns designed for urban tree canopy detection, as part of general urban structural inventorying. We recommend using LiDAR and satellite remote sensing data depending on canopy densities. We also recommend that future tree canopy segmentation is done within a cloud-computing environment to ensure sufficient geoprocessing capacity.

1. Introduction

Urban municipalities are constantly challenged in their policy development and spatial planning by the need for densification and extension of the built-up area. These needs arise as a general consequence of urbanization and are often constrained by parallel needs for stronger protection and preservation of green infrastructure, and its ecological condition, both within and beyond the built-up area (Artmann et al., 2019a; Artmann et al., 2019b).

Urban tree canopy is an important component of the urban and semi-urban vegetation. Mapping of individual tree canopies thus addresses several purposes, including ecosystem accounting (Gómez-Baggethun and Barton, 2013). Ecosystem accounting used in combination with other municipal accounts can contribute to a wider set of indicators for reporting and assessment of climate, environmental and welfare policy (Hanssen et al., 2019). Ecosystem accounts can contribute to awareness of changes in green infrastructure. In particular, tree canopy cover is a key indicator of urban ecosystem condition and a predictor of recreational and regulating ecosystem services integrated within ecosystem accounting (Venter et al., 2020; Nowak et al., 2017; Obst et al., 2017; Li

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et al., 2014; Chen et al., 2018; Kabisch et al., 2019).

In their discussion of the application of ecosystem accounting in urban areas, Wang et al. (2019) highlight the need for identification of ecosystem assets as the basic spatial units that are standard in landcover mapping for national ecosystem accounts based on remote sensing. Modeling of regulating ecosystem services of urban trees requires accurate detection of the individual tree canopies and their characteristics. High-precision tree canopy maps will therefore reduce the estimation error, improve the accounting, valuation and change detection of significant ecosystem services, and help to increase their policy relevance. Individual tree canopy detection based on airborne and terrestrial LiDAR-scanning (Light Detection and Ranging) hold much potential for ecosystem service modelling (Cimburova and Barton, 2020), and has proven to obtain reliable high-precision 3D measurements of tree parameters such as tree height, tree canopy area, volume, biomass, Leaf Area Index (LAI) and stand density (Matasci et al., 2018; Liu et al., 2017; Tanhuanpää et al., 2014).

Ecosystem service modelling is required for biophysical quantification of ecosystem services (Zulian et al., 2018; Vallecillo et al., 2018). Quantifying greenviews for recreation (Li et al., 2015) requires modeling and visualization of the perspective from a specific user's location towards the tree canopy (with its height and volume). Modeling tree condition as a basis for regulating services such as shading, requires data on the geolocation of individual trees in relation to buildings (Nowak, 2020a). Modeling individual tree canopy sizes instead of general tree canopy enables a more precise estimation of regulating services. Tree canopy density has also been shown to determine property prices (Escobedo et al., 2015; Mei et al., 2018).

Existing vegetation extent accounts for Oslo's built-up area (Oslo municipality, 2019) are based on infrared orthophoto, using the Normalised Difference Vegetation Index (NDVI) to account for the spatial distribution of vegetation in the built-up area. NDVI gives a very good planimetric measure of the size and spatial distribution of vegetated areas, but does not account for variables describing tree canopy characteristics (such as single tree canopy height, surface, and volume). Such variables may be surveyed by fieldwork or LiDAR-scanning. Manual field surveys of the entire Oslo built-up area would clearly be very costly, limited in both temporal and spatial coverage, and prone to human appraisal errors. Although segmentation of tree canopies from LiDAR point clouds within an urban environment have limitations (Tanhuanpää et al., 2014; La et al., 2015; Rahman and Rashed, 2015; Plowright et al., 2016; Ciesielski and Sterenczak, 2019; Hanssen et al., 2019), and cannot entirely replace fieldwork in order to determine tree species and assess the health of individual trees, it is able to estimate the 3D tree canopy structure, surface and volume. Tree canopy surface and volume relates to the Leaf Area Index (LAI) which is a key indicator for modelling regulating ecosystem services in the i-Tree Eco software application (Nowak, 2020b).

While tree canopy detection using LiDAR is not new to remote sensing, it is a necessary innovation for urban ecosystem accounting. The most recent examples of urban natural capital accounting use remote sensing satellite imagery at a spatial resolution of 10 × 10 m. (Paulin et al., 2020). Identification of individual tree canopy areas and tree heights (Lof et al., 2019) provides the necessary precision for urban ecosystem condition accounting at property and street level, as well as for tree valuation modeling (Randrup, 2005; Nowak et al., 2017). Periodic high-resolution urban tree mapping using LiDAR contributes to cost-effective inventoring, monitoring and planning that accounts for both public and private tree canopy as part of integrated urban forestry governance (Miller et al., 2015; Klobucar et al., 2020).

The objective of this paper is to demonstrate both the potential and the limitations of using existing LiDAR data scanned for general purposes, to improve extent and condition mapping in urban ecosystem accounting. We demonstrate how LiDAR-based segmentation of urban tree canopies and identification of their physical condition in terms of canopy height, canopy diameter, 3D surface and volume can be a replicable, complementary and useful information source for urban ecosystem condition accounting as a basis for ecosystem service modeling. We further assess the usefulness and uncertainty of using general purpose LiDAR data for policy and planning by compiling accounts of tree canopy change (2011, 2014 and 2017) for the Oslo built-up area and the policy focus area of the Oslo municipality Small House plan, which is subject to urban densification and tree felling regulations. The LiDAR segmentation is validated with field data from the Oslo municipal tree point database (Cimburova and Barton, 2020) and a reference dataset derived from orthophoto at spatial resolutions spanning from 0.08 to 0.4 m (The Norwegian Mapping Authority, 2020a). Finally, we discuss potential methodological improvements for future ecosystem accounting in Oslo municipality.

2. Material and methods

2.1. Study area

The study area for this paper is the built-up area of Oslo (Fig. 1). The city of Oslo (59.91° N, 10.74° E) is the capital of Norway and had 697 010 citizens in January 2021.

The municipality of Oslo covers 454 sq.km and is characterized by its proximity to nature and rich biodiversity. About two-thirds of the municipality's area consists of forests, greenery, and water areas (The Norwegian Mapping Authority, 2020b).

The City Council of Oslo, Norway, launched in 1997 their first Small House plan (Oslo municipality, 2018) to ensure that the City Council's decision on further densification and development projects are done in the best possible way, securing that architectural and environmental qualities of established detached house areas are taken good care of. The plan aims to preserve existing terrain and vegetation to the greatest possible extent and ensure that larger trees are not cut, unless special permission is granted (Oslo municipality, 2018).

To monitor changes in the vegetation cover, the municipality of Oslo presented in 2019 their first vegetation extent account - also known as 'green account' - in the city's built-up area based on infrared orthoimagery (Oslo municipality, 2019). The account revealed that 47% (68 sq. kilometers) of the built-up area is covered by vegetation, whereas only 27% (40 sq. kilometers) of the built-up area is regulated for green land-use purposes such as parks, sport areas and recreational areas (Oslo municipality, 2019). Due to the establishment of new green areas inside new residential areas, there was a four percent increase in the regulated green areas from 2013 to 2017. In the same period, there was a three percent reduction in the unregulated green areas, mainly due to densification in the areas included in the Small House plan. Parallel to this municipal green accounting, the Urban Experimental Ecosystem Accounting research project (URBAN EEA, 2020) tested out alternative remote sensing methods by means of LiDAR and Sentinel-1 and 2 satellite imagery (ESA, 2020) for the built-up area of Oslo, to account for changes in the extent, ecological condition, supply, use and monetary valuation of the urban and semi-urban vegetation.

