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NINA Report

Mapping urban tree canopy cover using airborne laser scanning

– applications to urban ecosystem accounting for Oslo

Frank Hanssen
David N. Barton
Megan Nowell
Zofie Cimburova

NINA

Norwegian Institute for Nature Research

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COVER PICTURE
ALS detected tree canopy cover Oslo between Royal Palace and Vigelandsparken. FKB map.

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- remote sensing
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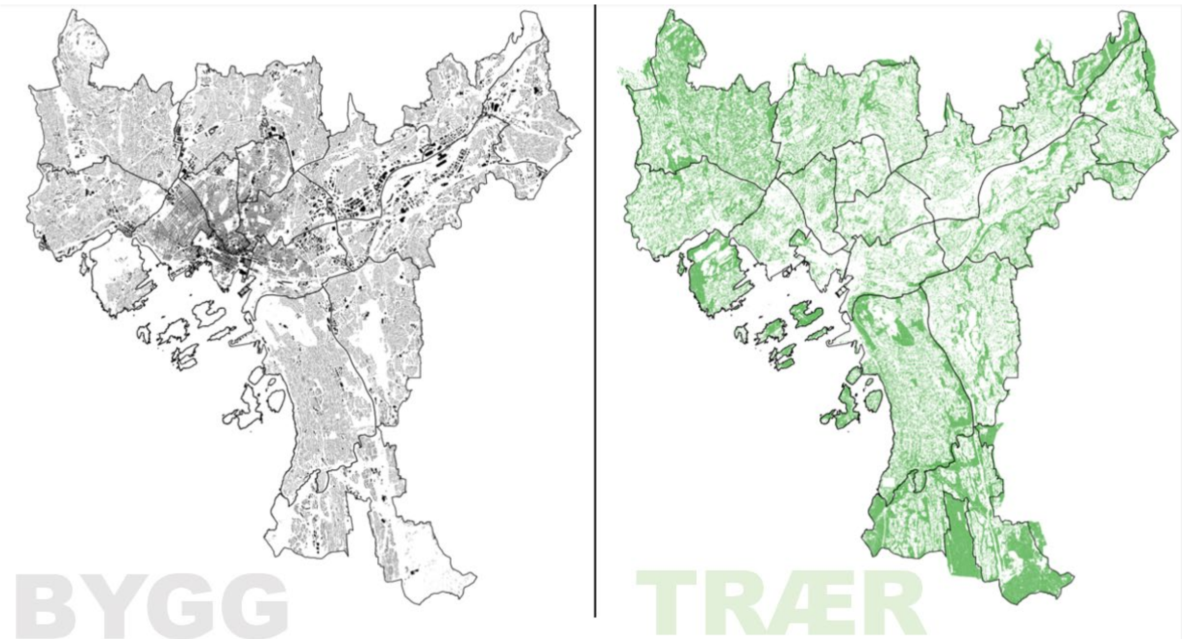
Sammendrag

Hanssen, F., D.N. Barton, M. Nowell, Z. Cimburova 2019. Mapping urban tree canopy cover using airborne laser scanning – applications to urban ecosystem accounting for Oslo. NINA Report 1677. Norwegian Institute for Nature Research.

Økosystemregnskap kan gi bykommuner informasjon om deres naturkapital og grønne infrastruktur. Kommuner kan rapportere om naturkapital på linje med rapportering om annen kommunal infrastruktur som krever investering og vedlikehold. Økosystemregnskap viser endring over tid i areal, vegetasjonstilstand, økosystemtjenester og deres økonomiske verdi.

Spesielt bytrær bidrar med en rekke opplevelse- og regulerende økosystemtjenester til byens innbyggere, og utgjør habitat for dyreliv i byen. Det er imidlertid ikke vanlig å føre regnskap over trær i byggesonen, og ihvertfall ikke på privat eiendom. Spesialiserte modeller, som f.eks. i-Tree Eco[1], kan beregne regulerende økosystemtjenester fra trær. De er avhengige av kvantifisering av trekrone-volum for å beregne bladareal (som også avhenger av treslag). Treets høyde, krone-størrelse og lokalisering i bybildet er også viktig for visuelle og estetiske effekter i ulike private og offentlige byrom.

I denne rapporten tester vi mulighetene for å beregne trekrone - egenskaper ved hjelp av laser scannede data fra fly – «airborne laser scanning» (ALS). Vi bruker eksisterende ALS data og ortofoto fra Norge Digitalt[2] [3], og demonstrerer en metode for identifisering av individuelle trekroner i byggesonen. Dette gir et nytt perspektiv på bylandskapet. Trær definerer byen like mye som bygg, som vist i figur 1 nedenfor.



Figur 1: Sammenligning av bygnings- og trestruktur i Oslo

I rapporten vurderer vi også endringer i antall trær og trekroner for årene ALS data for Oslo er tilgjengelig: 2011 – 2014 – 2017. Vi demonstrerer ulike kart- og regnskapsfremstillinger av disse dataene, med tanke på videreutvikling av Oslo Kommunes grøntregnskap, som en del av miljø-

[1] https://www.itreetools.org/eco/
[2] https://hoydedata.no/LaserInnsyn/
[3] https://www.norgeibilder.no/

og klimarapportering i Oslo Kommune. Vi rapporterer om endringer i trekrone-dekke for områder av spesiell interesse for bevaring av store trær.

Tabell 1: Trekrone-dekke sammenlignet med annen arealbruk i Oslo 2017

		Indre by (innenfor ring 2)	Oslo's byggesone totalt
Tette flater (ha)		1149	9761
	Bygg	385	1880
	Transport	183	1185
	Andre flater	581	6696
Permeable flater (ha)		69	3587
	Grøntområder	68	3366
	Dyrket	1	222
Vann (ha)		6	107
	Ferskvann	5	105
	Sjø	1	2
Trekrone areale* (ha)		205	4384
**Trekroner overlapper andre arealtyper unntatt bygg.*			

Hovedresultater i rapporten:

- I 2017 var det det 4384 hektar med trekrone-areal i byggesonen. Dette er over to ganger så stort som byens takareal i byggesonen. Innenfor Ring 2 var trekrone-arealet 205 hektar. Dette er et større areal til sammen enn arealet til transport, og mer enn halvparten så stort som takarealet i indre by. Trekrone-regnskapet konstaterer betydningen av trær som en hoveddel av byens infrastruktur.

- Antall større trær (>10m) har økt i tiden 2011-2017 i byen som helhet, og har vært omtrent konstant for mindre trær.

- I området dekket av Småhusplanen er det motsatt. Antall trær over 10m har blitt redusert, mens antall mindre trær har økt i samme område. Dette kan tyde på en fortettingseffekt som går spesielt utover store trær. Samtidig med vesentlige tap av store trær plantes det en del nytt i samme område.

- Den totale endringen i trekrone-volum er mindre omfattende i prosent enn for endring i antall trær. Det kan tyde på at endring i regulerende økosystemtjenester fra trær – som avhenger av bladareal – ikke er så stort som endringen i antall store trær skulle tilsi. Dette må vurderes lokalt, men kan skyldes bedre lysforhold for gjenværende trekroner.

Rapporten ender med en vurdering av kvaliteten på ALS data i forhold til ulike formål. ALS data er så langt bestilt av kommunen fra private leverandører hovedsakelig for identifisering av terrengforhold, bygg og annen teknisk infrastruktur. En begrensning i ALS data bestilt av kommunen hittil er mangler eller variasjon i klassifisering av vegetasjon og tetthet av laser-punkter. For fremtidig laserskanning anbefaler vi at kommunen prioriterer klassifisering av vegetasjon i ulike høyder, og tar i bruk en mest mulig homogen punkt-tetthet. Dette vil øke sammenlignbarheten over tid. Med disse forbedringene vil det være mulig å inkludere kartlegging av trekrone-areal i kommunens fremtidige Grøntregnskap.

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Abstract

Hanssen, F., D.N. Barton, M. Nowell, Z. Cimburova 2019. Mapping urban tree canopy cover using LIDAR – applications in urban ecosystem accounting for Oslo. NINA Report 1677. Norwegian Institute for Nature Research.

Ecosystem accounting applied to urban areas aims to provide municipal authorities with information on their natural capital, changes in physical assets over time, ecosystem services provided and their monetary value. Trees in urban areas are providers of a range of cultural and regulating ecosystem services of potential benefit to urban inhabitants. Tree canopy is not usually identified in landcover mapping of urban built zones. Specialised models for computing ecosystem services from urban forests, such as i-Tree Eco[4], rely on inventorying or sampling at the level of individual trees. This is necessary in order to identify tree canopy volume which is a key predictor of regulating ecosystem services. Individual tree height, canopy size and location are also key to evaluating visual impacts of trees in private and public open spaces.

Mapping tree canopy provides a new way of seeing the urban landscape. Trees define the urban form of Oslo as much as buildings do, as illustrated in figure 2 below.

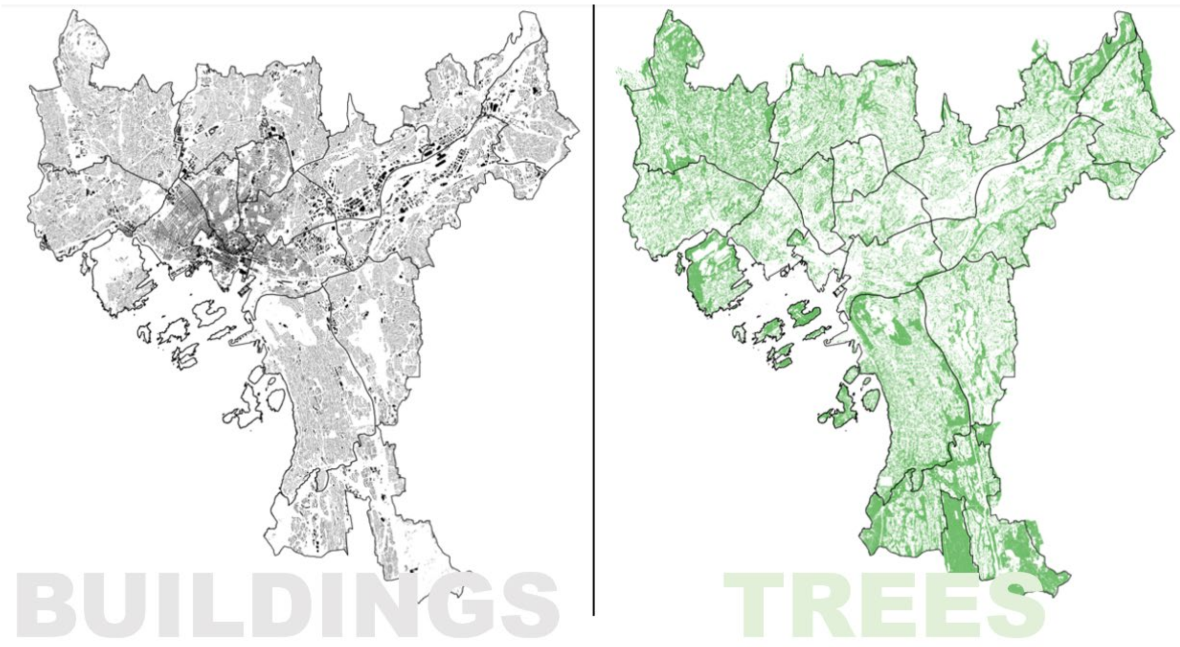

Figure 2: A comparison of the built-up areas and the tree covered areas in Oslo

In this report we demonstrate the use of available airborne laser scanning (ALS) and orthophoto data from Digital Norway[5] [6], for the segmentation of individual tree crowns.

In our study tree crown segmentation for 2011 – 2014 – 2017 in Oslo's built zone was compared to demonstrate different map and tabular approaches to urban tree accounts for different policy analysis purposes. We evaluate the trend in tree canopy characteristics in suburban "small house areas" currently undergoing urban densification.

[4] https://www.itreetools.org/eco/
[5] https://hoydedata.no/LaserInnsyn/
[6] https://www.norgeibilder.no/

Table 2: Tree canopy cover compared to other landcover in Oslo 2017

		Inner city (within ring road 2)	Total within Oslo's built zone
Sealed surfaces (ha)		1149	9761
	Buildings	385	1880
	Transport	183	1185
	Other surfaces	581	6696
Unsealed surfaces (ha)		69	3587
	Green spaces	68	3366
	Agriculture	1	222
Water (ha)		6	107
	Freshwater	5	105
	Sea	1	2
Tree canopy cover* (ha)		205	4384
**Tree canopy can overlap other surfaces, except buildings*			

Main results include:

- total tree canopy cover within Oslo's built zone in 2017 was 4384 hectares, more than twice the surface area of buildings in the built zone. Even within the inner city (ring 2), the tree canopy cover was 205 hectares, greater than the combined surface area of roads, and more than half the surface area of all buildings.

- in the city as a whole, trees > 10 m increased in numbers between 2011-2017, while in the Småhusplan area the number of tall trees decreased in the same period. In the Småhusplan area the number of small trees < 10 m high increased, while for Oslo as a whole it was roughly constant.

- The change in the total tree canopy volume of large trees is less pronounced in percentage terms than the change in number of tall trees. This means that the change in regulating services – which depend on canopy volume and leaf area index – may be less pronounced than changes in the number of trees would indicate.

The report ends with a discussion of the limitations in the vegetation classification using ALS data, which thus far has primarily been classified for the purpose of identifying terrain conditions, buildings and other technical infrastructures. In order to do this consistently, future airborne laser scanning projects should include classified vegetation points, and in addition have a uniform point density between the accounting periods. With these improvements we recommend that Oslo municipality in future includes tree canopy accounting in their green accounts.

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Contents

Forord

Forskningsprosjektet Urban Experimental Ecosystem Accounting (URBAN EEA) har som mål å teste metoder for økosystemregnskap som nå utvikles for nasjonalregnskap, tilpasset bykommuners behov for tiltaksvurderinger og arealplanlegging. URBAN EEA utprøver metoder for å kartlegge endring og tilstand av bynatur, fysisk tilgjengelighet og bruk av økosystemtjenester, og monetær verdisetting av byers naturkapital

Oslo Kommune ga i 2018 ut sitt første Grøntregnskap (Oslo kommune, Plan- og bygningsetaten, 2018)[7] som kartlegger endringer i 'faktisk' grønt i byggesonen mellom 2013-2017 ved bruk av infrarøde ortofoto.

Bytrær ved Oslo Rådhus. Photo: David N. Barton

Metoden som diskuteres i denne rapporten er et komplement til Oslo's Grøntregnskap med informasjon om kvalitetene på grønnstrukturen, med fokus på trekroner. Metodene viser hvordan man kan identifisere trekroner enkeltvis, og identifisere trekrone høyde, areal og estimere trekrone-volum

Vi håper arbeidet kan bidra til fremtidige oppdateringer av Oslo's Grøntregnskap og være til inspirasjon for andre bykommuner som ønsker å kartlegge deres naturkapital.

Rapporten er skrevet på engelsk for å gjøre arbeidet tilgjengelig for internasjonale forskningsmiljøer som tester økosystemregnskap i andre byer i verden, i forbindelse med FNs revidering av standarder for økosystemregnskap.

Oslo, Mai 2019

Frank Hanssen og David N. Barton

[7] https://www.oslo.kommune.no/getfile.php/13300369-1539862391/Innhold/Politikk%20og%20administrasjon/Etater%2C%20foretak%20og%20ombud/Plan-%20og%20bygningsetaten/Gr%C3%B8ntregnskap%20-%20fagrapport.pdf

Foreword

The Urban Experimental Ecosystem Accounting (URBAN EEA) project aims at testing ecosystem accounting methods designed for national accounts at the local level in support of municipal policy and planning. URBAN EEA tests mapping methods to account for changes in the extent, condition, supply, use and monetary value of urban nature within the Greater Oslo area.


Studenterlunden Photo: David N. Barton

Oslo Municipality recently completed the city's first green account (Grøntregnskap) documenting the change in vegetation cover within the city in the period 2013-2017 using infrared orthophoto (Oslo kommune, Plan- og bygningsetaten, 2018)[8]. The approach documented in the present report uses LiDAR data as a complement to the city's green accounts, providing information on the condition of green cover with a focus on tree canopy. The methods demonstrated here help to segment the individual tree canopies and information about their canopy height, crown diameter, their 3D surface area and volume.

We hope that this work provides support to Oslo in future updates of their green accounts, and provides examples for other urban municipalities in Norway.

Oslo, May 2019

Frank Hanssen and David Barton

[8] https://www.oslo.kommune.no/getfile.php/13300369-1539862391/Innhold/Politikk%20og%20administrasjon/Etater%2C%20foretak%20og%20ombud/Plan-%20og%20bygningsetaten/Gr%C3%B8ntregnskap%20-%20fagrapport.pdf

Abbreviations

ALS - Airborne Laser-Scanning

ASPRS - American Society for Photogrammetry and Remote Sensing

CHM - Canopy Height Model

daa - Acres

DTM - Digital Terrain Model

LAS-format - an industry-standard binary format for storing airborne LiDAR data

LiDAR - Light Detection And Ranging

GVI - Green View Index

NDVI – Normalized Difference Vegetation Index

RGB - Red-Green-Blue

TGI - Triangular Greenness Index

1 Introduction

The URBAN EEA project[9] conducts research on ecosystem services from urban green infrastructure in the Oslo Region, from individual city trees and green spaces in the built area to peri-urban forest and cultivated land. The project contributes to research and development on the UN's Experimental Ecosystem Accounting (EEA) and its application to urban areas.

Ecosystem accounts have the potential to be part of a system of integrated municipal accounts, and to contribute to a wider set of indicators for municipal reporting and assessment of climate and environmental policy. Figure 3 provides a conceptual model of how a system of ecosystem accounts might be integrated within a system of municipal accounts, in support of policy.