2.2. Tree canopy segmentation

There are two main methods for segmentation of tree canopies and their physical properties from LiDAR point clouds (Tanhuanpää et al., 2014). The *Area-based method* uses statistical dependencies between the LiDAR-parameters, such as relative and absolute height of laser echoes compared to field-surveyed forest variables (Næsset, 2009). The *Individual Tree Detection method* segments tree canopies either directly from the LiDAR point cloud (ESRI, 2020b) or indirectly from a LiDAR-derived canopy height model (Zhang et al., 2015). A range of individual tree detection methods has been developed to segment tree canopies from a canopy height model, all being favored for their raster geoprocessing capacity (Zhang et al., 2015).

Individual Tree Detection methods are sensitive to a range of factors

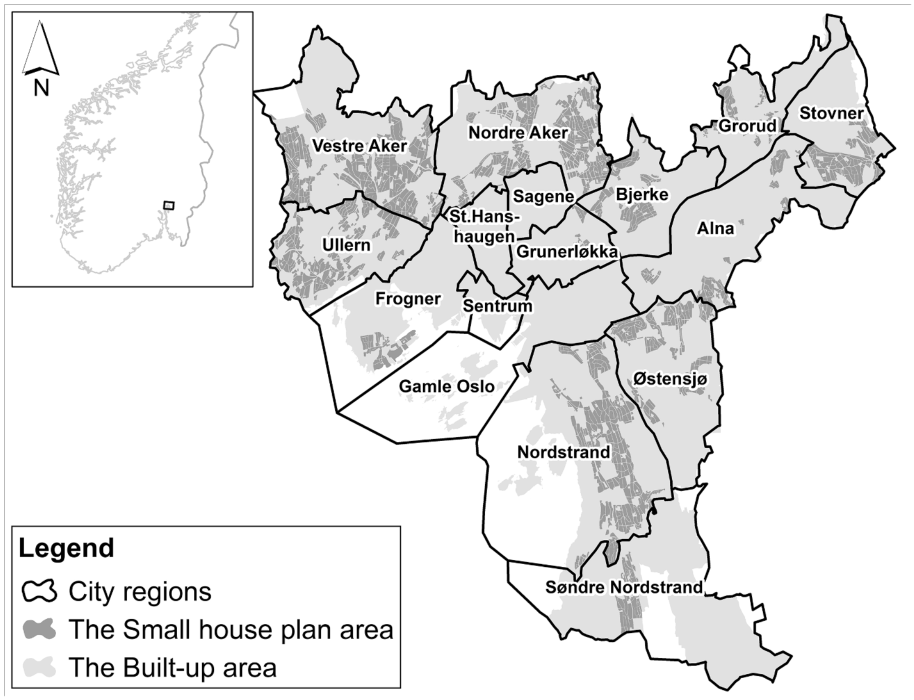

Fig. 1. The study area.

(Tanhuanpää et al., 2014; La et al., 2015; Rahman and Rashed, 2015; Plowright et al., 2016; Ciesielski and Sterenczak, 2019). First, temporal difference in data acquisition for field data and LiDAR data may hamper the detection precision of single tree canopies (Tanhuanpää et al., 2014). Second, applying a single segmentation algorithm and LiDAR point cloud may introduce some under- and oversegmentation due to the urban tree canopy‘s mixed stand, variation in shape and size, individual growth patterns, different light conditions and human activities modifying the tree shapes (Ciesielski and Sterenczak, 2019). Third, single tree detection in an urban environment is constrained by a range of technical infrastructures that may confuse the algorithms in their separation of true and false tree canopies (Tanhuanpää et al., 2014). According to Ciesielski and Sterenczak (2019) the accuracy of the different tree canopy segmentation methods ranges from 69% (Rahman and Rashed, 2015) to 99% (Plowright et al., 2016). Several studies have found that the accuracy of LiDAR-measured tree canopy area often is less accurate than the accuracy of LiDAR-measured tree height (Gill et al., 2000; Popescu et al., 2003). This issue may be caused by low point cloud density, the tree canopy shape itself and the overlap with adjacent tree canopies (Zhang et al., 2015). The accuracy of tree height relies, according to Stereńczak et al. (2008), on factors such as flight and data acquisition parameters, tree species, data processing technology and the method used for individual tree identification. Mielcarek et al. (2018) found that when segmenting from a high-density LiDAR point cloud, the height error is greater for complex, irregular deciduous canopies (such as oakes) than for conifers, due to the compact and cone-shaped form of

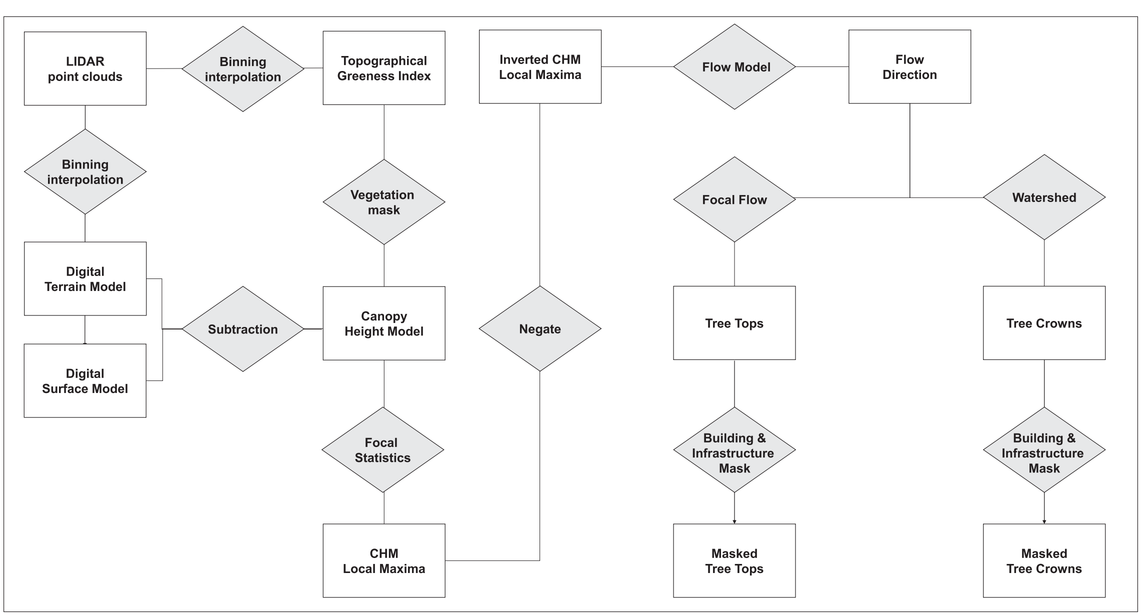

Fig. 2. The tree canopy segmentation workflow.

coniferous trees. It has also been observed that estimation of tree heights is sensitive to flight heights during laser scanning (Morsdorf et al., 2008).