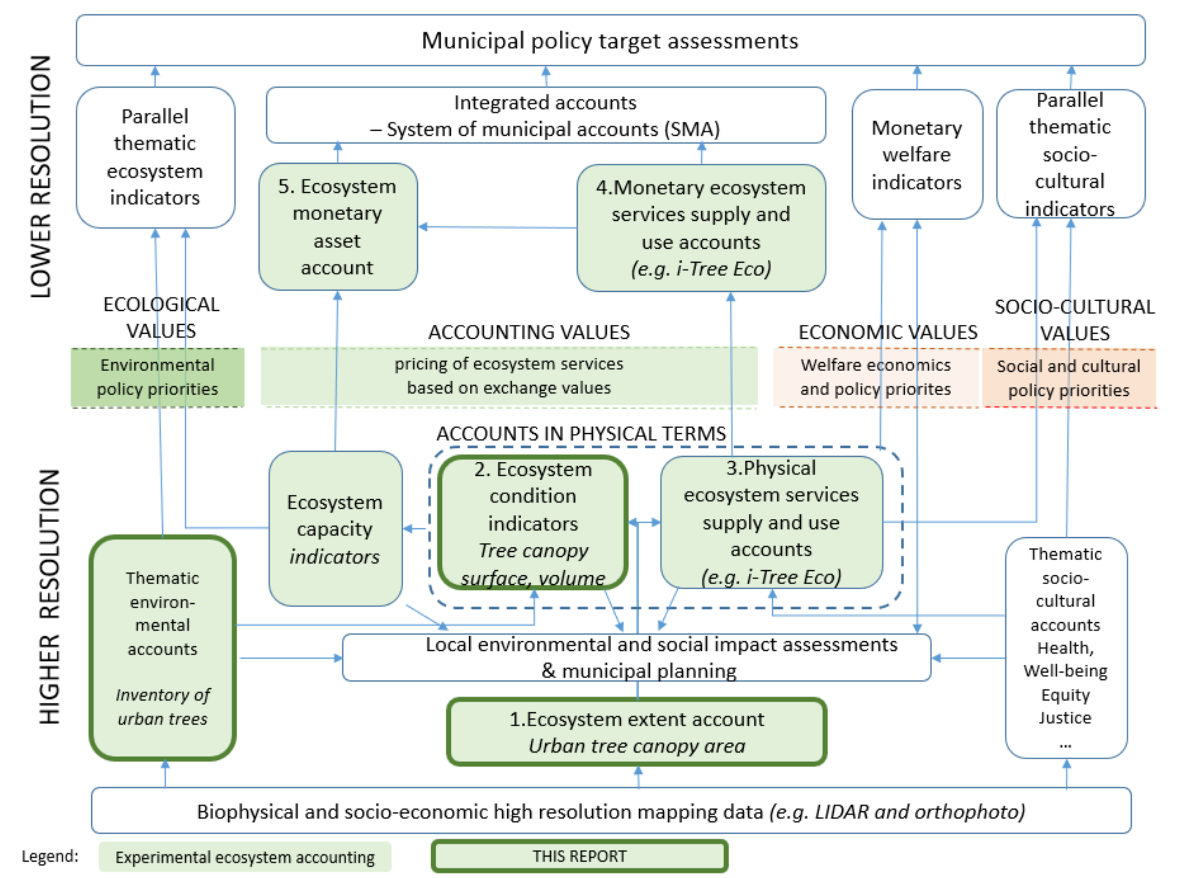


Figure 3 *Framework for a system of integrated municipal accounts, municipal reporting and assessment of climate and environmental policy. This report provides examples of accounts outlined in green.*
Source: Barton et al. 2017

Ecosystem accounting provides a framework and 'production line' for the information on urban ecosystems needed to compare the contribution of urban nature to the urban economy and well-being. The biophysical mapping of urban nature that is required to build ecosystem accounts also contributes to (non-monetary) ecological and socio-cultural indicators for municipal policy assessment. A basic objective of mapping methods in urban ecosystem accounting is to make green infrastructure as visible to planners as is built infrastructure. The long-term aim is to contribute to a suite of indicators reflecting different types of policy priorities and values with which to assess municipal policy targets. In this report we demonstrate a city-wide methodology for

[9] https://www.nina.no/english/Fields-of-research/Projects/Urban-EEA

accounting for tree canopy cover in the built area of Oslo, including tree canopy area (1. extent account) and tree canopy surface area and volume (2. condition account) (Figure 3). Canopy cover surface area is a key input to the i-Tree Eco[10] tool which is used worldwide to estimate regulating ecosystem services of urban forests and their monetary value. Mapping of tree canopy can also be used to make inventories of urban trees for specific management purposes, such as monitoring of large trees on municipal land, or inventories of all regulated trees (DBH>90cm) in private gardens.

In the context of access to nature Oslo is sometimes referred to as "the blue and the green and the city in between".

This report documents "the green in between" within the city's built zone.

1.1 Why account for urban tree canopy?

There are a number of other non-monetary reasons why – in the general context of awareness raising about urban green – accounting for urban tree canopy cover is important to consider with specific indicators. Tree canopy is the most important green structure by surface area in the built area of Oslo.

There is an increasing awareness about the value of urban tree canopies, and their contribution to urban quality of life, neighbourhood cohesion, wildlife habitat, and ecosystem services such as air-pollution mitigation, carbon storage, runoff control and temperature regulation. To manage urban trees it is necessary to know where they are and what condition they are in. There is an increasing demand for cost-effective and standardised procedures for automated production of high-resolution tree canopy maps.

Using results from tree canopy mapping in this report we can now document what visitors to Oslo remark upon when approaching Oslo from the air or sea, but which many living within Oslo may take for granted. Oslo's built zone has more tree canopy area seen from above than building roof area (Table 3).

***Table 3** Tree canopy cover in Oslo (2017)*

		Inner city within ring road 2	Total Oslo's built zone
Sealed surfaces total (ha)		1149	9761
	Buildings	385	1880
	Transport	183	1185
	Other surfaces	581	6696
Unsealed surfaces total (ha)		69	3587
	Green spaces	68	3366
	Agriculture	1	222
	Tree canopy*	205	4384
Water (ha)	Freshwater	5	105
**Tree canopy can overlap other surfaces, except buildings*			

In terms of human habitat structure trees are more ubiquitous in Oslo as a whole than buildings. Tree canopy is as much a physical 'place maker' in Oslo as are buildings. Tree canopy cover within Oslo's built zone defines Oslo's visual landscape as much as, or more than buildings do (Figure 4 and 5).

[10] https://www.itreetools.org/eco/

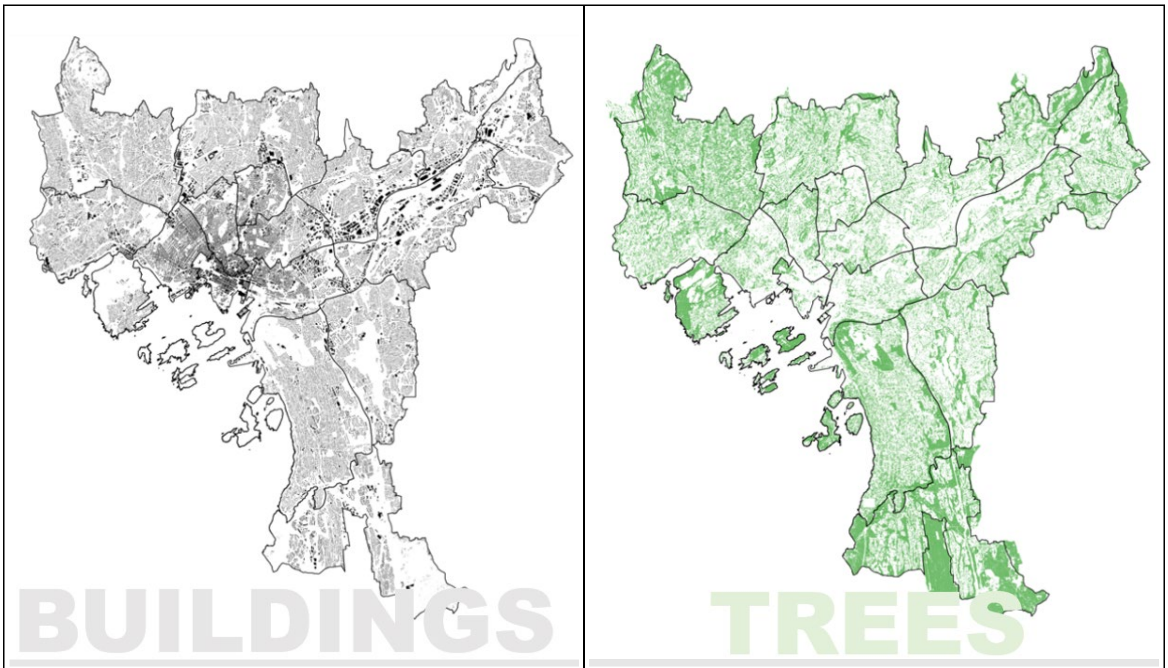


***Figure 4**. Building surface and tree canopy surfaces as physical infrastructure in Oslo's built zone.* Tree canopy is a physical 'place maker' throughout the city. Map: Megan Nowell, Data: PBE

Figure 5: Oslo's green infrastructure is not only its parks – city trees are ubiquitous and define the city fabric.

Seen from Oslo fjord the vertical green surface of tree canopies in the urban landscape is notable (Figure 6).

At street level the visual impact of tree canopy is several times as large by surface area as seen from above. The proportion of a street view filled with vegetation has been computed by MIT Senseable City Lab using the Green View Index (GVI). Oslo has one of the highest GVI's of cities in their Treepedia database[11] at 28,8%. That means that on average almost one third of street views in Oslo are described by tree canopy. The GVI is an indicator of a sample of Oslo's street trees limited to locations with Google Street Views. But it is indicative of new 'big data' approaches to accounting for urban green infrastructure. Using a combination of remote sensing data including Airborne Laser-Scanning and orthophotos, the method in this report provides an approach to carrying out a full inventory of city trees in an urban built zone.

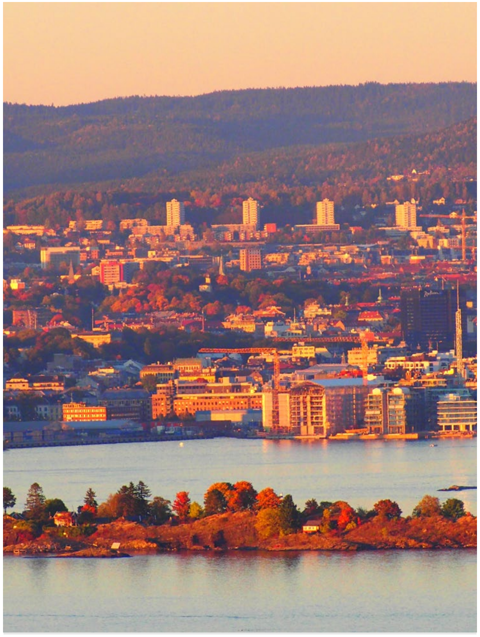


Figure 6. *Oslo's 'green in between' the built area, between the Marka forest and Oslofjord.* Photo: David N. Barton

One of Oslo's mottos is "the blue and the green and the city in between". With the methods in this report we show how to account for "the green in between" the built zone.

1.2 Modelling regulating ecosystem services of city trees

The mapping of tree crowns provides information on urban structure at the landscape level, and visual qualities of open spaces at the street and property level. Additionally, the identification of tree crown structure is key information in modelling regulating ecosystem services (carbon sequestration, carbon storage, energy saving effects, air pollution removal, avoided runoff, wildlife habitat) and disservices (emission of Volatile Organic Compounds). I-Tree Eco calculates biophysical indicators of regulating ecosystem services and monetary values of benefits. This information on ecosystem services can be used to further justify municipal funding for city trees as is done for other public utilities, and can inform municipal strategies for tree maintenance and planting (Barton et al., 2015).

[11] http://senseable.mit.edu/treepedia

The ecosystem services modelling tool i-Tree Eco[12] requires variables on tree canopy characteristics (Figure 7) which are usually observed through time consuming field surveys from the ground. Ecosystem services and the values generated by urban forests can be modelled with

i-Tree Eco Variables	Derived variables		Ecosystem services										
	Leaf Area	Leaf Biomass	Carbon Storage	Gross Carbon Sequestration	Net Carbon Sequestration	Energy Effects	Air Pollution Removal	Avoided Runoff	Transpiration	VOC Emissions	Compensatory Value	Wildlife Suitability	UV Effects
Species	D	D	D	D	D	D	I	I	I	D	D		
Diameter at breast height (DBH)			D	D	D						D	D	
Total height	D	D	D	D	D	D	I	I	I	I		D	
Crown base height	D	D	C				I	I	I	I		D	
Crown width	D	D	C				I	I	I	I			
Percent crown missing	D	D	C			D	I	I	I	I			
Crown light exposure (CLE)				D	D								
Crown health (condition/dieback)				D	D						D	D	
Field land use			D	D	D						D	D	
Distance to building						D							
Direction to building						D							
Percent tree cover						D	D	D				D	D
Percent shrub cover												D	
Percent building cover						D							
Ground cover composition												D	
Un-/Maintained Grass, Herbaceous % cover							I						

D Directly used   I Indirectly   C Conditionally used

***Figure 7** Tree characteristics as input to the calculation of different ecosystem services in i-Tree Eco*

several different tree appraisal methods. Common to them all is the need to conduct on the ground assessments of tree canopy condition. Ground based tree assessment for a whole city can be resource intensive, limited in their spatial coverage and prone to some human appraisal error. Several remote sensing methods are available to observe the extent and condition of urban trees. Among the remote sensing methods only LIDAR identifies 3D tree canopy structure, surface area and volume. Canopy surface area and volume are related to Leaf Area Index (LAI) which is a key indicator in i-Tree Eco of regulating ecosystem services of city trees. The tree crown modelling based on LiDAR data can be combined with available GIS data, ground-based tree inventory data and ecosystem service modelling techniques. The longer-term goal is to model regulating ecosystem services in i-Tree Eco mainly using remote sensing data, with minimal ground truthing. Ground based survey work is still required to obtain species information for individual trees and assess tree health, but the measurement of physical tree dimensions can largely be carried out by remote sensing.

[12] https://www.itreetools.org/

1.3 Tree segmentation approach

Data acquired from Airborne Laser-Scanning (ALS), also called LiDAR data (Light Detection And Ranging), contain three-dimensional information that can be used to estimate tree canopy height, crown diameter, 3D crown surface area and crown volume. The process of deriving this information from LIDAR-data is often referred to as tree canopy segmentation, a process that allows a cost-effective and accurate urban forest inventory down to individual trees.

We have implemented a simple Watershed segmentation method using the tree Canopy Height Model (CHM) as the basis for tree detection and delineation of individual trees. This method assumes that the shape of a tree crown resembles a watershed. Watershed segmentation is an image processing technique originally developed to outline drainage basins from a Digital Terrain Model (DTM). Conceptually, this technique can be described as gradually filling basins with water. Where the water of two adjacent basins connects, a boundary is detected. As the water rises, these boundaries delineate each drainage basin. Due to the morphological similarities between a DTM and a CHM, this technique has been applied to delineate individual tree crowns from an inverted CHM.

The most foremost application of the segmented tree canopies is the ability to have an updated inventory for improved management of existing urban trees, tree planting programs, zonal planning, change detection analysis and mapping and valuation of ecosystem services.

2 Data

Airborne LIDAR is a surveying method that measures the distance to a target (i.e. a tree) by illuminating it with laser light pulses. The reflected pulses are measured with a sensor. Differences in laser return times and wavelengths are used to make digital 3-D representations of the target. LiDAR is often called laser scanning and 3-D scanning, with terrestrial, airborne, and mobile applications. In this study we have used data from an airborne laser scanner as illustrated in figure 8 below.

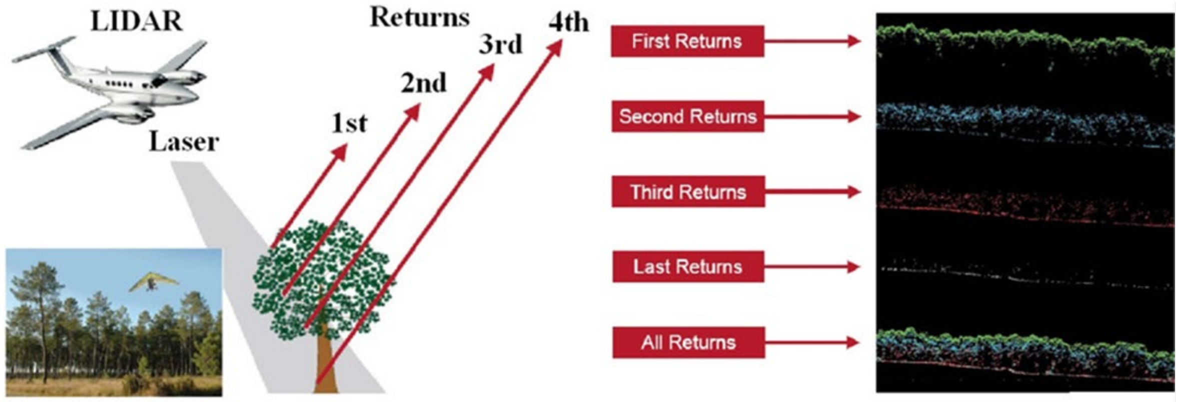


Figure 8: The principles of airborne laser scanning

LIDAR- data from three different laser- scanning projects in Oslo (scanned in 2011, 2014 and 2017) was downloaded from the national archive for elevation data in Norway[13]. LIDAR data is a point cloud where each point can be classified into several categories. These categories are defined by the American Society for Photogrammetry and Remote Sensing (ASPRS, 2010). Table 4 lists the ASPRS- categories classified in the downloaded LIDAR data from Oslo, whereas table 5 gives an overview of the average point density, point classification and RGB - colour information in the data.

Table 4: *Applied ASPRS classification codes (ASPRS, 2010).*

ASPRS code	Meaning
1	Not classified
2	Ground
3	Low vegetation
4	Medium vegetation
5	High vegetation
7	Low and high points (noise)
9	Water
10	Points on bridge
24	Power line

Table 5: *Overview of the applied LIDAR data from Oslo*

	Average point density per m^2	Point classification	RGB- colour information
Oslo 2011 (Blom ASA, 2012)	43	1-2-3-4-5-7-9-10-24	Yes
Oslo 2014 (Blom ASA, 2014)	25	1-2-7-10	Yes
Oslo 2017 (Terratec AS, 2017)	10	1-2-7-10-13	No

[13] https://hoydedata.no/LaserInnsyn/

3 Study area

Our study area is Oslo Municipality's built zone (figure 9).

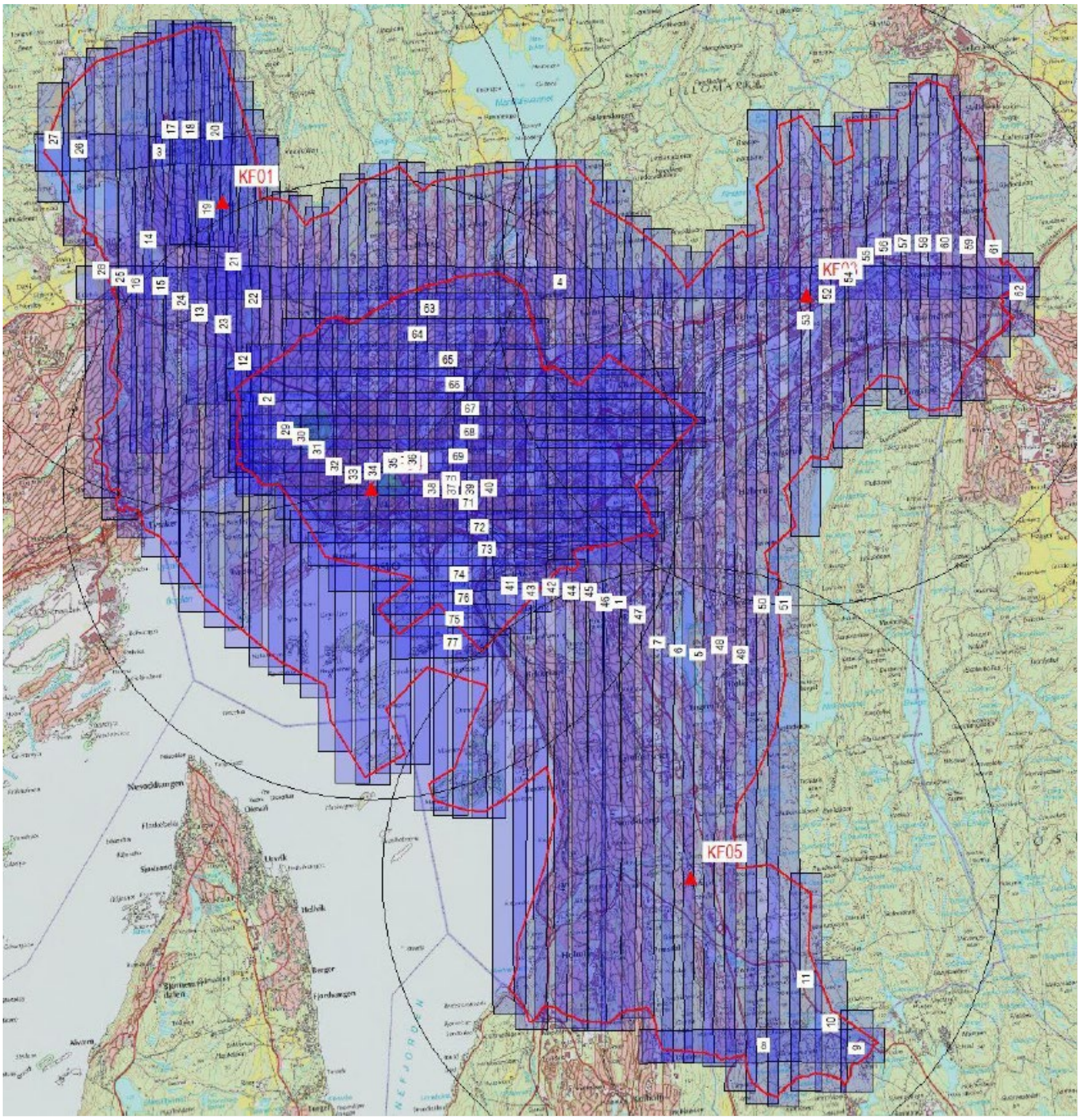


Figure 9: *Coverage map of scanning blocks in the Oslo 2017 laser scanning project (Terratech, 2017). The scale from light blue to dark blue indicates the point density from low to high in the scanning blocks.*

Detailed topographical mapping data[14] have been used as analysis masks to flag trees that are mistakenly segmented in built up areas (buildings and other physical infrastructures). Administrative borders, such as municipality borders and city region borders have been used as processing extents. Finally, vegetation masks (the Topographical Greeness Index, described in section 4.2) have been derived from available orthophoto imagery[15].

[14] https://kartkatalog.geonorge.no/metadata/geovekst/felles-kartdatabase-fkb/0e90ca71-6a02-4036-bd94-f219fe64645f

[15] http://norgeibilder.no/

4 Methods

Tanhuanpää *et al.* (2014) describe two main methods for extracting tree canopy and forest characteristics using airborne LiDAR, respectively the *Area-based method* (Næsset, 2002) and the *Individual Tree Detection method* (Hyyppä & Inkinen, 1999). The *Area-based method* is founded on statistical dependencies between ALS-parameters (e.g. relative and absolute height of laser echoes) and forest variables collected in the field. The *Individual Tree Detection method* helps to delineate tree crowns either directly from the LIDAR- point cloud (Zhang et al., 2015) or indirectly from a LiDAR-derived canopy height model (CHM).

The LiDAR-derived canopy height model interpolates a raster surface from LiDAR points hitting the tree canopy surface. A range of methods have been developed on this principle, all being favoured for their processing speed and the accessibility to software that commonly uses regularly spaced data such as e.g. raster's (Zhang *et al.*, 2015).

For this study we have implemented a simple Watershed segmentation method on a filtered CHM (Pyysalo & Hyyppa 2002, Suárez et al. 2005). As we only have classified vegetation points from 2011, it was necessary to tag unclassified vegetation points (from 2014 and 2017) located inside vegetated areas. In the absence of high-resolution IR- imagery (and a corresponding NDVI- mask) we choosed to calculate a simplified vegetation mask based on the Triangular Greenness Index (TGI) described by Hunt et al., 2013. Finally, objects incorrectly segmented as trees were masked out using a mask of buildings and other technical infrastructures.

The process of segmenting tree canopy from LIDAR in this study is organised as stepwise workflows. Each workflow is organised as stringed sequences of certified geoprocessing tools and algorithms in the ESRI visual programming interface Model builder (ArcGIS 10.6). This platform was selected for its powerful raster processing capabilities.

4.1 Organising the LIDAR point cloud

The big amount of LIDAR data (2011, 2014 and 2017 was downloaded from https://hoydedata.no/LaserInnsyn/ as tiles in the LAS-format (an industry-standard binary format for storing airborne LiDAR data) and scripted into city region folders (1 folder per region per year, in total 16 regions per year for Oslo).

For each city region in Oslo a LAS Dataset was created using the "**Create LAS Dataset**" tool (see figure 10). A LAS dataset stores references to LAS files on disk and allows us to examine the LAS files in their native format, quickly and easily, providing detailed statistics and area coverage. A LAS dataset can also store references to feature classes containing surface constraints such as breaklines, water polygons, area boundaries, or any other types of surface features that is to be enforced in the LAS dataset.

In brief

Due to the voluminous amount of data, the LIDAR point cloud is often divided into numerous data tiles by the data provider.

The purpose of this step is to optimize the data prior to the tree canopy segmentation process. For this purpose, we created a map index that reference all the data tiles and their associated surface characteristics (see figure 10).

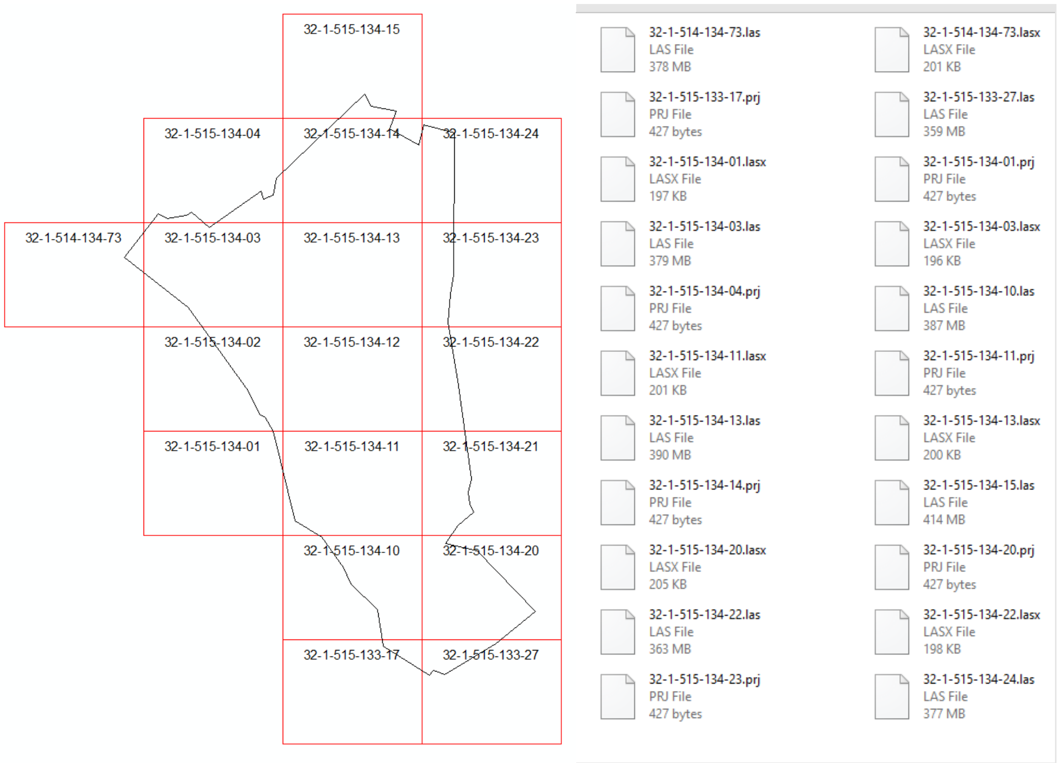


***Figure 10:** LAS Dataset for the city region St. Hanshaugen (2017)*

4.2 Creating a vegetation mask for the tree canopy segmentation

> **In brief**
>
> Classification of vegetation points in the LIDAR point cloud is essential for tree canopy segmentation. This classification can be performed by the data provider or internally if resources are available.
>
> The purpose of this step is to compensate for unclassified vegetation points in the 2014 and 2017 LIDAR data. For this purpose, we derived spatial information about leaf chlorophyll. content from aerial imagery.

As there were no resources available for classification of vegetation points, we had to rely on the existing vegetation points in the Oslo 2011 data (Class 3: Low vegetation, Class 4: Medium vegetation and Class 5: High vegetation). Unfortunately, as described in Chapter 1, the Oslo 2014 and 2017 data lack classified vegetation points. To overcome this lack of vegetation points (in the 2014 and 2017 Oslo data) and support the classified vegetation points from the Oslo 2011 data we decided to derive available Red-Green-Blue (RGB) values from the LIDAR – data, create orthophoto image tiles (at a spatial resolution of 1 x 1 meter) and from them derive a vegetation mask based on a visible band index for remote sensing of chlorophyll. For this purpose, we extracted available RGB-values from the Oslo 2011 and 2014 LIDAR data (there were no RGB-values in the Oslo 2017 LIDAR dataset). High resolution NDVI-data (Normalised Difference Vegetation Index) derived from Sentinel 2 or other RS sensors could have been used as an alternative vegetation mask but was not considered due to its relatively low spatial resolution (10 x 10 m). We did not have access to high-resolution IR- imagery and could therefore not implement a high-resolution NDVI-mask.

The RGB values were extracted and converted into orthophoto image tiles with the "**Create LAS Dataset**" tool and the "**LAS dataset to Raster**" tool (figure 11 and 12). As a part of this workflow we used a **Binning interpolation** to determine the RGB values of the three-band image tiles. This interpolation provides a **Cell Assignment Method** for determining each output cell using the points that fall within its extent, along with a **Void Fill Method** to determine the value of cells that do not contain any LAS points. In this workflow we used the Cell Assignment Method

“NEAREST”. This method uses a Nearest Neighbour assignment to determine the cell value. As Void Fill Method we used the **“NATURAL_NEIGHBOR”** method which uses natural neighbour interpolation to determine the cell value.

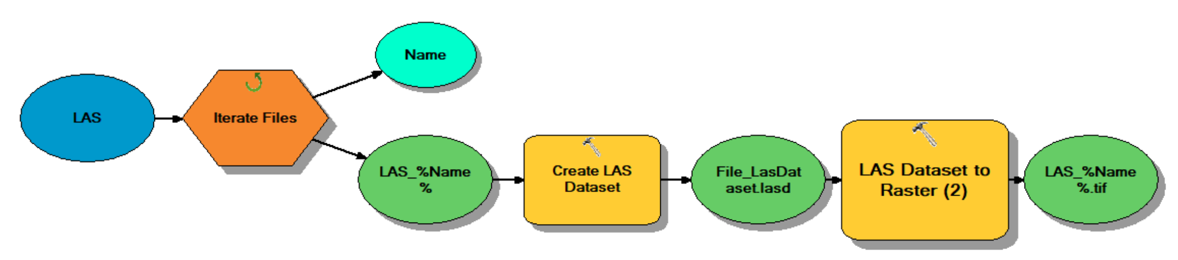


***Figure 11**: The orthophoto workflow*

***Figure 12:** Interpolated LIDAR Ortophoto for 2014 in the city district Ullern..*

The vegetation mask was derived from the orthophoto image tiles using the Triangular Greenness Index (TGI) (Hunt *et al.*, 2013). The TGI is defined as the area of the triangle defined by the reflectance signals for red, green, and blue (figure 13). Hunt *et al. (2013* used Band 1, 2, and 3 of the Landsat Thematic Mapper instrument. Hunt *et al. (2013)* studied several vegetation indices from corn fields in Nebraska. They measured chlorophyll with a handheld meter and collected optical data from the Landsat, aircraft, and field instruments. Optical bandwidths were mathematically combined to simulate digital camera results. Hunt and his co-workers (2013) correlated the results from over twenty different vegetation indices against their field-based chlorophyll measurements and TGI was found to be one of the best. Also, TGI proved to be relatively insensitive to the size of the plants’ leaves (described by the leaf area index).

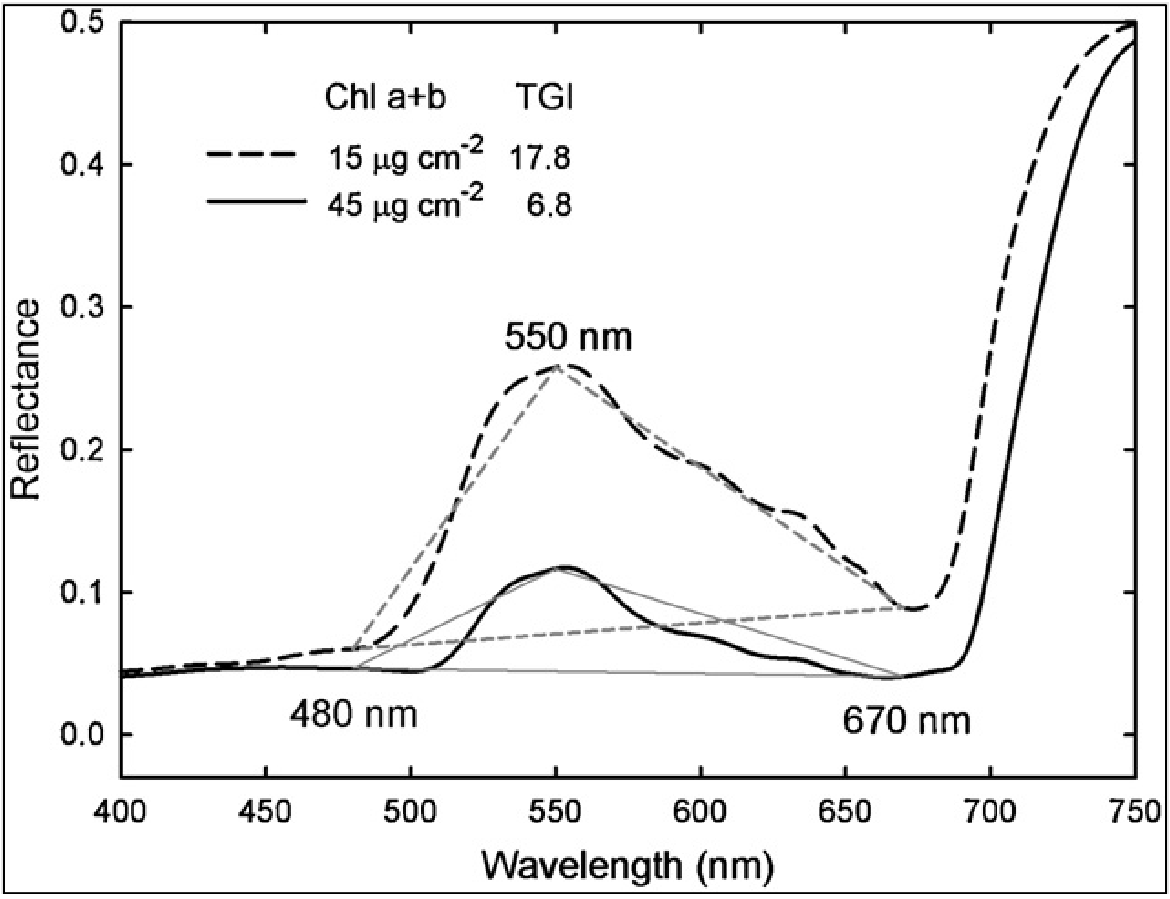


Figure 13: The area of the triangle defined by the reflectance signals for red, green, and blue (Hunt et al., 2013)

McKinnon and Hoff (2017) used peak wavelength sensitivities (Red = 625 nm, Green = 525 nm, Blue = 460 nm) of a typical CMOS camera sensor (Complementary Metal Oxide Semiconductor) in their work, and normalized them the by the green signal as explained in equation 1 below:

Topographical Greeness Index (TGI) = T_{Green} – 0,39 * R_{Red} – 0.61 * R_{Blue} (1)

We calculated the TGI > 0 from the interpolated RGB bands with the use of equation 1 in the "Raster Calculator tool" (figure 14):

TGI = ("%Band2%" - (0.39 * "%Band1%") - (0.61 * "%Band3%")) >= 0

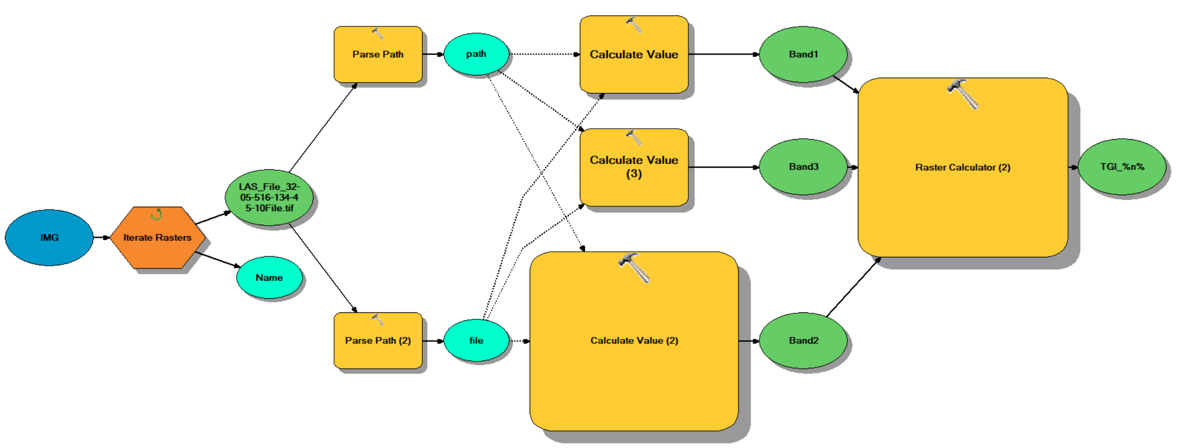


Figure 14: The Triangular Greeness Index (TGI) workflow

The TGI-raster tiles were then reclassified (1=vegetation, 0 non-vegetation), converted to polygon tiles and merged into one TGI vegetation mask for each city region. As shown in figure 15, the TGI vegetation mask corresponds relatively well to vegetated areas. There are however some deviations, especially in shadowed areas next to buildings.