2.3. The segmentation workflow

The tree canopy segmentation was performed with ArcGIS 10.6 Spatial Analyst (ESRI, 2019a) according to the workflow illustrated in Fig. 2.

2.4. The LiDAR point clouds

We downloaded the tiled LiDAR point cloud data for 2011, 2014 and 2017 (see Table 1) from the national archive for elevation data in Norway (The Norwegian Mapping Authority, 2018) and merged the data tiles into one LAS Dataset per city region per year to ease processing time and processor requirements.

2.5. Modelling the canopy height model

The Canopy Height Model (CHM) is the vertical difference between the Digital Terrain Model (DTM) and the Digital Surface Model (DSM). To reduce the geoprocessing overhead we chose to interpolate the tiled, yearly point clouds for each city region into integer DSM and DTM rasters with a spatial resolution of 0.5 m. The DSM was interpolated from unclassified and low-medium–high vegetation points (ASPRS code 3, 4 and 5 only available in the 2011 dataset) using a Binning interpolation type with a *Maximum* Cell Assignment Type and a Linear Void Fill method (ESRI, 2019c). As shown in Table 1, we were restricted to using unclassified points (ASPRS code 1, unassigned) to interpolate the DSM rasters for 2014 and 2017. The DTM was interpolated using ground points (ASPRS code 2) and the Binning interpolation type with an *Average* Cell Assignment Type and a Linear Void Fill method (ESRI, 2019c). For each year and city region, the DTMs were subtracted from the DSMs to derive the CHMs (Fig. 3, left panel). Due to the lack of NDVI-data and classified vegetation points in the 2014 and 2017 point clouds, we applied a Triangular Greenness Index (TGI) vegetation mask (Hanssen et al., 2019; Hunt et al., 2013) derived from RGB values in the 2011 and 2014 LiDAR point clouds (Fig. 3, right panel). Due to the lack of RGB values in the 2017 LiDAR point cloud (see Table 1) we were restricted to use the 2014 TGI vegetation mask also for 2017.

2.6. Smoothing and filtering the CHM using a Local Maxima search filter

To smooth and filter the vegetation- masked CHMs and find Local Maxima (Franceschi, 2017), we utilized a circular neighborhood search filter with a diameter of 3 m, enabled in the Maximum Statistics function of the ArcGIS 10. 6 Focal Statistics tool (ESRI, 2019d). The diameter of this filter was used as a proxy based on visual inspections of tree canopies in orthophotos and from best practices described in literature (Barnes et al., 2017). However, a search filter of 3 m will probably have a best fit for larger tree canopies. In addition, it is challenging to find a perfect search filter size as this varies locally and often is determined by species-specific morphological structures of the different tree species.

2.7. The watershed segmentation method

For the segmentation of individual tree canopies, we utilized a watershed segmentation method (Pyysalo et al., 2002; Suárez et al., 2005). This segmentation method belongs to the Individual Tree Detection method category and assumes that the form of an inverted tree canopy resembles a watershed and has been applied in several studies (Chen et al., 2006). Conceptually, this method can be described as gradually filling several basins with water. Where the water of adjacent basins connects, a boundary is detected, and as the water level rises, these boundaries outline each drainage basin (Beucher and Lantuéjoul, 1979). The watershed segmentation method was applied to the vegetation masked and filtered CHMs, which were negated to imitate watersheds. To calculate the flow direction from each pixel in the negated CHMs, we utilized the ArcGIS 10.6 Flow Direction tool (ESRI, 2020e) and the inherent eight-direction (D8) flow model (Jenson and Domingue, 1988) that assumes that there are eight valid output directions representing the eight neighboring pixels into which a flow could travel. We used the ArcGIS 10.6 Focal flow tool (ESRI, 2020f) to identify the drainage points (resembling the treetops) and the ArcGIS 10.6 Watershed tool (ESRI, 2020g) to delineate the watersheds (resembling the tree canopies). The result of the watershed segmentation of tree canopies from the 2014 LiDAR point cloud data is illustrated in Fig. 4. Finally, the segmented tree canopies for 2011, 2014 and 2017 were masked for false trees using a detailed infrastructure and building map from 2011. Unfortunately, we did not have access to such maps for 2014 and 2017 and were therefore constrained to use the 2011 mask for all three years.

2.8. Calculating the tree canopies geometrical 3D surface and volume

To estimate a proxy indicator for urban ecosystem condition related to regulating ecosystem services and correlated with field observations of tree canopy in the i-Tree Eco tool suite (Nowak, 2020a), we calculated the simplified geometrical 3D surface area and volume of each segmented tree canopy. The simplified geometrical 3D surface area (S geom) (Nowak, 1996) was calculated according to equation (1):

$$Sgeom = \left(\frac{\boldsymbol{\pi}^*\boldsymbol{D}^*(\boldsymbol{H}+\boldsymbol{D})}{2}\right) \tag{1}$$

Where D is the minimum bounding circle diameter around each segmented tree canopy and H is the segmented tree top height. The simplified volume of the tree canopies was calculated using the standard formula for the volume of a cone, according to equation (2):

$$Volume = \frac{1}{3}{}^*\pi^*r^{2*}h \tag{2}$$

Where r is the radius derived from the minimum bounding geometry diameter of each segmented tree canopy and h is the height of each segmented tree.

2.9. Ecosystem accounting

We tabulated extent-condition accounts for tree canopy by tree height segment in aggregate for the city, and mapped change to a basic spatial reporting unit of 0.25 square km^2 corresponding to Statistics Norway mapping grid (Strand and Bloch, 2009). We also mapped change in tree canopy at census tract and city district level to demonstrate alternative reporting units of relevance to the municipality of Oslo.

2.10. Validating the tree canopy segmentation

We validated the tree canopy segmentation results against available field data (municipal tree point database for managed trees) and land cover reference datasets manually digitized from orthophotos.

First, we compared the results of tree canopy segmentation from the 2014 LiDAR point cloud data with a concurrent version of a spatial database of trees managed by the Oslo Urban Environmental Agency. At the time of the validation, this database contained, 29 928 trees recorded over several years of the agency's sub-contracted planting and management (Cimburova and Barton, 2020). The registered trees in the database are represented as points with associated attributes (stem coordinates, species names, stem diameter and/or circumference and condition indicators). We performed this validation as a simple overlay analysis, counting the number of tree points that intersected the closest segmented tree canopy polygon.

Table 1
Acquisition month, point density, ASPRS point classification and RGB colour information for the three LiDAR point clouds.