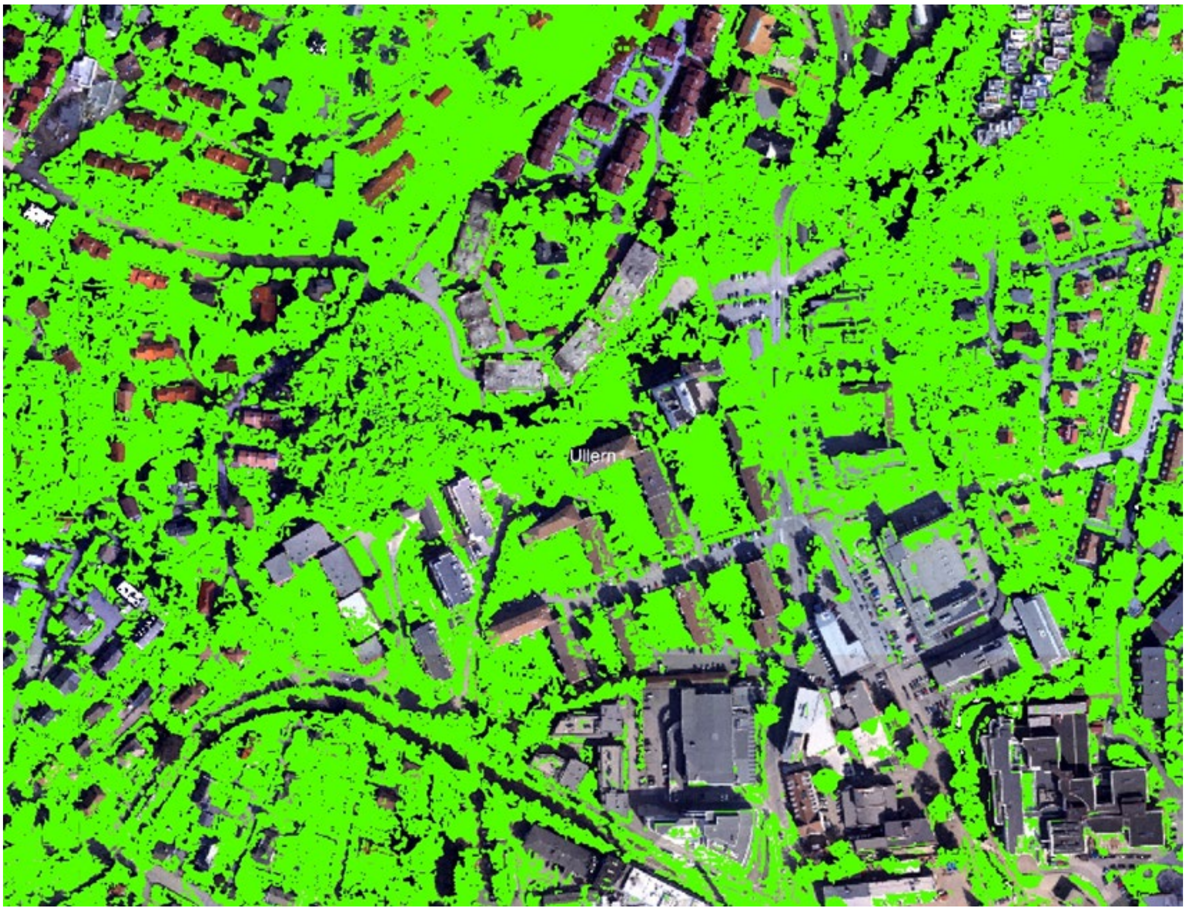


Figure 15*: The Triangular Greeness Index (TGI) mask for the URBAN EEA field sample block 150 in the city district Ullern.*

4.3 Segmenting tree canopy

The tree canopy segmentation workflow consists of 3 steps (figure 16). Due to heavy raster processing the segmentation had to be done stepwise at a city region level.

1. Calculate the Canopy Height Model (CHM)
2. Preparing the CHM
3. Segmentation of trees and tree canopy delineation

In brief

The purpose of this step is to identify the treetops and tree canopies of all trees in Oslo above 2.5 m. For this purpose, we utilize the tree canopy model, and a method that assumes that the shape of an upside-down tree crown resembles a drainage basin, and that the treetop resembles its drainage point.

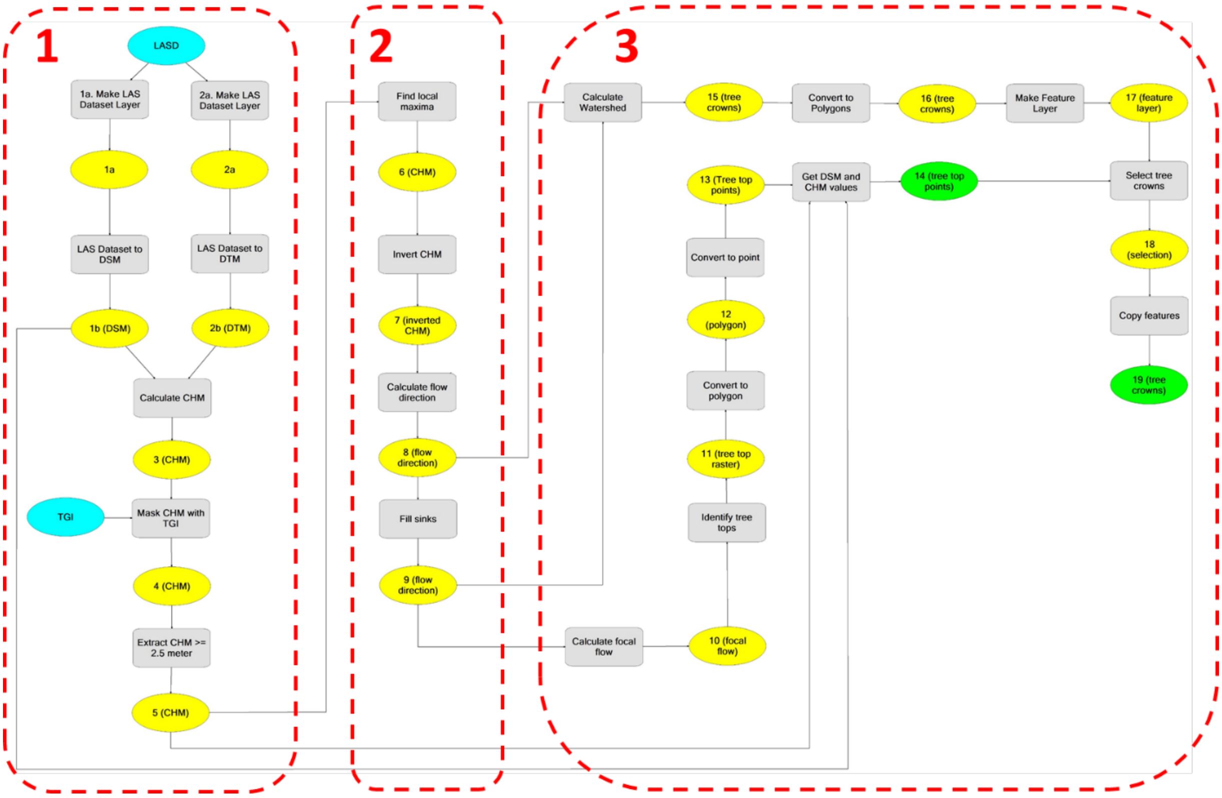


Figure 16: *The tree canopy segmentation workflow with input data (turquoise boxes), functions (grey boxes), intermediate results (yellow boxes) and the final results (green boxes). Part 1 of the workflow represent the calculation of the Canopy Height Model (CHM), part 2 represent the preparation of the CHM and part 3 represent the segmentation of tree tops and the delineation of tree canopies. A larger version of this figure is enclosed in the report appendix.*

4.3.1 Calculate the Canopy Height Model (CHM)

The Canopy Height Model (CHM) is calculated as the difference between the Digital Terrain Model (DTM) and the Digital Surface Model (DSM), as illustrated in figure 17.

In brief

The purpose of this step is to calculate the height of the tree canopy, given by the elevation difference between the Digital Terrain Model and the Digital Surface Model

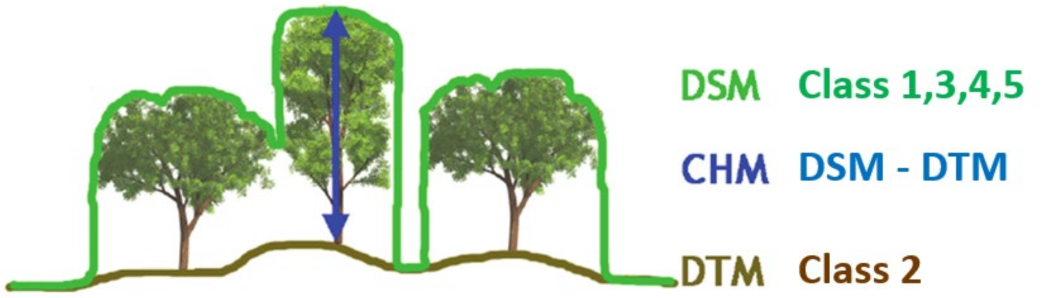


***Figure 17**: The Canopy Height Model (CHM)*

The **DSM** is first created as a LAS Dataset (Point cloud) based on class codes 1-3-4-5 (all returns). Class code 1 represents unassigned points that often contain unclassified vegetation points (valid for the Oslo 2014 and 2017 data). The DSM LAS Dataset was converted to a DSM integer raster (0.5 x 0.5 m) using a Binning interpolation type (with a Maximum Cell Assignment Type and a Linear Void Fill Method). The **DTM** was created the same way as a LAS Dataset (Point cloud) based on class code 2 (all returns). The DTM LAS Dataset was then converted to a DTM integer raster (spatial resolution of 0.5 x 0.5 m) using a Binning interpolation type (with an Average Cell Assignment Type and a Linear Void Fill Method). The **CHM** is given by the difference between the **DSM** and the **DTM** (figure 18, left image). CHM-pixels outside vegetated areas (figure 18, right image) and tree canopies below 2.5 m are set to NoData.

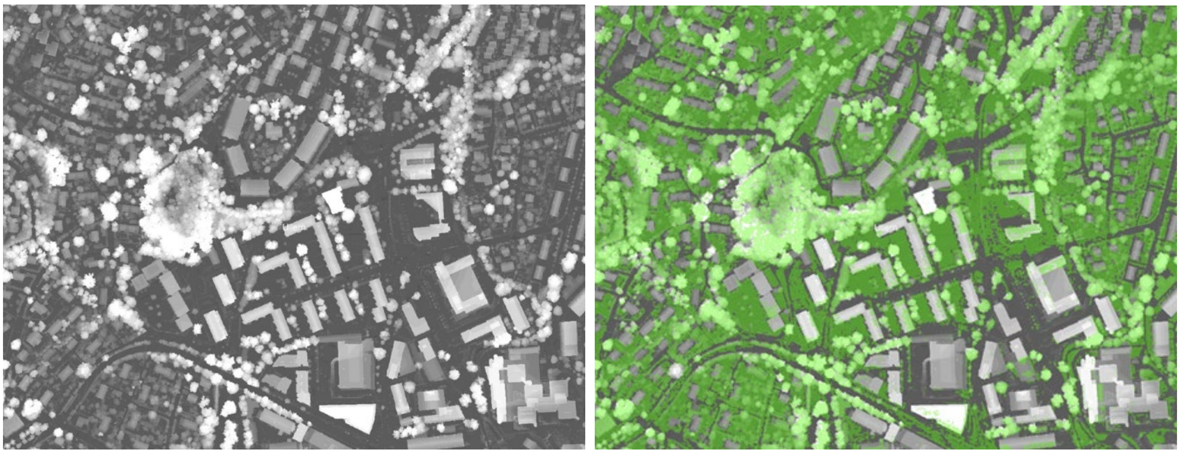


Figure 18: The CHM (to the left) and the TGI- vegetation mask (to the green) in the city district Ullern (based on Oslo 2014 LIDAR- data). The colour scale describes the transition from lower CHM (in dark grey) to higher CHM (in white).

4.3.2 Preparing the CHM

In brief

The purpose of this step is to invert the CHM to imitate a drainage basin, and then calculate the internal flow direction between each cell within the imitated drainage basin resembling the tree canopy

For this study we have implemented a simple Watershed segmentation method using CHM as the basis for detection and delineation of individual trees within an urban environment (Pyysalo & Hyyppa 2002, Suárez *et al.* 2005). This method assumes that the shape of a tree crown resembles a watershed. The method is an image processing technique developed to outline drainage basins from a DTM. Conceptually, this technique can be described as gradually filling basins with water. Where the water of two adjacent basins connects, a boundary is detected. As the water rises, these boundaries delineate each drainage basin (S. Beucher & Lantejoul, 1979). Due to the morphological similarities between a DTM and a CHM, this technique has been applied to delineate individual tree crowns from an inverted CHM (Chen et al., 2006).

First the CHM was smoothed using Maximum Statistics enabled by the "**Focal Statistics tool**". The purpose of this operation is to find the Local Maxima (figure 19) (Franceschi, 2017), using a circular neighbourhood search filter diameter of 3 m. It is challenging to find a perfect search filter as this varies locally and often is species specific, based on the morphological structure of the different tree species. After some visual inspections in orthophotos and using best practices from literature (see Barnes et al., 2017), we decided to use a search filter of 3 m (in diameter). It should however be underlined that this is fixed proxy that will probably have a best fit for larger trees.

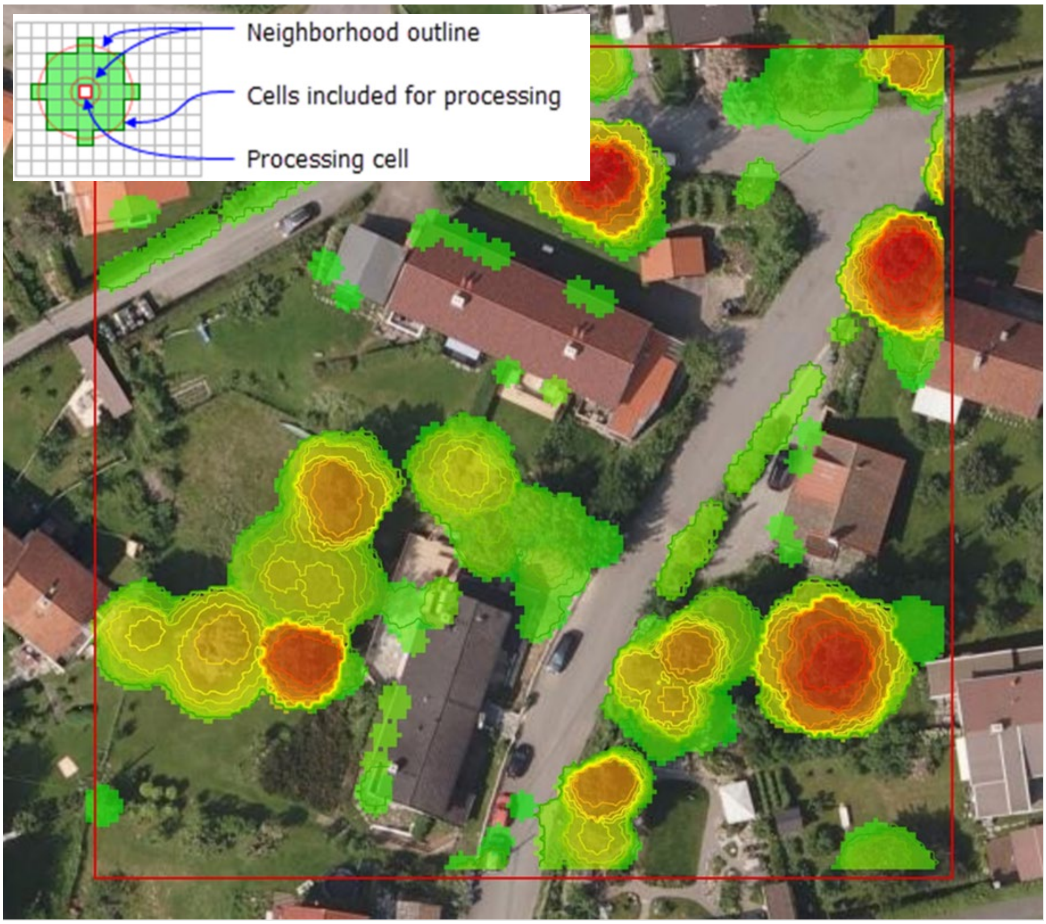


***Figure 19**: Smoothing of the CHM by the Local Maxima filter. Green area are lower CHM values whereas red areas represent higher CHM values.*

The smoothed CHMs were then inverted by negating the elevation values in the raster. The negated CHM raster was then treated as an imitated watershed. To determine the direction of flow from every cell in the inverted CHM we used the “**Flow Direction tool**” and the **eight-direction (D8) flow model** that assumes that there are eight valid output directions representing the eight neighbouring cells into which flow could travel (Jenson and Domingue,1988). Following this approach, the flow direction is determined by the direction of the maximum drop from each cell, as expressed in equation 2 below.

Maximum_drop = Change_in_z-value / distance * 100 (2)

The distance between cells is calculated between the centroids of the cells. The cell size of our negated CHM is 0.5 x 0.5 m, which gives a distance between two orthogonal cells of 0.5 meter, and a distance between two diagonal cells of 1 meter (the square root of 1). If the maximum descent to several cells is equal, the neighbourhood will be enlarged until the steepest descent is found. When a direction of the steepest descent is identified, the output cell is coded with the value representing that direction. If all neighbours are higher than the processing cell, it will be considered noise, be filled to the lowest value of its neighbours, and have a flow direction toward this cell. However, if a one-cell sink is next to the physical edge of the raster or has at least one NoData cell as a neighbour, it is not filled due to insufficient neighbour information. To be considered a true one-cell sink, all neighbour information must be present. If two cells flow to each other, they are sinks and will have an undefined flow direction (Jenson and Domingue (1988).

4.3.3 Segmentation of trees and tree crown delineation

In brief

The purpose of this step is to detect the drainage points (treetops) and delineate the drainage basin (tree crowns)

In this step of the segmentation workflow we have used the “**Focal flow tool**” to detect the local maxima of each tree (representing the tree tops) and the “**Watershed tool**” to delineate the CHM watersheds (representing the tree crowns).

The **Focal Flow tool** uses a "moving window" to identify which of a cell's eight neighbours flows into it. A flow in this context is defined by any cell within the neighbourhood that has a higher value than the processing cell itself. To test if a neighbourhood cell flows into the processing cell, the value of each neighbourhood cell is subtracted from the processing cell. A positive value means that the neighbourhood cell does not flow into the processing cell, where as a negative value mean that it does. Where no cells flow into the processing cell the value will be 0. The combination of flow from multiple neighbourhood cells into a single processing cell is accomplished through the binary representation of the processing cell. Each bit of the binary representation for the processing cell correlates to a neighbourhood cell location. The cell to the immediate right of the processing cell is given the value 1, the neighbour to the lower right is 2, the neighbour directly below is 4, and so forth—until the value of 128 (powers of two, since representation occurs in binary) is reached for the last neighbour to the upper right (figure 20).

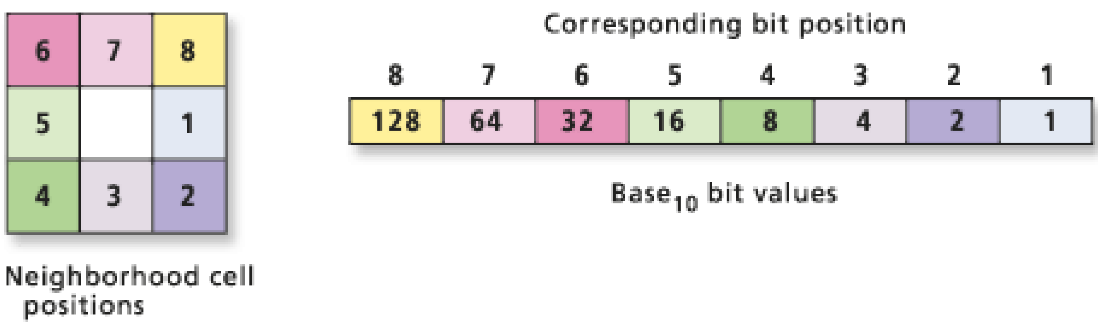


***Figure 20**: Focal Flow direction encoding*

If a neighbourhood cell flows into the processing cell, the bit that represents the neighbourhood location is turned on or assigned to 1. Conversely, if a neighbourhood cell does not flow into the processing cell, the bit that represents the location is turned off, or assigned to 0. Once all neighbourhood locations have been tested for flow, none, one, several, or all bits can be turned on (assigned a 1). The binary representation for all bits is converted back to $base_{10}$ bit value in accordance with the flow-bit pattern. The $base_{10}$ bit value is then assigned to the processing cell. This encoding assigns a unique number to each possible combination of upstream numbers. The total number of combinations of flow into a processing cell is 255. Cells with a 0 value are equal to the individual tree tops.

Finally, we segmented the tree crowns from the flow direction map (described above) using the "**Watershed tool**". A watershed is the upslope area that contributes a flow (e.g. water) to a lower common outlet or drainage point (in this case the tree tops). The boundaries between the watersheds represent the tree canopy delineations. The steps in section 4.3.1, 4.3.2 and 4.3.3 are illustrated in figure 21 and the corresponding tree canopy segmentation is illustrated in figure 22.

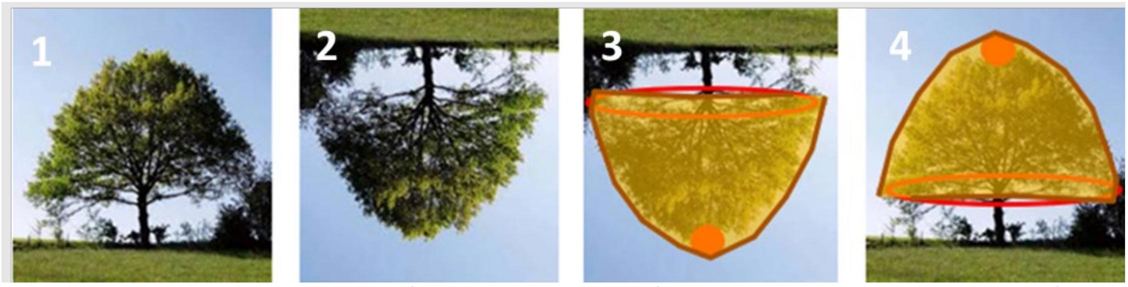


***Figure 21**: Image 1 illustrate the tree Canopy Height Model (CHM). Image 2 illustrate the inverted CHM. Image 3 illustrate the calculated drainage basin (resembling the tree crown) and its drainage point (resembling the treetop). Image 4 illustrate the re-inverted tree crown and treetop features.*

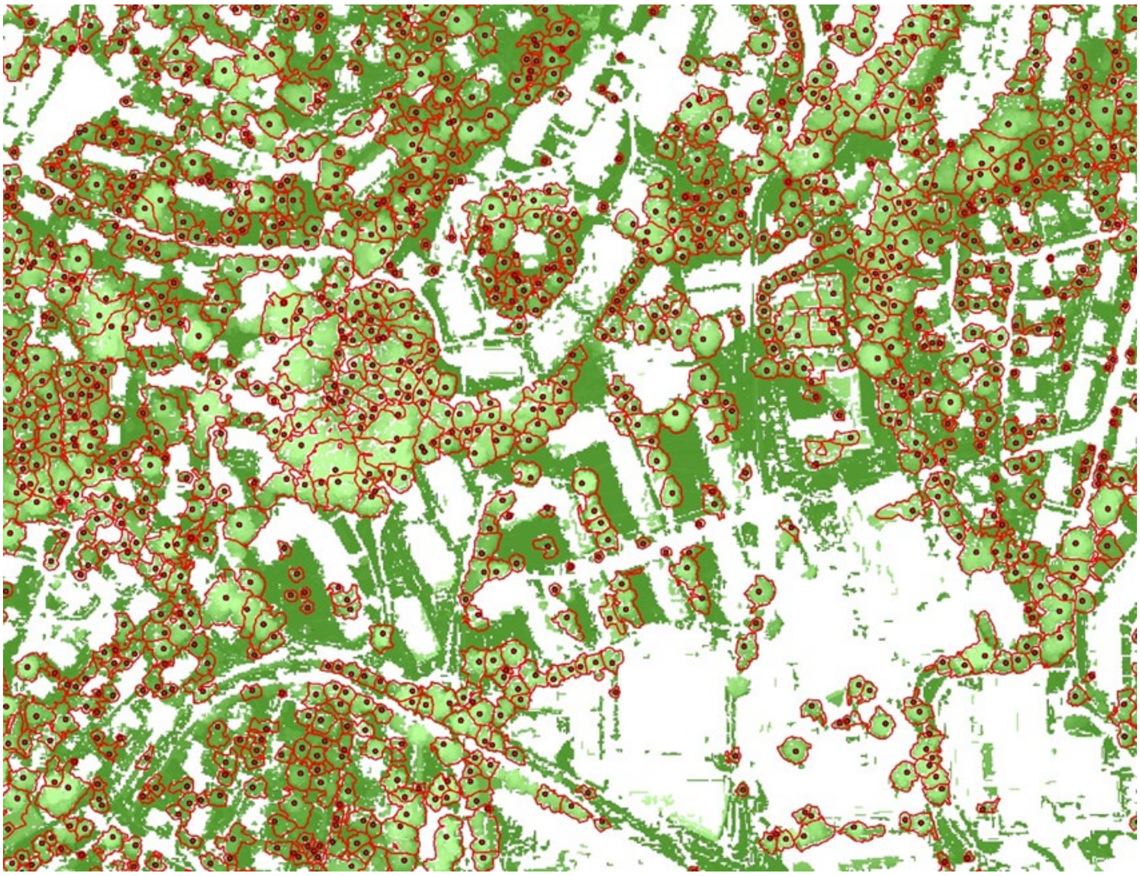


Figure 22: Segmented tree tops and delineated tree crowns displayed on the CHM and the TGI vegetation mask.

Finally, the diameter for calculation of tree crown volume of the, sometimes irregular, tree crowns were approximated circularly using the “Minimum Bounding Geometry (MGB)” tool. This created a minimum bounding circle envelope around each tree crown. The attribute table of the MGB circle dataset were then joined to the tree crown dataset with the help of the unique CROWN_ID.

4.4 Estimating tree canopy surface and volume

In brief

The purpose of this step is to estimate tree canopy surface and volume. The tree canopy volume will be combined with tree species information to estimate the Leaf Area Index (LAI) as a condition indicator and input to the i-Tree Eco model for calculating regulating services of city trees.

The tree canopy volume can be used to approximate the Leaf Area Index (LAI). There are several ways to estimate the volume of our segmented tree canopies from Oslo. For this study we are comparing three methods, namely standard ArcGIS 2D area surface, simplified geometrical 3D area surface (Nowak,1996) and a simplified volume of a cone resembling a tree crown.

The 2D area surface of each tree crown feature is automatically calculated (according to the units of the actual coordinate system) when data are stored in a geodatabase. The Surface Area of a 3D shape (e.g. a tree crown) is the total area of the outside of that shape. Depending on the complexity of the shapes form, the 3D area can be calculated at different complexities and with many different equations. We chose to calculate the simplified geometrical 3D surface area (Nowak 1996) according to equation 3:

$$\boldsymbol{S\ geom} = \left(\frac{\boldsymbol{\pi * D * (H+D)}}{\boldsymbol{2}}\right) \qquad \textbf{(3)}$$

Where ***D*** is the minimum bounding circle diameter around each segmented tree crown and ***H*** is the segmented tree top height:

The simplified volume of the tree crowns was calculated using the formula for the volume of a cone, according to equation 4:

$$\boldsymbol{Volume} = \frac{1}{3} * \pi * r^2 * h \qquad \textbf{(4)}$$

Where ***r*** is the half of the minimum bounding geometry diameter of each segmented tree crown and ***h*** is the height of each segmented tree.

4.5 Masking out false trees

> **In brief**
>
> The purpose of this step is to remove objects (buildings and technical infrastructure) that are incorrectly segmented as trees.

To remove objects incorrectly segmented as trees, we applied a mask of buildings and other technical infrastructures (point and linear features were buffered with 1 meter). Segmented trees with tree tops located inside this mask were excluded. In addition, we also filtered out all segmented trees having an invalid tree canopy height (see figure 23). Statistics about this are presented in Chapter 5. One consequence of this masking process is that actual trees (within the vegetation mask) under power lines or close to buildings, monuments, powerline poles, tele-communication poles, street light poles and traffics signs etc. will be excluded.

Figure 23: *The image to the left displays the unmasked trees (in red) and the building mask (blue). The image to the right displays the trees (in red) remaining after filtering for interception with the building mask (blue).*

5 Modelling results

5.1 Number of trees

The LIDAR-based tree segmentation model identifies tree tops (point dataset) and tree crowns (polygon dataset) for all trees above 2.5 m (figure 24, 25 and 26), following the same definition as Tanhuanpää et al. (2014). The corresponding data attribute information is described below in table 6:

Table 6: Calculated outputs

CrownID	The unique ID of each segmented tree
2DAREA	The 2D surface area of each segmented tree crown
PERIMETER	The perimeter of each segmented tree crown
G_ELEV	The ground elevation of each segmented tree
C_ELEV	The canopy height (tree top height) of each segmented tree
MGBDIAM	The minimum bounding geometry diameter of each segmented tree crown
SGeom	Simplified geometrical 3D area surface
Volume	Simplified volume of the tree crown

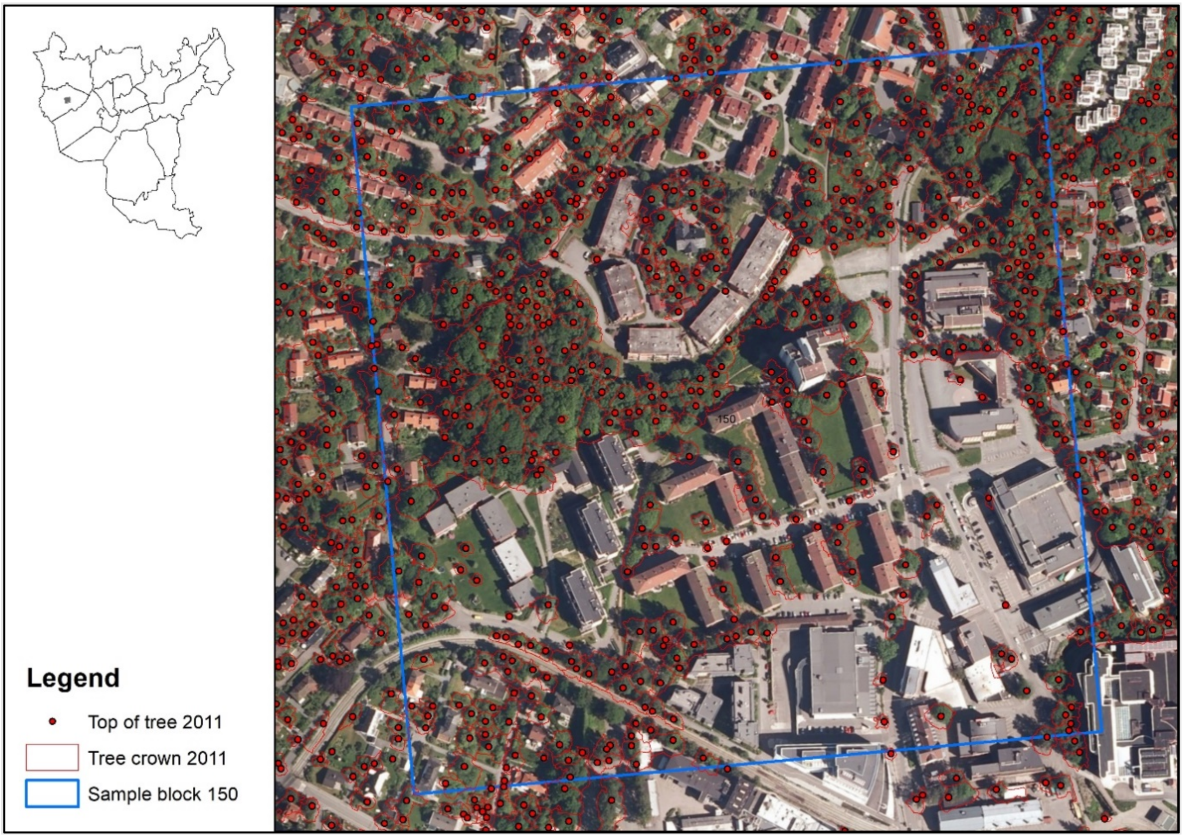


Figure 24: *Masked (filtered for buildings and technical infrastructures) tree segmentation 2011 in the URBAN EEA field sample block 150 in the city district Ullern.*

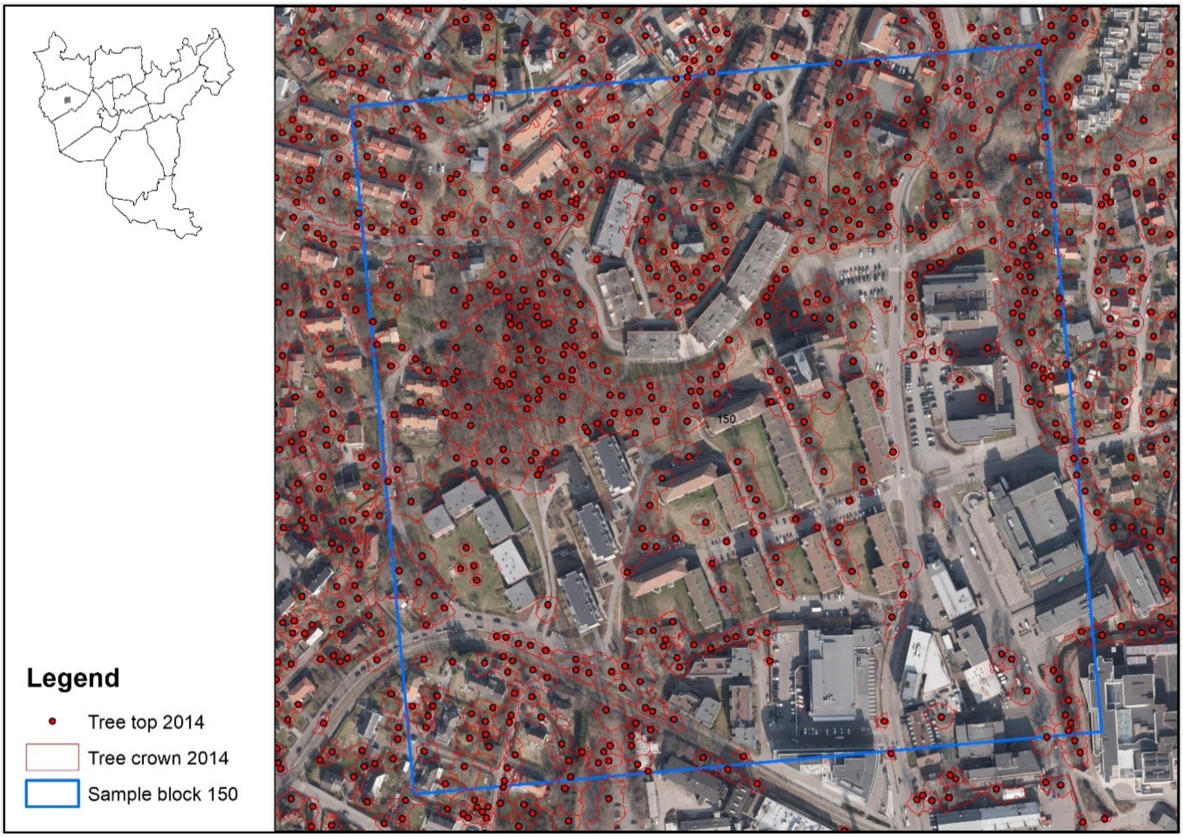


Figure 25: *Masked (filtered for buildings and technical infrastructures) tree segmentation 2014 in the URBAN EEA field sample block 150 in the city district Ullern.*

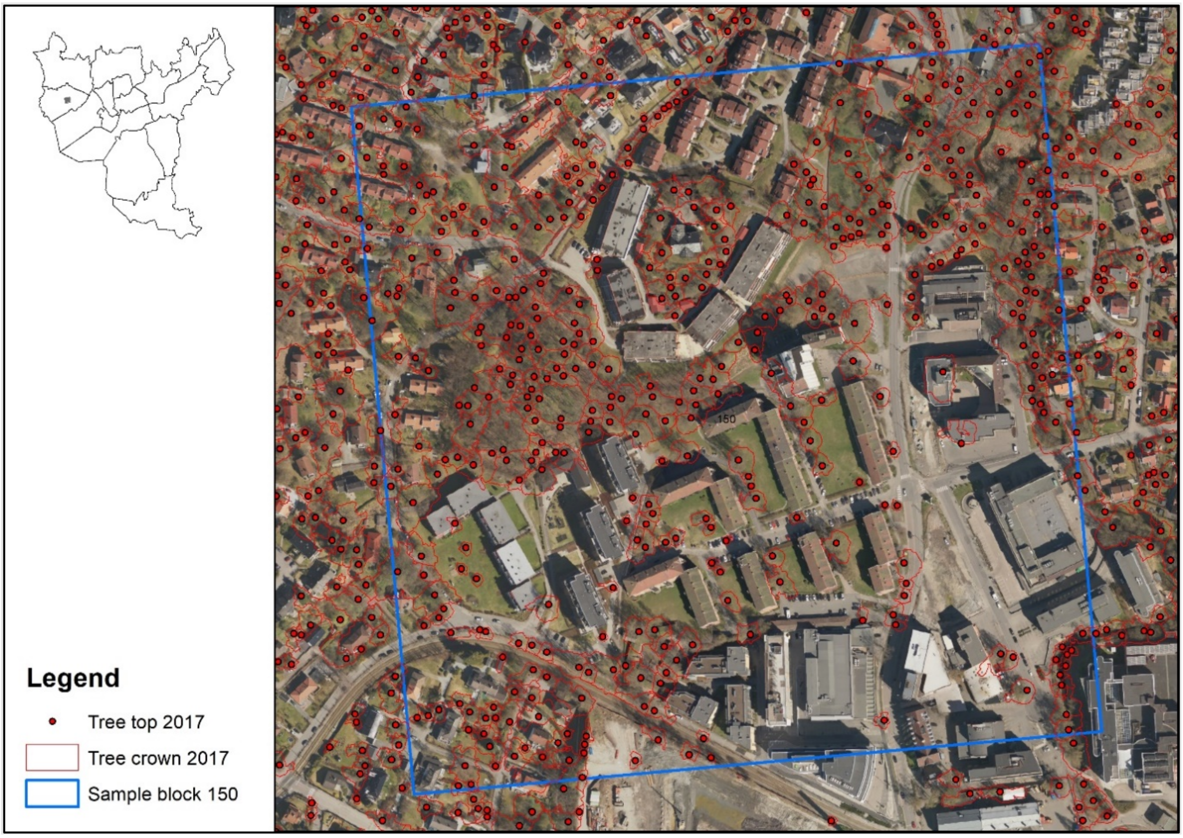


Figure 26: *Masked (filtered for buildings and technical infrastructures) tree segmentation 2017 in the URBAN EEA field sample block 150 in the city district Ullern.*

> **In brief**
>
> The TGI-corrected infrastructure-masked Lidar data identified approximately 393 000 individual canopies taller than 2.5 m in Oslo's built zone. For Oslo as a whole, the number of large trees increased (>10 m height), while the number of smaller trees fell somewhat. For the area in the "small house plan" the number of large trees fell, while small trees increased.