	Acquisition month	Min. point density per m^2	Mean point density per m^2	ASPRS point classification	RGB- colour
Oslo 2011	July	5	43	1-2-3-4-5-7-9-10-24	Yes
Oslo 2014	June/July	10	25	1-2-7-10	Yes
Oslo 2017	August	Unknown	10	1-2-7-10-13	No

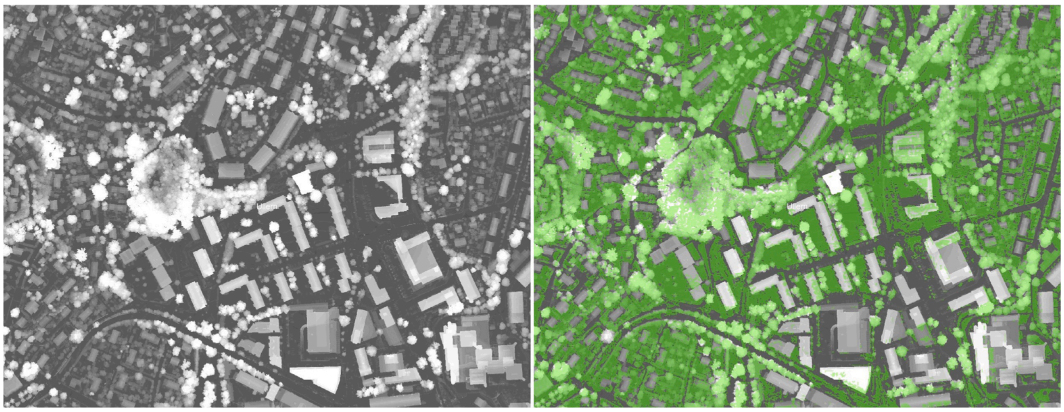

Fig. 3. The CHM (left panel) and the TGI vegetation mask (right panel) for 2014.

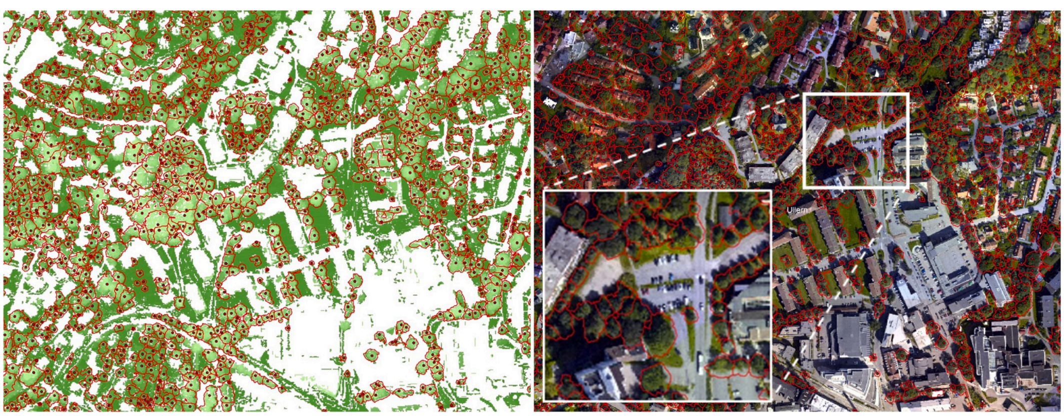

Fig. 4. The result of the watershed segmentation of tree canopies (outlined in red) compared to the TGI vegetation mask (left panel) and orthophoto (right panel), all originating from the same 2014 LiDAR point cloud data. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Next, we compared the LiDAR segmentation results from 2014 and 2017 with a reference land cover dataset digitized manually using visual interpretation of very high resolution orthophotos captured in April-May 2015 for 93 sampling plots (90 × 90 m.) across the Oslo built-up area. As matching years were unfortunately not available, the reference datasets closest to the year of the LiDAR data, namely 2015, was used. The root mean square error (RMSE) and mean difference (mDiff) were calculated to compare the segmented tree canopy area with the tree canopy area of the reference dataset in 2015. The RMSE (Eq. (3)) is a measure of the absolute accuracy in the model, while the mean difference (Eq. (4)) reports the bias or presence of systematic errors in the model. RMSE and the mean difference were calculated using the following equations:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(\boldsymbol{\theta}_i - \widehat{\boldsymbol{\theta}}_i\right)^2}{\boldsymbol{n}}} \tag{3}$$

$$mDiff = \frac{\sum_{i=1}^{n}\left(\boldsymbol{\theta}_i - \widehat{\boldsymbol{\theta}}_i\right)}{\boldsymbol{n}} \tag{4}$$

where θ_i is the reference tree canopy area for plot I, $\widehat{\theta}_i$ is the LiDAR tree canopy area for the same plot and n is the number of plots. The relative RMSE and relative mean difference were calculated as the percentage of the mean reference value.

3. Results.

3.1. Tree canopy statistics

3.1.1. The built-up area

The results of tree canopy segmentation from LiDAR point cloud data for 2011, 2014 and 2017 in the Oslo built-up area indicate a general increase in the number of trees taller than 15 m (Fig. 5). The number of trees within the 6–10 m height class has remained relatively constant in the period 2011–2017, probably as an effect of active management of urban tree canopies. Tree height, 2D- and 3D tree canopy area and volume statistics are displayed in Table S1 in the supplementary material section of this paper.

Tables 2 and 3 present the relative and absolute changes in 2D tree

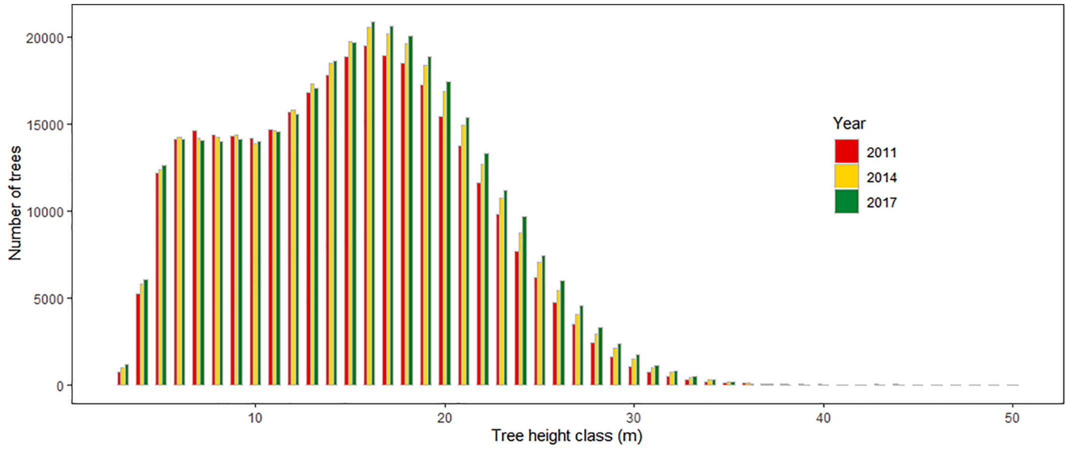

Fig. 5. Tree canopy height (in m) in the Oslo built-up area. The y-axis represents the number of trees and the x-axis represents identified tree canopy height.

Table 2
Combined extent-condition accounting table for 2D tree canopy area in the Oslo built- up area.

Tree height band	3–5 m	5–10 m	10–15 m	15–20 m	20–25 m	25–30 m	30–35 m	35–40 m	3–40 m
Change 2011–2017 (%)	34.08	5.37	8.73	14.91	23.58	37.00	61.76	30.76	17.15
Total 2011 (daa)	257.79	4814.76	8385.3	12537.7	9568.47	3288.69	523.03	78.39	39454.13
Additions (daa)	47.82	241.37	771.33	1916.48	1887.6	917.22	240.71	8.22	6030.73
Losses (daa)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Total 2014 (daa)	305.61	5056.13	9156.63	14454.18	11456.06	4205.9	763.74	86.61	45484.86
Additions (daa)	40.03	17.21	0.00	0.00	368.59	299.56	82.29	15.89	736.87
Losses (daa)	0.00	0.00	−39.15	−47.56	0.00	0.00	0.00	0.00	0.00
Total 2017 (daa)	345.64	5073.34	9117.48	14406.63	11824.65	4505.46	846.03	102.5	46221.73

Table 3
Combined extent-condition accounting table for tree canopy volume in the Oslo built- up area.

Tree height band	3–5 m	5–10 m	10–15 m	15–20 m	20–25 m	25–30 m	30–35 m	35–40 m	3–40 m
Change 2011–2017 (%)	37.18	6.80	9.43	15.63	24.18	38.34	61.70	35.35	21.35
Total 2011 (Mill. m3)	0.59	22.37	66.22	141.37	140.95	59.79	11.59	2.12	444.97
Additions (Mill. m3)	0.12	1.14	6.00	21.61	27.20	16.95	5.22	0.14	78.38
Losses (Mill. m3)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Total 2014 (Mill. m3)	0.70	23.50	72.22	162.98	168.15	76.75	16.80	2.26	523.37
Additions (Mill. m3)	0.10	0.38	0.25	0.49	6.87	5.97	1.93	0.61	16.60
Losses (Mill. m3)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Total 2017 (Mill. m3)	0.81	23.88	72.47	163.46	175.02	82.72	18.74	2.87	539.97

canopy area and tree canopy volume per height band in Oslo built-up area, with both additions (blue) and losses (red) to the “tree canopy cover assets” during the accounting period.

Changes in 2D tree canopy area per height band aggregated to the basic spatial statistical unit of 0.25 square km^2 defined by Statistics Norway (Fig. S1), census districts (Fig. S2) and city regions (Fig. S3) are

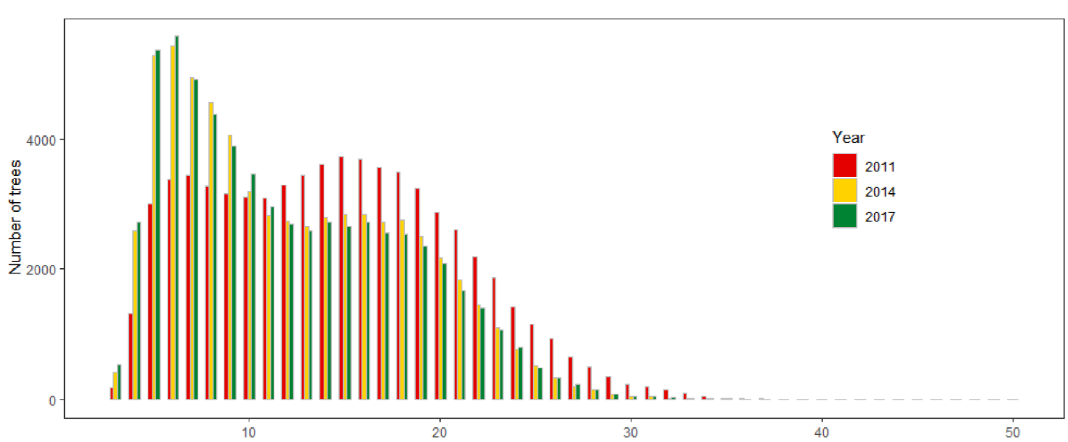

Fig. 6. Tree canopy height (in m) in the Small House plan area. The y-axis represents the number of trees and the x-axis represents identified tree canopy height.

reported in the supplementary material section of this paper. Different spatial aggregation units lead to different conclusions about the spatial distribution of tree canopy loss and regeneration.

3.1.2. The Small House plan area

In contrast to the built-up area, our results indicate that the Small House plan area had a large increase in small trees below 10 m, and a decrease in tall trees above 10 m in the period 2011–2017. See Fig. 6 and Table S2 in the supplementary material section of this paper.

Tables 4 and 5 presents the relative and absolute changes in 2D tree canopy area and tree canopy volume per height band for the Small House plan area, with additions (blue) and losses (red) to the "tree canopy cover assets" during the accounting period.

Fig. S4 in the supplementary material reveals the spatial distribution of net loss and gain of tall trees across the Small House plan area in the accounting period. Using this management area as a reporting unit we reach different conclusions than for Oslo as a whole. This is explored further in the discussion section.

3.2. Validation

3.2.1. Comparison with the municipal tree point database for managed trees

We found that the results of tree canopy segmentation from the 2014 LiDAR point cloud data have an unexpectedly low representation of the registered geolocations for trees from the municipal tree point database for managed trees. Only 69% of the registered tree points in the municipal tree database coincided with a segmented tree canopy polygon (Hanssen et al., 2019). Geolocations of trees recorded in the municipal tree point database have been recorded manually using aerial photographs and tree top points based on the 2011 LiDAR data from the Planning and Building Agency. None of the tree points have been verified using ground-based GPS measurements, and therefore the accuracy of geolocations in the municipal tree point database is unknown[1].

3.2.2. Comparison with reference datasets derived from orthophotos

The validation showed that for 93 reference plots, the segmentation models tend to overestimate the tree canopy area (Fig. 7). The model for 2014 overestimated the tree canopy area by 32.61% (Relative RMSE 19.98%, mean difference 0.06 ha). The 2017 segmentation model had the best fit for the 2015 reference data, with a relative RMSE of 0.25% and a relative mean difference of −16.38% (see Table 6).

4. Discussion

Segmentation of single tree canopies from LiDAR point clouds has proven to obtain reliable high-precision 3D- measurements of tree parameters such as tree height, tree canopy area, volume, biomass, Leaf Area Index (LAI) and stand density (Matasci et al., 2018; Liu et al., 2017). In our study we have demonstrated the potential and limitations of using publicly available, LiDAR data scanned for general purposes, to improve the accuracy and precision of urban ecosystem accounting. In addition, we have also estimated, validated and discussed how tree canopy segmentation based on such data can provide replicable, complementary and useful information for urban ecosystem condition accounting as a basis for ecosystem service modeling. The usefulness and uncertainty of using LiDAR for policy and planning have also been assessed by compiling accounts of tree canopy change (2011, 2014 and 2017) at single tree level for the Oslo built-up area and the policy focus area of the Small House plan, and aggregating into different reporting units (statistical grids, census districts and city regions).

4.1. Interpretation of results

Our results indicate a general increase in the number of tall trees > 15 m in the built-up area. The number of small trees < 15 m also seems to have a moderate increase, except for trees between 6 and 10 m which seem to remain relatively constant over the period 2011–2017. In this period, the built-up area had a 17.15% increase in the tree canopy area and a 21.35% increase in the tree canopy volume. For the Small House plan area, our results show a large increase in small trees < 10 m, a decrease in tall trees > 10 m, an overall 1.04% decrease in the tree canopy area and a 2.13% decrease in the tree canopy volume.