The canopy height is estimated at the top of the tree, and the tree crown is delineated at the lowest part of the tree crown. The 2011 segmentation resulted originally in a total amount of 372 404 trees. Of this, 1,73 % (6448) of the segmented trees was located inside the FKB-mask. The masked 2011 dataset contains 365 956 individually segmented tree canopies (328 963 in the built-up zone and 67 536 in the Småhusplan-area). The Small House Plan (Småhusplan) area is identified separately because it is subject to urban densification and special regulations for felling of large trees. The 2014 segmentation resulted originally in a total amount of 421 913 tree canopies. Of this, 4,15 % (17 548) of the segmented canopies was located inside the FKB-mask. The masked 2014 dataset contains 404 365 canopies (345 766 in the built-up zone and 64 037 in the Småhusplan-area). Finally, the 2017 segmentation resulted originally in a total amount of 420 660 tree canopies. Of this, 6,48 % (27271) of the segmented trees were located inside the FKB-mask. The masked dataset contains 393 389 trees (352 288 in the built-up zone and 63 189 in the Småhusplan-area).

5.2 Canopy height, area and volume

Table 7 shows that the median tree canopy heights for the Oslo built-up-area spans from 15 m (2011), to 15 m (2014) and 16 m (2017). For the same area the median tree canopy area spans from 93.67 m^2 (2011), to 102.85 m^2 (2014) and 101.51 m^2 (2017). The median tree canopy volume spans from 849,9 m^3 (2011), to 961,8 m^3 (2014) and 953,4 m^3 (2017). The statistical distribution of the tree canopy height, 2D/3D canopy area and canopy volume are displayed in Figure 27, 28 and 29.

Table 7: *Tree height 2D- and 3D tree crown area and Volume statistics for segmented trees in the Oslo built-area.*

	Canopy Height (m)			*2D canopy area (m^2)*			*3D canopy area (m^2)*			*Canopy volume (m^3)*		
	Min.	*Median*	*Max.*	*Min.*	*Median*	*Max.*	*Min.*	*Median*	*Max.*	*Min.*	*Median*	*Max.*
2011	2.5	15.0	50.0	1.0	93.7	4005.1	25.8	711.5	23789.5	6.6	849.9	118217.3
2014	2.5	15.0	50.0	0.6	102.9	1826.0	21.4	770.6	20714.7	4.8	961.8	68764.7
2017	2.5	16.0	50.0	0.2	101.5	2704.1	4.3	768.4	36999.0	0.4	953.4	174899.8

For the city as a whole the change in number of shorter trees (< 13 m) was variable, while the number of taller trees (> 13 m) increased consistently between 2011-2017 (see figure 27). This change was observed despite weaknesses in the data which might have tended to overestimate the number of tall trees in 2011-2014 due to lacking correction for infrastructure (see reliability below).

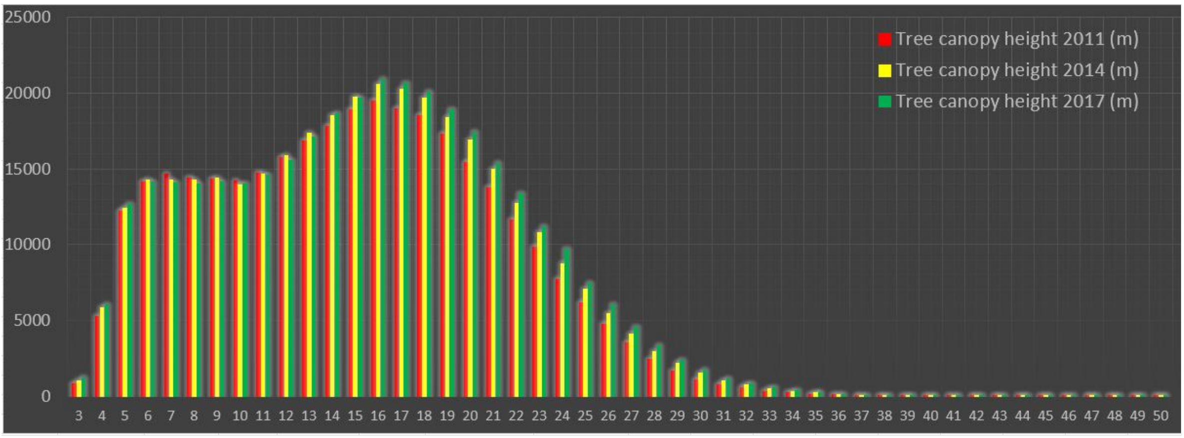


Figure 27: *Tree canopy height (in m) in the Oslo built-up area. The y-axis represents the number of trees and the x-axis represents identified different tree heights from 2.5 (rounded up to 3) to 50 m. The long tail of the distribution above 35 m may be caused by signals of temporary man-made structures such as cranes.*

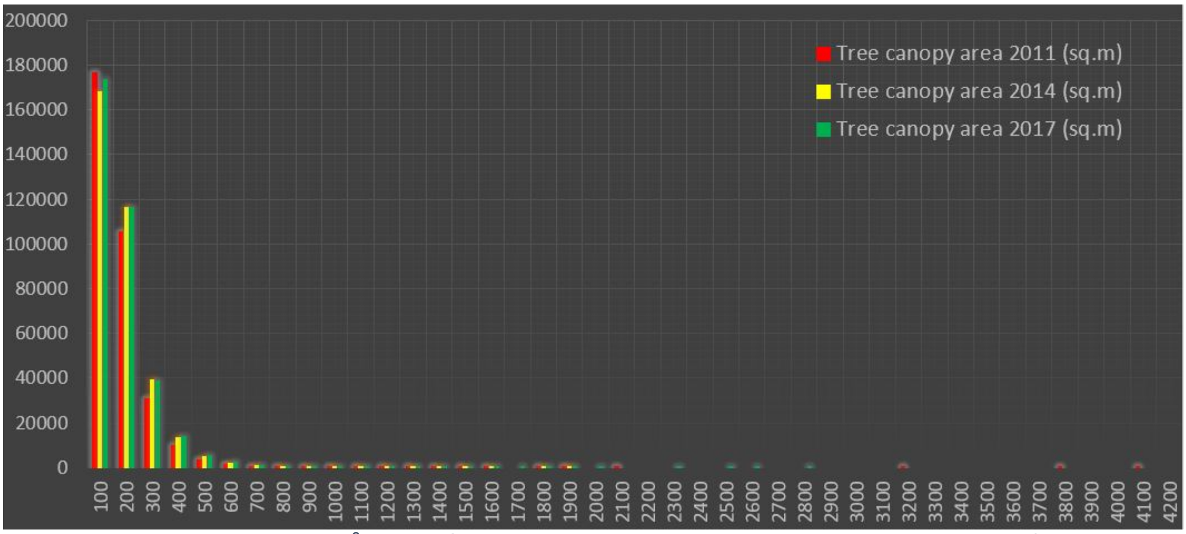


Figure 28: *Tree canopy area (m^2) in the Oslo built-up area. The y-axis represents the number of trees and the x-axis represents classified 2D tree crown area intervals.*

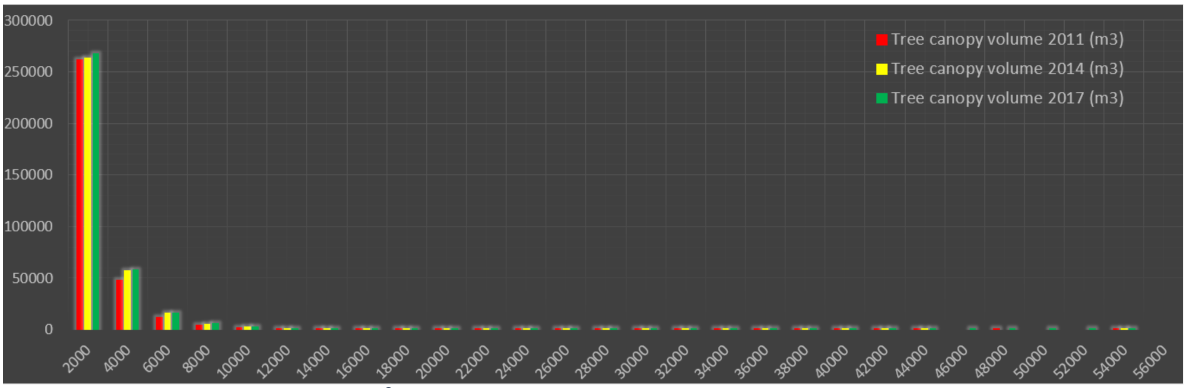


Figure 29: *Tree canopy volume (m^3) in the Oslo built-up area. The y-axis represents the number of trees and the x-axis represents classified tree crown volume intervals.*

Table 8 shows that the median tree canopy heights for the *Oslo Småhusplan area* changed from 14 m (2011), to 11 m (2014) and then to 11 m (2017). For the same area the median tree canopy area changed from 95.05 m^2 (2011), to 105.74 m^2 (2014) to 106.09 m^2 (2017). The median tree canopy volume changed from 833,2 m^3 (2011), to 753 m^3 (2014) to 753 m^3 (2017).

Table 8: Tree height and tree canopy area statistics for segmented trees in the Oslo Småhusplan-area

	Canopy height (m)			2D canopy area (m²)			3D canopy area (m²)			Canopy volume (m²)		
	Min.	Med.	Max	Min.	Med.	Max.	Min.	Med.	Max.	Min.	Med.	Max.
2011	2.5	14	50	1.8	95.1	4005.1	25.8	710.5	23616.8	6.6	833.2	118217.3
2014	2.5	11	46	3.9	105.7	1460.2	62.3	209.7	15138.2	22.0	753.0	52637.3
2017	2.5	11	44	0.2	106.1	1782	4.3	712.8	19154.7	0.4	753.0	82249.5

The statistical distribution of the tree canopy height and canopy volume in the Småhusplan area are displayed in figure 30 and 31.

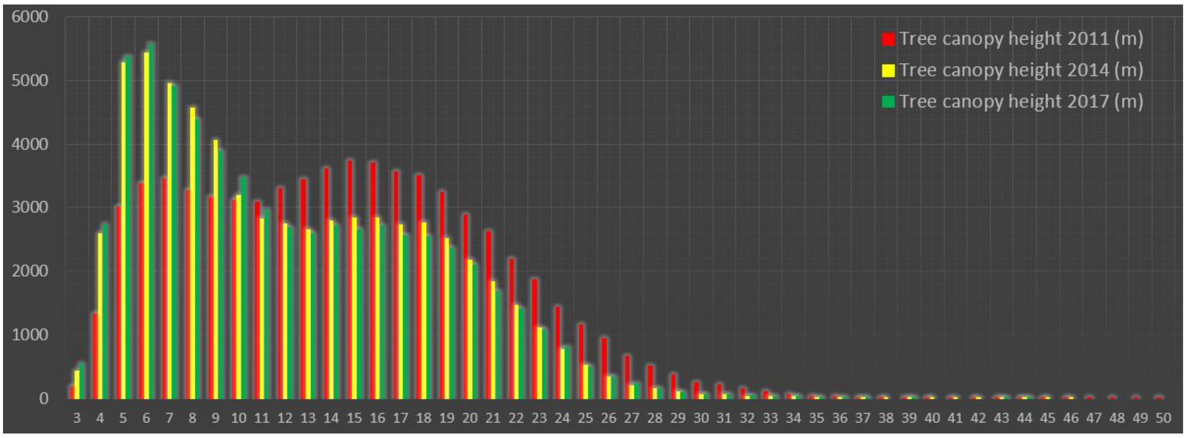


***Figure 30:** Tree canopy height (in m) in the Småhusplan area (policy focus). The y-axis represents the number of trees and the x-axis represents the different tree heights from 2.5 (rounded up to 3) to 50 m. The long tail of the distribution above 35 m may be caused by signals of temporary man-made structures such as cranes.*

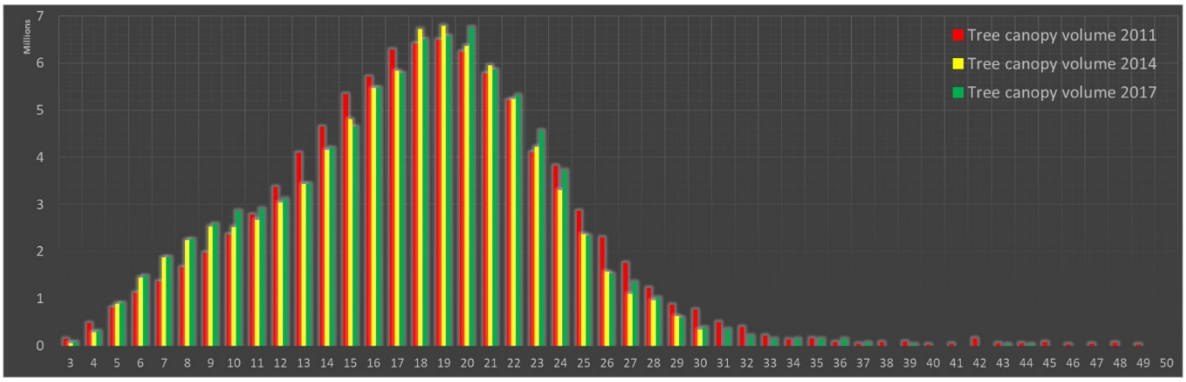


***Figure 31:** Tree canopy volume (in m³) in the Småhusplan area (policy focus). The y-axis represents the tree canopy volume (in million m³) and the x-axis represents the different tree heights from 2.5 (rounded up to 3) to 50 m.*

Between 2011-2017 we observe a clear loss in taller trees (>10 m), but an increase in short trees (< 10 m). There is a similar gain in tree crown volume for short trees. While there is a loss in volume for taller trees (10 m - 17 m) there is a gain in estimated total volume for taller trees (18m-23m), and then a loss in volume for the tallest trees (> 23 m). Because it is a height specific effect in the Småhusplan area it does not seem to be an effect of estimation assumptions or data quality. In the Småhusplan area one possible explanation for this could be adaptation of tree canopies to increased light availability caused by the tree thinning associated with construction.

For ecosystem services it implies that the visual effect of loss of individual tall trees, might be compensated for over time by growth in overall canopy. This would imply that visual aesthetic changes are relatively greater than changes in regulating functions of the tree canopy as a population.

5.3 Comparison with field data from Oslo PBE

The Agency for Planning and Building (PBE) in Oslo municipality manages the most complete database of private and public trees (point data) in the Oslo built-up area. The FKB tree database misses some private garden trees and lacks forest trees. It contains in total **102 329 trees** which are precisely measured in the field using GPS. As the FKB-database does not contain any tree attributes we can only compare it spatially with the ALS segmented trees. **74,7 % (76507)** of the FKB-trees in the FKB-database overlapped with the unmasked ALS trees in the Oslo built-up area. **73.6 % (75311)** of the FKB trees overlapped with the masked ALS trees. Figure 32 illustrates the differences between the two datasets at different scales.

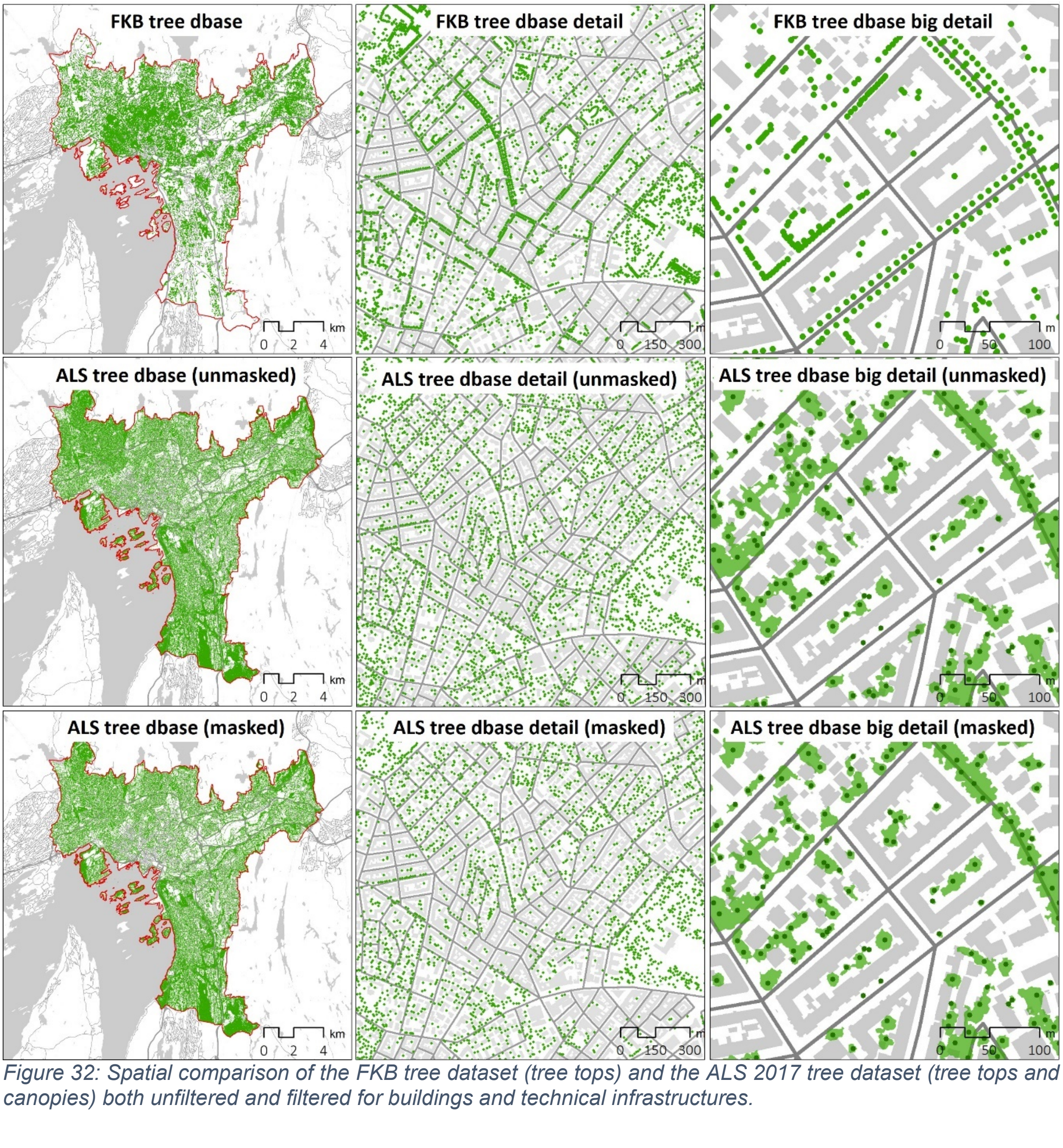


Figure 32: Spatial comparison of the FKB tree dataset (tree tops) and the ALS 2017 tree dataset (tree tops and canopies) both unfiltered and filtered for buildings and technical infrastructures.