4.2. Methodological considerations

4.2.1. Validation of the segmentation accuracy

Validation of the segmentation accuracy relies on relatively concurrent acquisition of both field data and LiDAR data (Tanhuanpää et al., 2014). Our study unfortunately suffers from a lack of such temporally and spatially coherent field data. The only field data we had access to was a small municipal tree point database for managed trees from the Oslo Urban Environment Agency. Comparing a concurrent version of this database (in total 29.928 tree points) with the 2014 segmented tree canopies (in total 402 610 polygons) showed that 69% of the managed trees intersected with segmented tree canopy polygons. Even though the database only accounts for a small subset of all trees in the Oslo built-up area in 2014, the identified segmentation accuracy level for the managed trees is in the lower end of comparability with other studies where the tree canopy segmentation accuracy ranged from 69% to 99% (Ciesielski and Sterenczak, 2019). Compared to the reference dataset from 2015, the LiDAR-based tree canopy segmentation model seems to overestimate the tree canopy area. The segmentation model performed better in 2017 than in 2014. The validation procedure was important for understanding how much error was introduced into the extent accounts. Our results indicate that the segmentation model may contribute around 0.06 and 0.03 ha more tree canopy cover to the ecosystem accounts for 2014 and 2017, respectively.

4.2.2. Factors that may have influenced the segmentation accuracy

The overestimation described above (in section 4.2.1) is more likely influenced by several factors such as the use of one single watershed algorithm, single point clouds, a single fixed Local Maxima filter and the lack of proper concurrent correction masks for vegetation, technical infrastructures and buildings. In addition, segmented tree canopies with an irregular form will get an accordingly increased minimum bounding circle diameter and a following overestimation of the tree canopy area and volume.

Several studies have found that segmentation accuracy of tree canopy area size often is less accurate than the accuracy of the tree canopy height (Gill et al., 2000; Popescu et al., 2003). According to (Zhang et al., 2015) this may be related to multiple factors such as LiDAR point cloud density, tree canopy shape and overlap with adjacent tree canopies. In our study, the LiDAR point clouds for 2011, 2014 and 2017 are constrained with both different point densities and incomplete point classification with respect to vegetation. Classification of vegetation is only present in the 2011 LiDAR dataset, and the point density differs both between, and spatially within, the three datasets (see Table 1). Jakubowski et al. (2013) suggested that an average point density of 2 points per m^2 is enough for detection of large individual trees (>15 m). Others, like Zhang et al. (2015), claim that segmentation of individual trees and extraction of tree parameters (such as tree height, base height, canopy diameter) rely on at least 9 points per m^2 for large trees, and even higher point densities for smaller trees. The average point density of the LiDAR datasets in our study range from 43 (2011), 25 (2014) and 10 (2017) points per m^2, whereas the minimum point density range from 5 in 2011 to 10 in 2014 (for 2017 the minimum point density is not reported).

[1] Pers. com. M. Wells, Oslo Urban Environmental Agency.

Table 4
Combined extent-condition accounting table for 2D tree canopy area in the Small House plan area (policy focus).

Tree height band	3–5 m	5–10 m	10–15 m	15–20 m	20–25 m	25–30 m	30–35 m	35–40 m	3–40 m
Change 2011–2017 (%)	146.11	77.21	9.05	−11.05	−23.69	−63.90	−74.64	−67.46	−1.04
Total 2011 (daa)	55.09	955.15	1500.77	2034.09	1539.62	547.02	101.53	13.89	6747.16
Additions (daa)	74.21	809.81	155.67	0.00	0.00	0.00	0.00	0.00	283.59
Losses(daa)	0.00	0.00	0.00	−14.49	−314.03	−341.21	−75.78	−10.6	0.00
Total 2014 (daa)	129.3	1764.96	1656.45	2019.6	1225.59	205.81	25.75	3.29	7030.75
Additions (daa)	6.28	0.00	0.00	0.00	0.00	0.00	0.00	1.23	0.00
Losses (daa)	0.00	−72.3	−19.84	−210.19	−50.72	−8.33	0.00	0.00	−353.89
Total 2017 (daa)	135.58	1692.65	1636.6	1809.41	1174.87	197.48	25.75	4.52	6676.86

Table 5
Combined extent-condition accounting table for tree canopy volume in the Small House plan area (policy focus).

Tree height band	3–5 m	5–10 m	10–15 m	15–20 m	20–25 m	25–30 m	30–35 m	35–40 m	3–40 m
Change 2011–2017 (%)	130.71	68.83	13.43	2.12	−5.80	−43.19	−56.49	−25.32	−2.13
Total 2011 (Mill. m3)	0.15	5.36	14.51	28.35	27.78	11.91	2.69	0.42	91.16
Additions (Mill. m3)	0.17	4.24	2.40	3.11	0.00	0.00	0.00	0.00	1.45
Losses (Mill. m3)	0.00	0.00	0.00	0.00	−1.74	−5.06	−1.47	−0.20	0.00
Total 2014 (Mill. m3)	0.32	9.60	16.91	31.46	26.04	6.85	1.22	0.21	92.61
Additions (Mill. m3)	0.02	0.00	0.00	0.00	0.13	0.00	0.00	0.98	0.00
Losses (Mill. m3)	0.00	−0.55	−0.45	−2.51	0.00	−0.09	−0.05	0.00	−3.39
Total 2017 (Mill. m3)	0.34	9.05	16.46	28.95	26.17	6.77	1.17	0.31	89.22

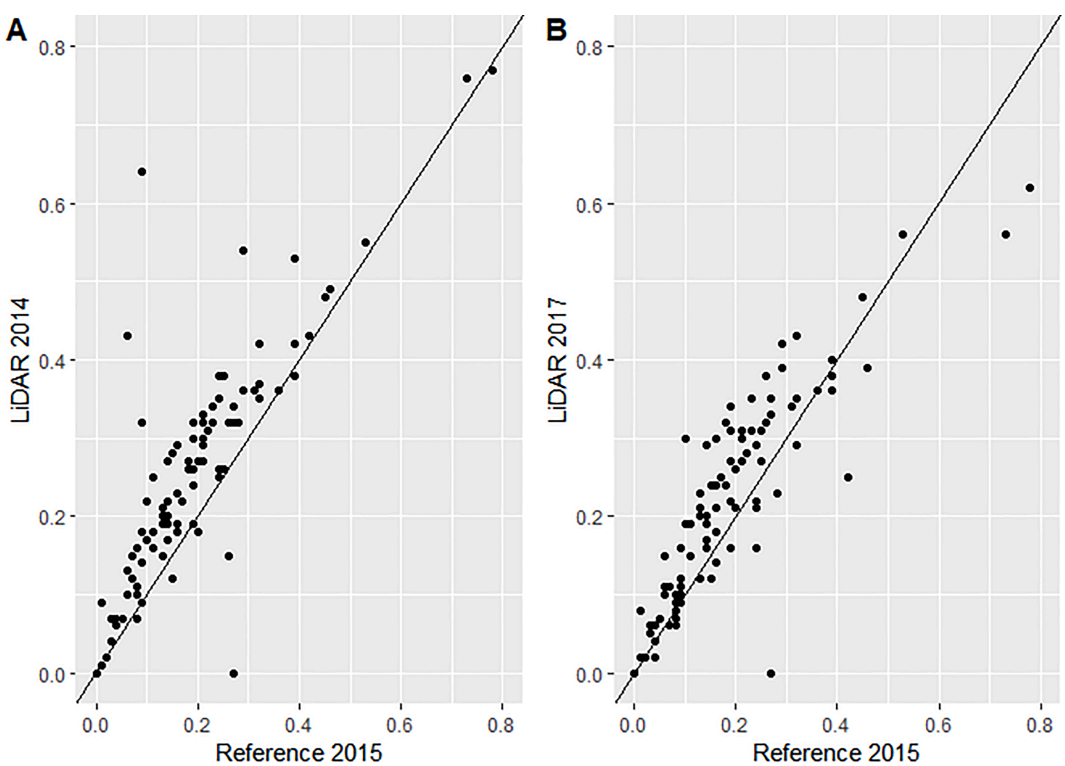

Fig. 7. Tree canopy obtained by tree canopy segmentation was plotted against tree canopy area from the reference datasets with the 1:1 line of fit. The LiDAR model from 2017 (B) was a better fit than that of 2014 (A).

Table 6
Comparison of LiDAR tree canopy segmentation results with reference datasets.

	RMSE (ha)	Relative RMSE (%)	Mean difference (ha)	Relative difference (%)
LiDAR 2014	0.04	19.98	−0.06	−32.61
LiDAR 2017	0.0005	0.25	−0.03	−16.38

Ciesielski and Sterenczak (2019) found that the use of single algorithms and single point clouds may introduce under- and over-segmentation due to the urban tree canopy‘s mixed stand, variation in shape and size, single tree growth, different light conditions and human activities modifying the tree shapes. For our study, we applied a standard watershed segmentation method combined with a Local-Maxima filtering of the CHM. This segmentation approach is frequently used and often favored for its efficacy (Zhang et al., 2015), but known to have several limitations. The interpolation and spatial resolution of the CHM may introduce several errors and uncertainties (Smith et al., 2004), which may affect the subsequent tree canopy segmentation process (Suárez et al., 2005). Also, the smoothing of the CHM may lead to under- or overestimates of the tree height (Tiede et al., 2005).

Barnes et al. (2017) found that a spatial resolution of 0.15 m provided a successful delineation of small larch canopies (canopy height < 20 m). For large larch canopies (canopy height > 30 m) they found that a spatial resolution of 0.5 m gave the most successful delineation. In our study, a spatial resolution of 0.5 m was considered the smallest operational pixel size allowed for in our ArcGIS desktop computing environment.

Many studies have implemented image smoothing techniques such as Gaussian filtering to cope with height anomalies and associated error sources introduced as a part of the acquisition and processing of LiDAR data (Barnes et al., 2017). The use of pit-filling algorithms and the application of pit-free CHM generation methodologies have been introduced in more recent studies (Stange et al., 2020; Barnes et al., 2017). Last, but not least, the size of the Local Maxima filter has a significant influence on the smoothed CHM. Chen et al. (2006) recommend using a filter size no larger than the smallest tree canopy within the study area. Barnes et al. (2017) suggests different Local Maxima filter sizes (in diameter) for different tree heights: Trees <= 15 m (1 m); trees 15–30 m (2 m) and trees >= 30 m (3 m). As the main focus in our study has been medium to large tree canopies in the Small House plan area, we decided to smooth our CHMs with a Local Maxima filter size of 3 m in diameter (equal to 6 pixels at a spatial resolution of 0.5 m). The Local Maxima filter size, the applied CHM pixel size and the inherent local variation in point density may explain the underestimation in number of smaller tree canopies and overestimation in number of larger tree canopies in our segmentation results. Another reason for underestimating small trees may be the effect of a lower detection and delineation accuracy of smaller trees within or under dense overlapping canopies, than for open areas (Matasci et al., 2018).

4.2.3. Challenges with single tree canopy segmentation in an urban environment

As pointed out by Tanhuanpää et al. (2014), single tree detection in an urban environment is affected by man-made vertical structures that may confound the segmentation algorithms in the separation of true and false tree canopies. To cope with this challenge, we applied TGI vegetation masks from RGB values in the 2011 and 2014 LiDAR point clouds to extract potential true tree canopies within vegetated pixels of the CHM. Due to the lack of RGB-information in the 2017 LiDAR point cloud, we unfortunately had to use the 2014 vegetation mask as a proxy-mask for the 2017 CHM. To exclude potential remaining false trees in the vegetated pixels (such as building roofs, towers, traffic signs, traffic-lights, poles, power lines, etc.) we used a detailed infrastructure and building map from 2011. Unfortunately, we did not have access to similar maps from 2014 and 2017. Since the construction rate in the built-up area of Oslo has been rather high in this period, and due to the above mentioned temporal masking incoherence, it is probable that some buildings and infrastructure constructed after 2011 may have been mistakenly segmented as tree canopies and contributed accordingly to the overestimation of tree canopy.

4.3. Detecting tree canopy change with LiDAR data designed for municipal planning

A comparison of Figs. S1, S2 and S3 (in the supplementary section of this paper) shows that the aggregation of changes at city district level hides local variation in tree canopy cover and condition (height) which could be relevant for policy and planning. For example, a policy to make tree canopy more equitably distributed across residential areas would need spatial targeting at neighbourhood (census tract level) or below. Furthermore, monitoring of tree canopy change in special management areas, such as the Small House plan area requires bespoke reporting on the management area rather than at administrative level. For spatial planning purposes, it could also be very useful to monitor tree canopy change within the core units of zonal planning as described in § 11-7 in the Norwegian Spatial Planning Act (Ot.prp nr. 32, 2007–2008). An important aspect to declare in this context is whether tree canopy segmentation based on general purpose LiDAR data is sufficiently accurate for these purposes.

With LiDAR data combining canopy height and area we can identify a significant loss of tall trees in the Small House plan area. Modeling of tree canopy volume indicates a net reduction in volume for the Small House plan area of −2.13% 2011–2017 (see Table 5), indicating that the loss of large trees > 20 m, may not have been compensated by planting in terms of regulating ecosystem services linked to canopy volume / leaf area. The loss of large tree canopy is likely to have an even larger effect on greenviews. This is also the intention of the Planning and Building Agency's restrictions on felling trees > 90 cm circumference at breast height. The structural data provided by LiDAR is thus important for urban ecosystem condition accounts (height and volume based on segmented area).

Spatial mapping of net change at neighbourhood level (as shown in Fig. S4 in the Supplementary material section) can be a useful tool for prioritizing monitoring, targeted communication with owners and plantings on public land to compensate for loss of private trees that are publicly visible. The LiDAR-based tree canopy segmentation products may also be useful for targeting Oslo's wider "100 000 trees by 2030" campaign to local deficit areas that are uncovered by change mapping at 250 m^2 pixel level. However, at this resolution the use of Sentinel-2 landcover mapping with canopy classification would be a lower cost alternative of better accuracy.