Using the original vegetation classification for 2011 by PBE-Oslo Kommune, rather than the TGI-corrected Lidar method shown in this report, Barton et al. (2015) refers to approximately 700 000 trees in Oslo's built zone, against approx. 393 000 for 2017 identified in this report. PBEs 2011 data used by Barton et al. (2015) counts canopy tops which may overestimate the number of stems. The TGI-corrected Lidar data segments individual canopies which may underestimate the number of individual stems.

In brief
The TGI-corrected segmentation method used in this report underestimates tree canopy area relative to a vegetation classification of ALS raw data by 95.2 % (2011).

The large difference between the number of trees reported in the City Tree Strategy and our results could mainly be explained as a combination of inaccuracy related to the segmentation method, the unevenly distributed point density, the lacking vegetation coding in the LIDAR data (2014 & and 2017) and the application of the TGI vegetation mask.

The TGI-corrected segmentation method used in this report overestimates tree canopy area relative to a vegetation classification of the ALS raw data by 95.2 % and underestimates the number of individual trees by 72.9 % (2011). The reason for the smaller number of segmented trees from 2011 (297 679 vs. 728 396 trees) is probably that several crowns are detected as one tree. This is probably an underestimating effect of the fixed kernel size (3 m in diameter) of the Local Maxima for trees < 30 m. The reason for the larger tree canopy estimation in our segmented tree canopies from 2011 (36 474 767 m^2 vs. 18 684 601 m^2) could be (i) misdetection of other structures or (ii) limits for tree canopy border in the tree segmentation process (crowns are detected larger than they are). It would be necessary to know more about the process used for the segmentation of the PBE ALS 2011 tree data in order to draw further conclusions on the deviating results.

Table 9: Comparison of PBE (2011) canopy area and tree number with TGI-corrected tree crown segmentation. Tree numbers and tree canopy areas were compared in an intersection of study areas of both datasets to ensure comparability.

	Canopy area (tree height 5-35 m)	**Number of trees (tree height 5-35 m)**
TGI-corrected segmentation	36 474 767 m^2	297 679
PBE LiDAR estimation (2011)	18 684 601 m^2	728 396

5.4 Comparison between Sentinel-1&2 (S4N). and Sentinel-2 and ALS tree pixels

As a part of the research project Sentinel4Nature "*Monitoring and mapping of environmental gradients using Sentinel 2 data in combination with supplemental data from Sentinel-1*" (Blumentrath et al., 2016), tree pixels were segmented at a spatial resolution of 10 x 10 m (figure 33). Sentinel-1[16] carry a C-band Synthetic Aperture Radar (SAR) instrument and has a spatial resolution ranging from 5 to 40 m. Sentinel-2[17] has a Multi Spectral Instrument (MSI) covering 13 spectral bands ranging from 443 nm to 2190 nm (including 3 bands for atmospheric corrections), a spectral resolution ranging from 1 nm– 180 nm and a spatial resolution of 10, 20 and 60 m.

[16] https://sentinel.esa.int/documents/247904/1653440/Sentinel-1_Data_Access_and_Products
[17] http://www.d-copernicus.de/fileadmin/Content/pdf/Sentinels_update_170510_final_printed.pdf

To compare the spatial coverage of the segmented ALS tree crown data with the S4N-tree coverage (Sentinel 1 and 2), we rasterized and reclassified the segmented tree data from Oslo 2017 into the same spatial resolution, position and orientation as the Sentinel-2 tree pixels (figure 33 and 34).

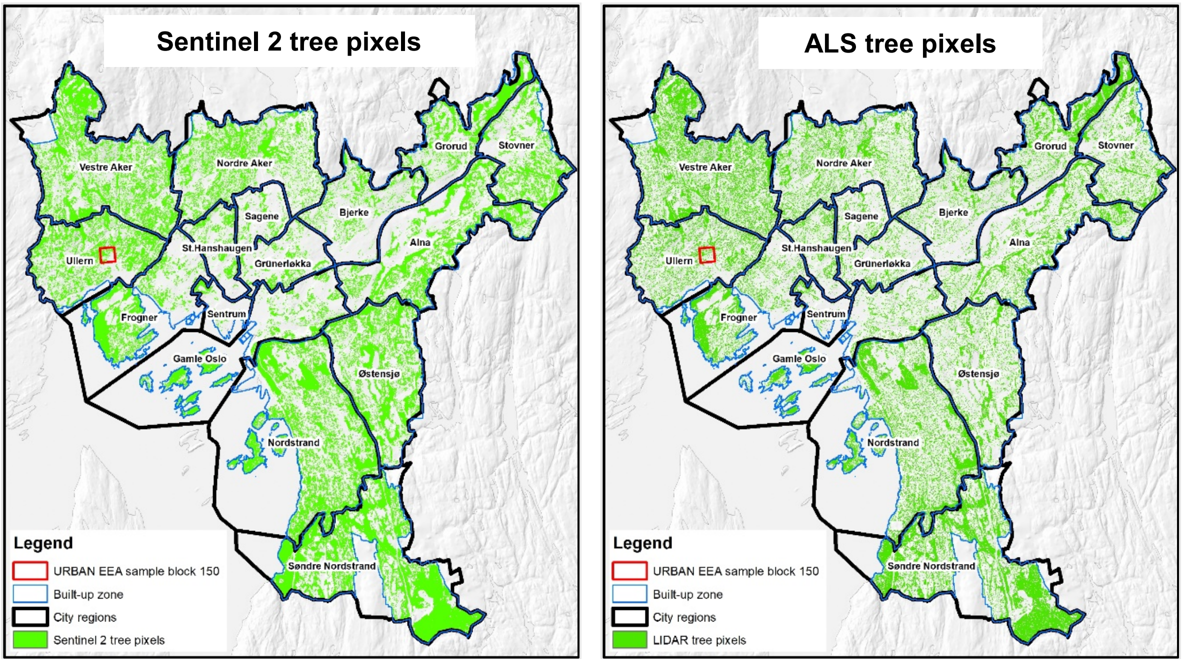


Figure 33: Comparison of Sentinel-2 and segmented LIDAR tree pixels for the Oslo built-up zone medio 2017.

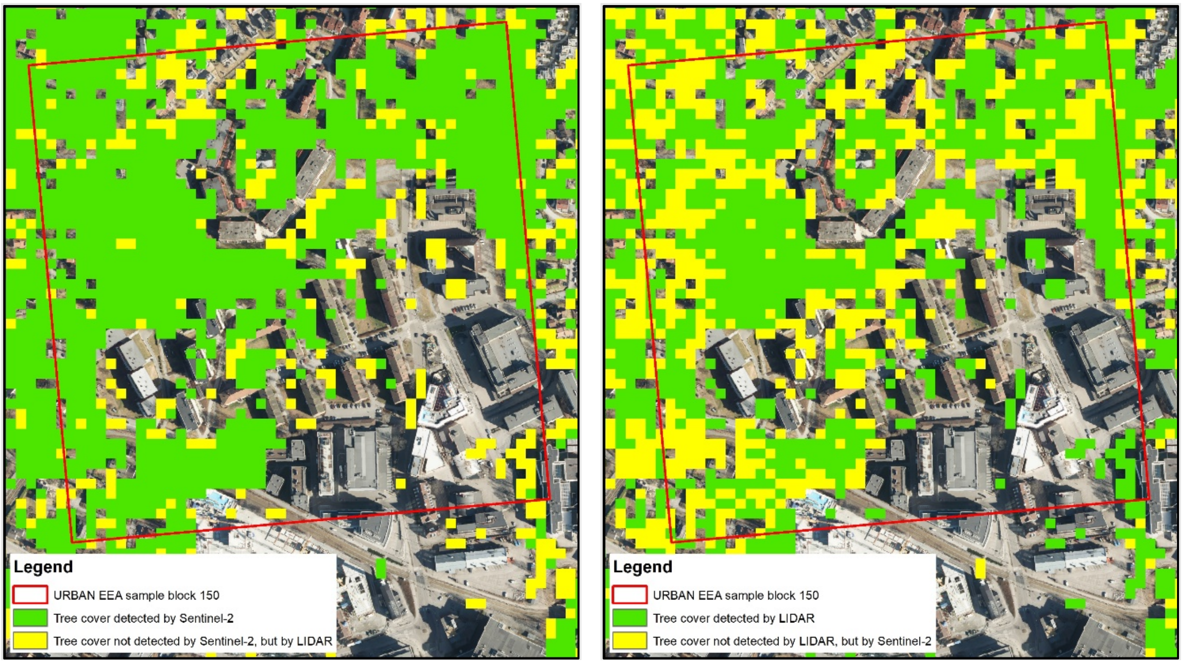


Figure 34: Spatial distribution of tree cover detection between Sentinel-2 (2017) and LIDAR (2017) for the URBAN EEA sample block 150 in the Ullern city region.

Comparing the Sentinel-2 and the aggregated ALS tree pixels reveal a relative similar spatial distribution pattern. The aggregated ALS tree pixels give a more detailed tree canopy map throughout the entire urban landscape. This was expected due to the original segmentation units of the ALS tree canopy (0.5 x 0.5-meter pixels) compared to the Sentinel2 tree canopy segmentation units (10 x 10 m).

Table 10: Comparison of the 2D tree canopy area (given in daa) within the Oslo built-up zone as detected from LIDAR and Sentinel2.

City region (Oslo built-up area	Lower resolution data overestimates canopy area (y/n)	ALS (daa)	Sentinel-2 (daa)
Alna	yes	3379	4506
Bjerke	yes	1491	1584
Frogner	yes	2508	2934
Gamle Oslo	yes	1770	2116
Grorud	yes	2425	2676
Grünerløkka	yes	850	948
Nordre Aker	yes	3719	4680
Nordstrand	yes	6320	8238
Sagene	no	551	516
Sentrum	no	260	243
St.Hanshaugen	yes	846	891
Stovner	yes	2102	2813
Søndre Nordstrand	yes	7482	9324
Ullern	yes	2695	3957
Vestre Aker	yes	6829	7233
Østensjø	yes	2669	4981

Sentinel-2 contain less details and seems to overestimate tree canopy area in the urban landscape with many spatially segregated individual trees. Two exceptions are found in the inner city and may be in part be explained by misclassification of building sites in ALS data (Sentrum). This needs further work as the explanation is not clear-cut for the Sagene district. At an aggregated city region level, the relationship between the two variables are highly significant (*r = 0.98*) (table 10 above and figure 35 & 36).

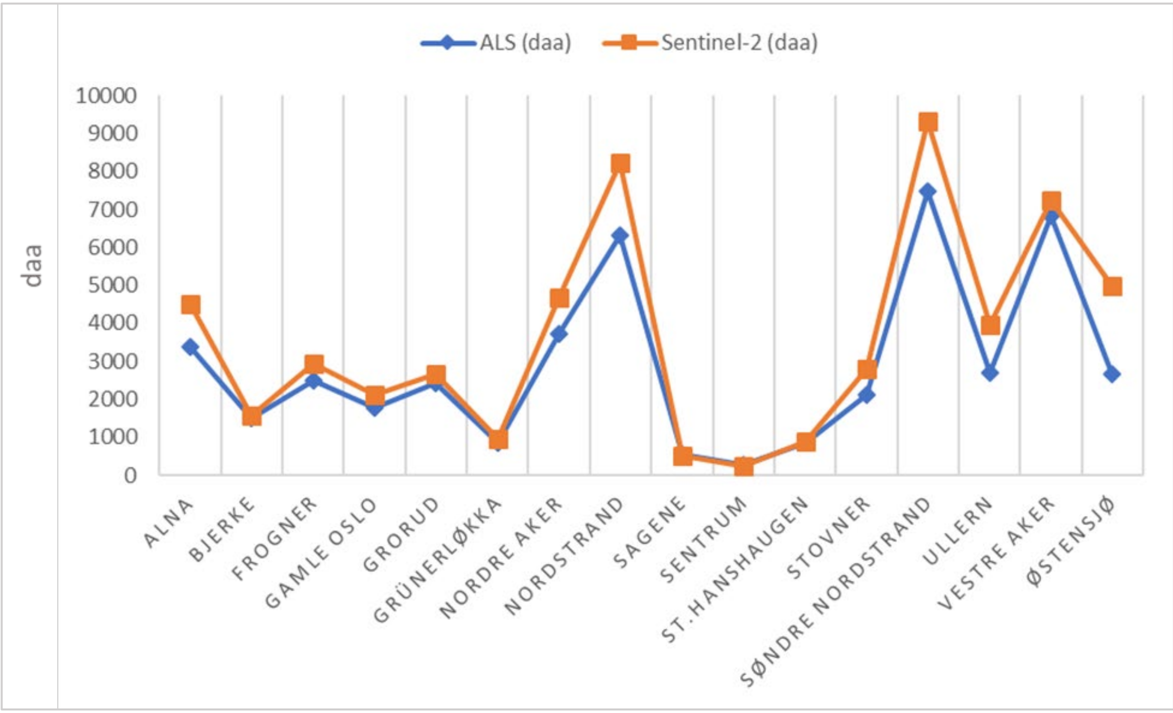


Figure 35: Statistical distribution of the 2D tree canopy area (given in daa) within the Oslo built-up zone as detected from ALS and Sentinel 2.

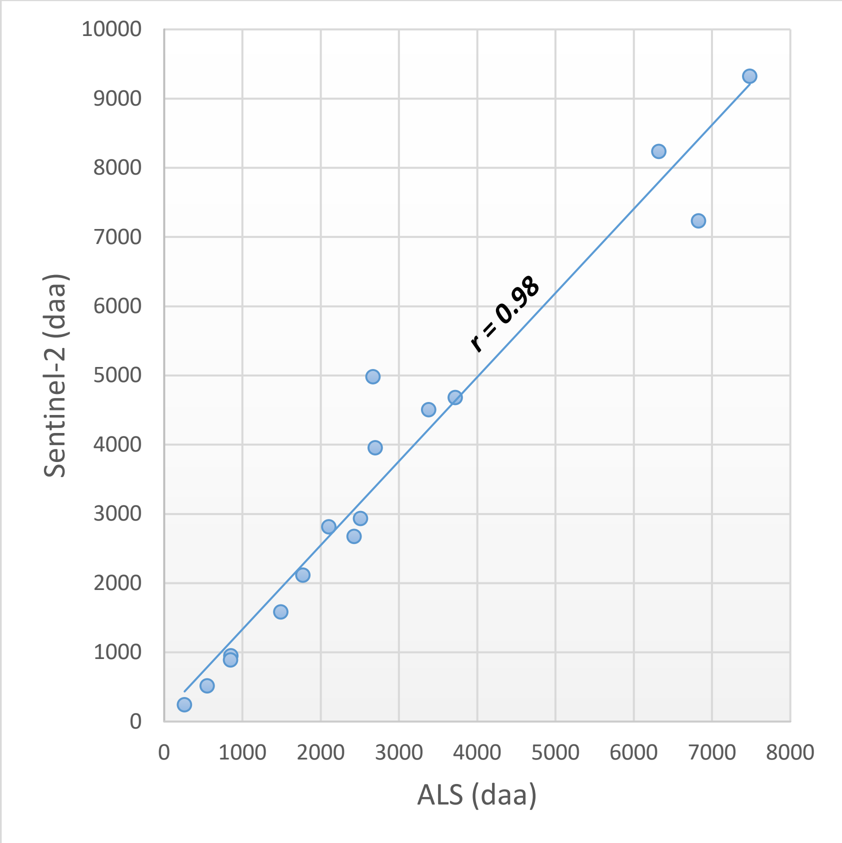


Figure 36: Correlation between the ALS tree canopy 2D area and the Sentinel2 tree cover area within the Oslo built up zone.

As mentioned above, the Sentinel4Nature (S4N) project used Sentinel 1 & 2 to estimate relative tree canopy cover for a 10 x 10km study area in Oslo (blue outline), at a pixel resolution of 10 x 10 m (figure 37, left map). The relative ALS tree canopy area was aggregated to the same pixel resolution and compared to the S4N relative tree canopy cover (figure 37, right map).

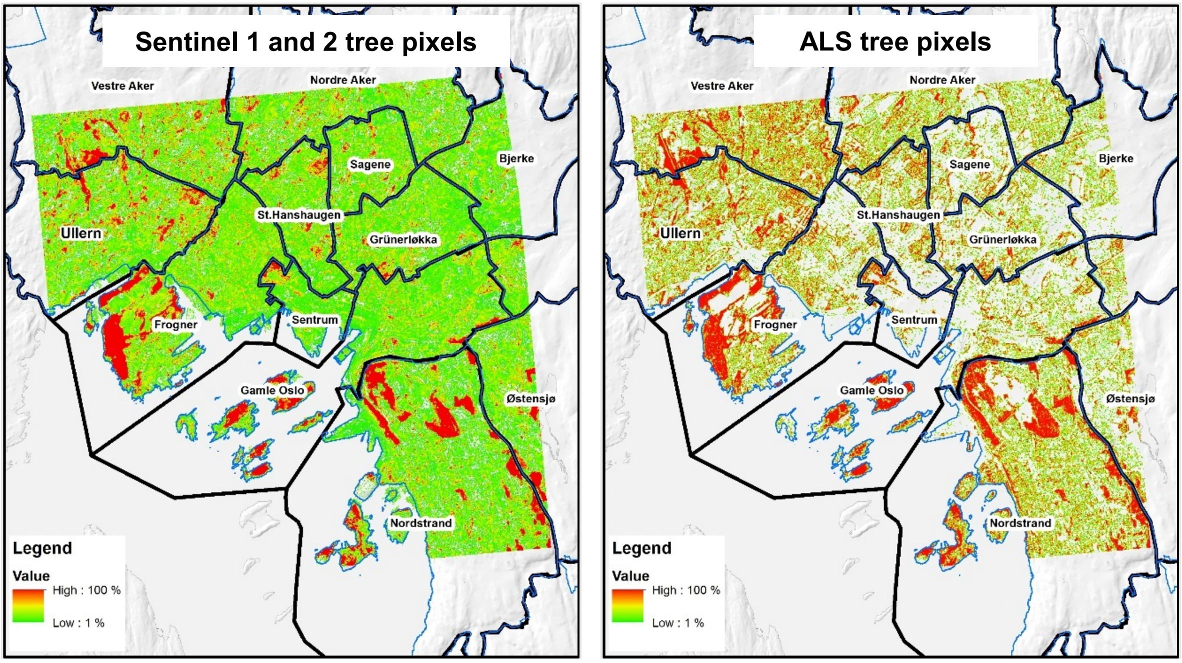


Figure 37: Relative tree canopy cover for a 10x10km study area in Oslo as estimated in the S4N-project (left map) and based on the aggregated ALS tree canopy cover (right map).

The comparison reveals a very similar spatial configuration of relative tree canopy cover, and a tendency that S4N heavily overestimates the relative tree canopy coverage. A statistical pixel-by-pixel comparison between S4N and the aggregated ALS relative tree canopy coverage estimates reveal a slightly positive, but not significant, relationship between the two variables (*r = 0.63*) (figure 38).