Otto von Bismarck once said that it is preferable, for laws as for sausages, not to know how they are made. Similarly, there is relatively little research on how the quality of inputs and assumptions that go into ecosystem extent and condition mapping affect the usefulness for decision-support purposes (Hou et al., 2013; Schulp and Landuyt, 2017). Fig. 8 summarizes how accurate our segmentation results are relative to different purposes in municipal planning. For city-wide, district and area planning estimates of aggregate tree canopy area, and total ecosystem service estimates using i-Tree Eco, we think the LiDAR-based tree canopy segmentation is accurate enough for the purpose of raising awareness. With the varying LiDAR raw data quality, we do not find it accurate enough for change detection within a common 4-year accounting period. Tree canopy maps zoomed to neighbourhood level also provide the awareness raising that tree canopy is of similar importance for landscape structure as buildings in many places. At the level of public parks and streets, the LiDAR tree canopy segmentation may be useful as a 'first-cut' inventory of trees to be verified by ground-truthing. At the property level for the computation of tree cover in condition indices, the segmentation may not be accurate enough. At individual tree level, the LiDAR tree canopy segmentation data do not provide enough information to compute tree compensation values (Randrup, 2005), and site inspection is necessary.

To improve accuracy and broaden the usefulness of the approach, we recommend designing a more coordinated, coherent and regularly scheduled data acquisition program both for field data sampling, LiDAR campaigns and simultaneous acquisition of high-resolution orthophoto-imagery. From a cost-effectiveness perspective, LiDAR could be prioritized for built-up areas with tree canopy densities <20%. The LiDAR campaigns in these areas should provide vegetation classified point clouds and adequate point densities for segmentation of both small and large tree canopies according to Zhang et al. (2015). Areas with >20% tree canopy density can be covered with satellite remote sensing (such as e.g. Sentinel-2) which offers equal or better accuracy and is free of charge. From a methodological perspective we recommend applying a CHM smoothing algorithm that is adapted to local tree size and morphology classes. From a computational perspective, based on our experiences from tree canopy segmentation in a desktop GIS-environment, we recommend doing the segmentation in a cloud-based

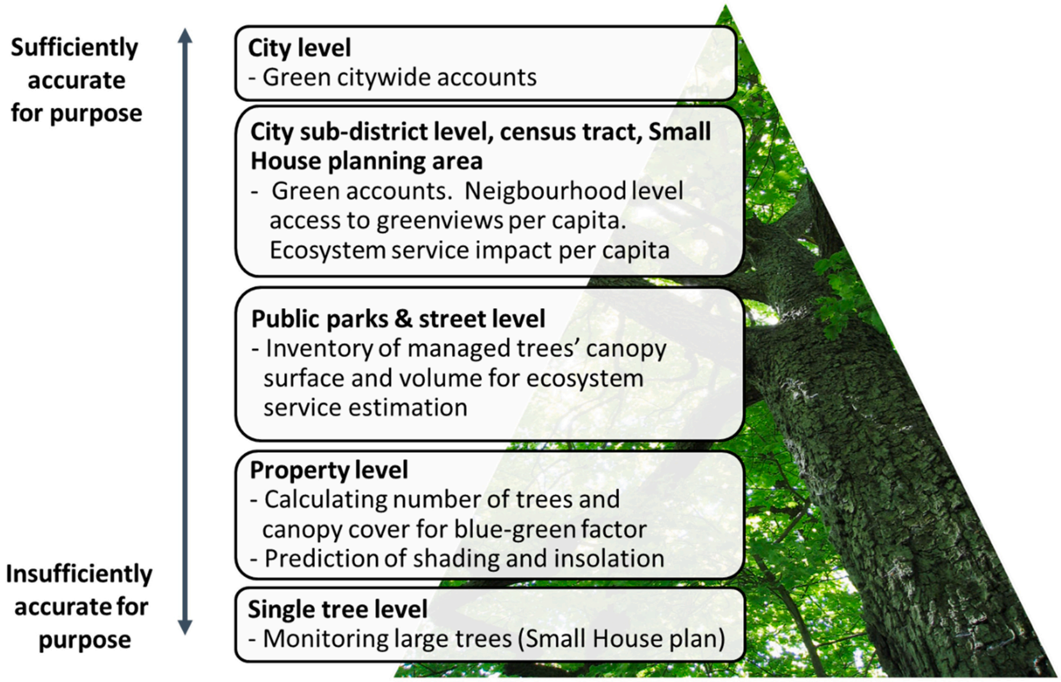

Fig. 8. Purposes of urban tree canopy accounting. Photo: Andrew Dunn (CC BY-SA 2.0).

platform such as for example Google Earth Engine. Stange et al. (2020) successfully implemented an alternative to the watershed segmentation technique in Google Earth Engine, but were also unable to account for varying canopy sizes over the study area.

5. Conclusions

This study estimates that the built-up area of Oslo from 2011 to 2017 had an increase in the number of tall trees (above 15 m), a moderate increase in the number of small trees (below 15 m) and a relatively constant number of trees between 6 and 10 m. In the same period the Small House plan area had a large increase in number of small trees (below 10 m) and a decrease in tall trees (above 10 m). The built-up area had a 17.15% increase in the tree canopy area and a 21.35% increase in the tree canopy volume, whereas the Small House plan area had a 1.04% reduction in the tree canopy area and a 2.13% reduction in the tree canopy volume.

A successful validation of the results require access to concurrent and representative field data. Restricted to a sparse amount of field data (29 928 observed trees), we found that our results from 2014 have a low to medium accuracy performance (detection rate of 63%). Validating the results with reference datasets from 93 random plots (registered in 2015) indicated that the LiDAR-based tree canopy segmentation results overestimate the tree canopy area.

This study demonstrates the potential and limitations of utilizing general purpose LiDAR data to provide ecosystem condition data to complement landcover data in urban ecosystem extent-condition accounts. We outline how LiDAR-based tree canopy segmentation can provide replicable and complementary information useful to provide estimates of urban tree canopy height, area and volume which are necessary for ecosystem service modeling and valuation.

For future municipal ecosystem service accounting, we recommend a coordinated, coherent and regularly scheduled data acquisition program both for field data sampling and LiDAR. Municipal LiDAR campaigns in Norway should aim to identify tree canopy as part of the general urban structural inventorying. This will determine how the raw data are processed and classified. We recommend differential use of LiDAR and satellite remote sensing data. LiDAR campaigns should be prioritized for built-up areas with tree canopy density <20%. The LiDAR-campaigns should provide adequate point densities and vegetation classification for segmentation of both small, medium and large tree canopies. Areas with >20% tree canopy density can be covered with satellite remote sensing (e.g. Sentinel-2) which offers equal or better accuracy and is free of charge. We further recommend applying a CHM smoothing algorithm that is adapted to local tree size and morphology classes, and to do the segmentation in a cloud-based platform such as e.g. Google Engine.

CRediT authorship contribution statement

Frank Hanssen: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing - review & editing, Visualization. **David N. Barton:** Conceptualization, Validation, Investigation, Writing – original draft, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Zander S. Venter:** Validation, Formal analysis, Investigation, Writing - review & editing, Visualization. **Megan S. Nowell:** Validation, Formal analysis, Investigation, Writing - review & editing, Visualization. **Zofie Cimburova:** Validation, Formal analysis, Investigation, Writing - review & editing, Visualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.

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