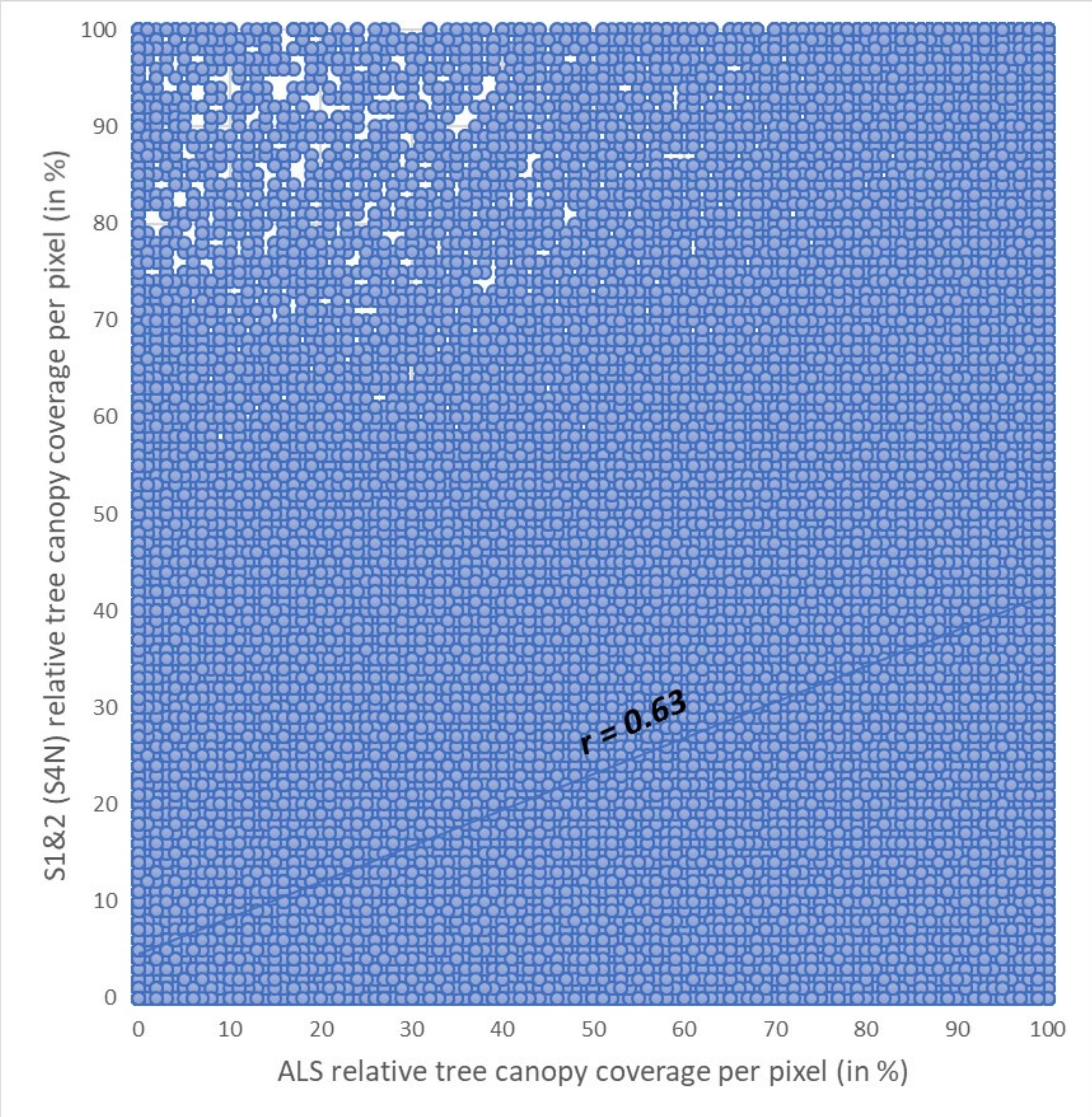


Figure 38: Comparing the relative tree canopy coverage estimates of S4N (Sentinel 1 and 2) and ALS.

In Table 11 differences between Sentinel 1&2 and ALS are analysed at the level of SSBs 500 x 500 m reporting units.

Table 11: Aggregated mathematical 2D tree canopy area difference (SSB500 reporting units) between Sentinel-2 vs. ALS and Sentinel-1-2 vs. ALS.

Area categories	Difference = S1 & 2- ALS Number of SSB500 units	Difference = S2 – ALS Number of SSB500 units
No S1 & 2 data (S4N)	0	0
No S2 data	0	4
No ALS data	4	0
No S2 and no ALS data	0	5
No S1 & 2 (S4N) and no ALS data	1	0
-0.1 to -25 daa	1	74
0.1 to 25 daa	18	139
25.1 to 50 daa	14	72
50.1 to 75 daa	22	15
75.1 to 100 daa	8	1
100.1 to 125 daa	24	0
125.1 to 150 daa	52	0
150.1 to 175 daa	73	0
175.1 to 200 daa	59	0
200.1 to 225 daa	32	0
225.1 to 250 daa	2	0

As table 11 and figure 39 below show, the differences between Sentinel-2 and ALS are largest from -25 to 75 daa, whereas the differences between Sentinel-1 & 2 and ALS are largest from 125 to 225 daa relative canopy.

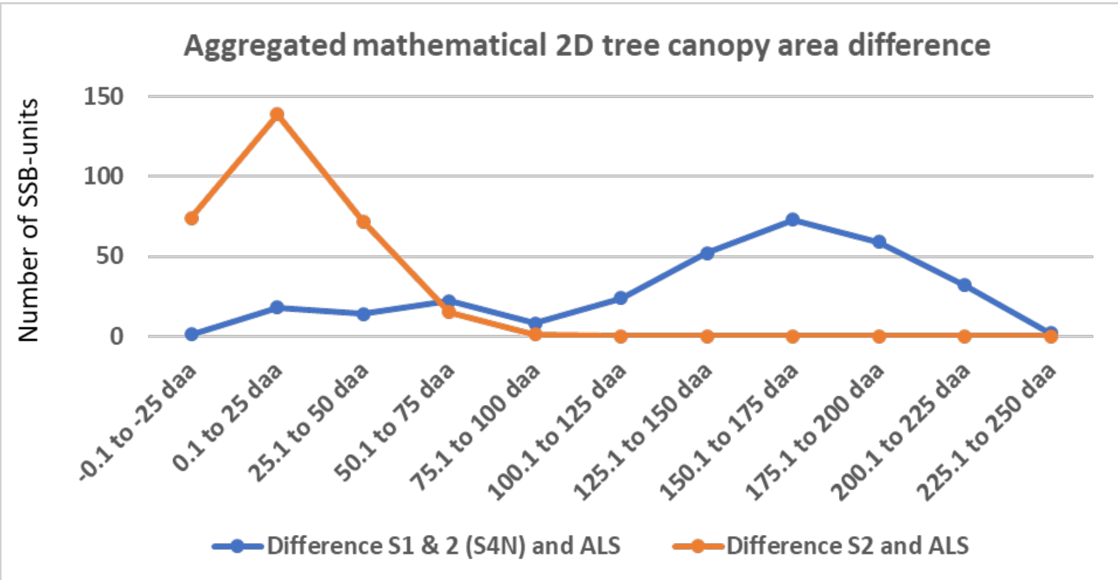


Figure 39: aggregated mathematical 2D tree canopy area difference between Sentinel-2 vs. ALS and Sentinel-1-2 vs. ALS. The Y-axis represent number of SSB-units and the X-axis represents area classes in daa,

Comparing the aggregated 2D tree canopy area (SSB500 reporting units) between Sentinel-2 vs. ALS reveals a highly significant relationship (r = 0.93) between the two variables (figure 40). The relationship between Sentinel-1 & 2 vs. ALS is weakly positive, but not significant (r=0.45) (table 11, figure 41).

In summary, use of Sentinel-2 alone (S2) overestimates tree canopy cover in the SSB500 grids with smallest tree cover (the most built-up areas). For larger tree canopy areas (> 100 daa) Sentinel-2 and ALS produce similar tree canopy extent. This bias in the inner urban area can be corrected by combining optical (S2) and radar (S1) remote sensing, but increases differences for areas with greater forest cover in the outer city. The conclusion is that the ALS based approach is best for urban areas with canopy densities of ca. <20%, while for canopy densities > 20% satellite optical remote sensing data is enough and more cost-efficient for canopy extent accounting.

In brief

The ALS based approach is best for urban areas with canopy densities of ca. < 20%, while for canopy densities > 20%, satellite optical remote sensing data is enough and more cost-efficient for canopy extent accounting.

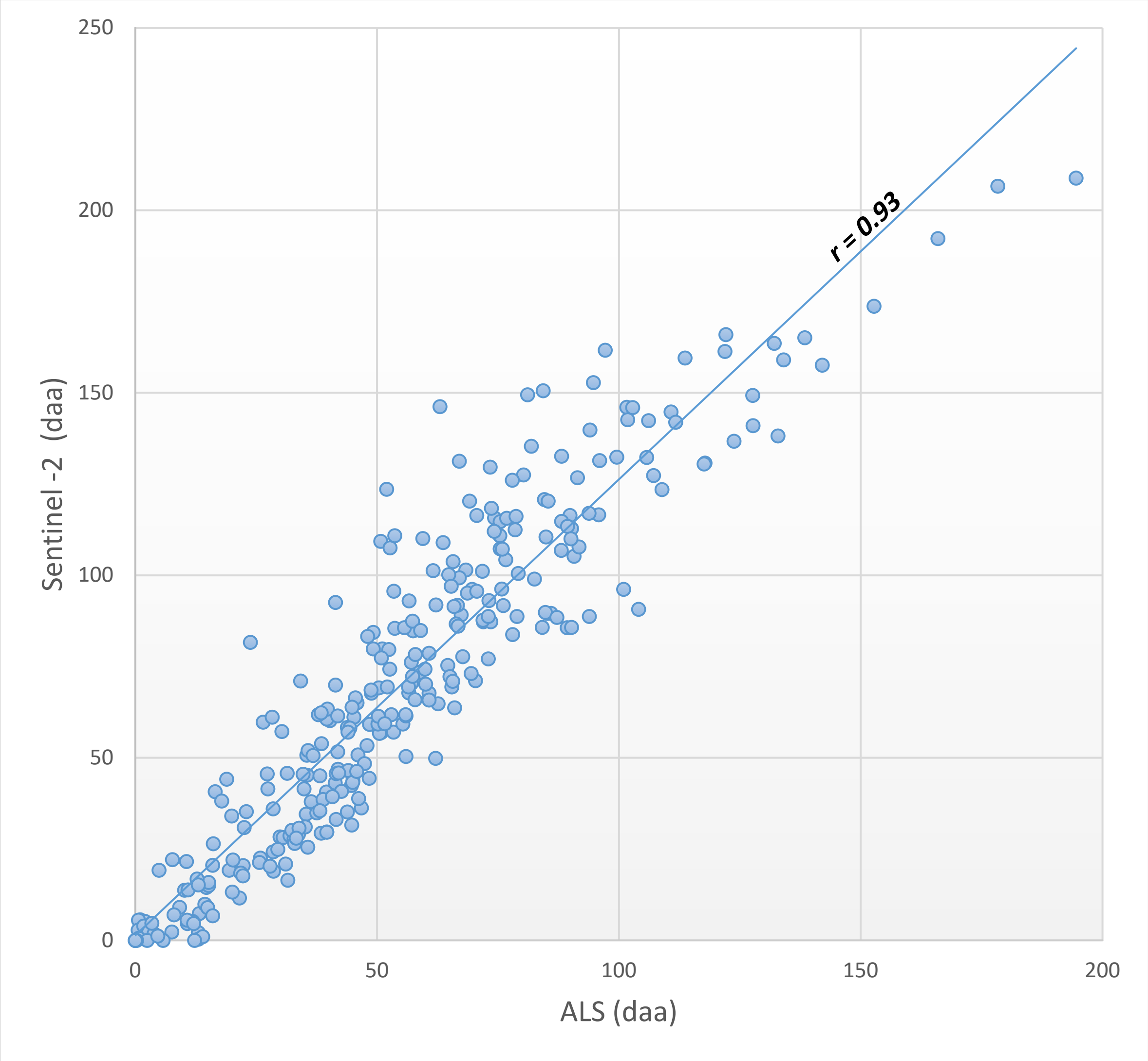


Figure 40: The relationship between 2D tree canopy area (aggregated to SSB500 reporting units) detected by Sentinel-2 and ALS.

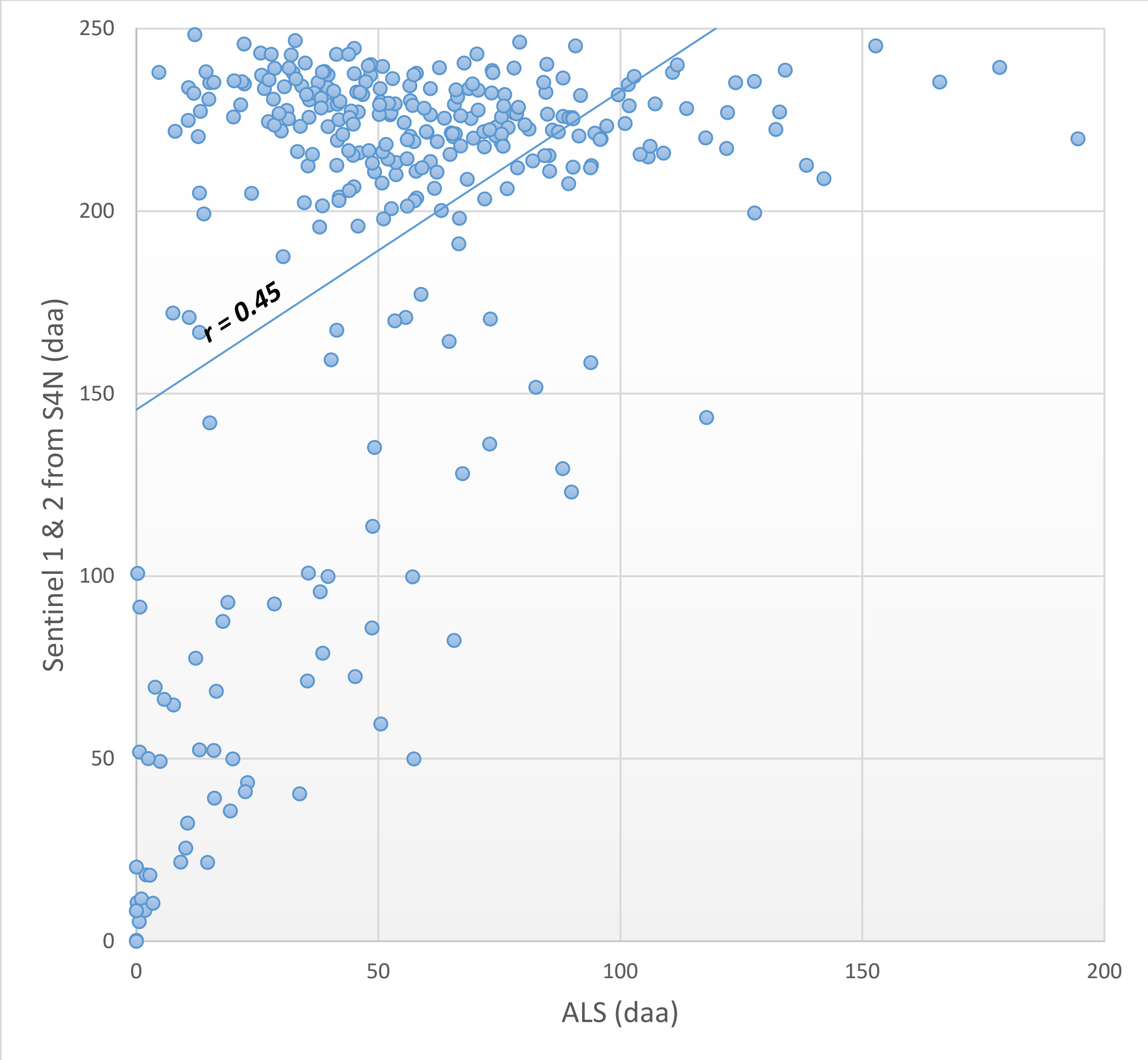


Figure 41: The relationship between 2D tree canopy area (aggregated to SSB500 reporting units) detected by Sentinel-1 & 2 and ALS.

6 Discussion

6.1 Accuracy

In brief

ALS data was available with average point densities per m2 ranging from 10 (2017), to 25 (2014) to 43 (2011). To reduce raster processing time, we chosed to interpolate the CHM at 0.5m, but this is likely to have affected detection possibilities for individual small canopy sizes.

Further, we chose a Local Maxima filter for smoothing the canopy height model of 3 m, appropriate for larger trees > 30 m. This means that tree canopy areas of trees < 30m in height may have been under-estimated. In hindsight this may have reduced the ability to detect smaller canopy heights typical of urban street trees.

Lidar data purchased by Oslo Municipality for 2014 and 2017 were not classified for vegetation, as they were in 2011. Our TGI-corrected Lidar method underestimates the total number of trees in Oslo. Our analysis of direction of change in tree canopy is more reliable, but also contains error. We were unable to mask out technical infrastructure for 2011 and 2014 due to lacking FKB-masks. Taken together, changes in crown cover of tall trees in 2014 is likely to be overestimated relative to 2011 and 2017. We therefore place greater confidence in our identification of change in canopy for 2011-2017.

The purpose of this study was to investigate the possibilities of utilizing airborne laser scanning data (ALS) for mapping of urban trees and their geometrical characteristics in Oslo. For this purpose, we have implemented a standard Watershed segmentation method implemented on a local-maxima filtered Canopy Height Model (CHM). This CHM raster-based approach is frequently used and often favoured for its efficacy (Zhang et al., 2015).

There are, however, several limitations with such raster-based approaches. First, when the CHM is derived from the LIDAR-point cloud, several errors and uncertainties are introduced due to the chosen interpolation method and grid spacing (Smith *et al.*, 2004). These errors and uncertainties may affect the subsequent tree segmentation (Suarez et al., 2005). Second, the smoothing of the rough surface of the tree canopy may lead to under- or overestimates of the tree height (Tiede *et al.*, 2005).

Barnes *et al.* (2017) found that is hard to utilise a single segmentation algorithm and one input ALS-dataset to assess forest environments comprising of mixed stand ages and species. They found that the segmentation success is highly sensitive to the selection of algorithm, generation method and spatial resolution of the CHM. In addition, the ALS-data may have several height anomalies that can influence the quality of the segmentation accuracy. Several error sources are acknowledged as a part of the acquisition and processing of ALS data including 1) penetration of laser beams through the canopy, 2) merging of ALS flight lines, 3) classification of ground and non-ground points and 4) interpolation of point clouds to raster data. Many studies have implemented image smoothing techniques such as Gaussian filtering to address these problems. More recent solutions have introduced the use of pit-filling algorithms and the application of pit-free CHM generation methodologies (Barnes *et al.*, 2017).

In this study, we have used existing ALS data for Oslo with average point densities per m^2 ranging from 10 (2017), to 25 (2014) to 43 (2011). This spatial and temporal variation in point density will certainly influence the precision of the tree canopy segmentation, and the comparison of number of trees and tree canopy area between years. In addition, the ALS-data for 2014 and 2017 are lacking a classification of vegetation (ASPRS codes 11,12 and 13). Beyond these limitations, we have not evaluated the quality of the ALS-data according to the error sources identified by Barnes *et al.* (2017).

The DSM and DTM were interpolated with a spatial resolution of 0.5 m. 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. To reduce raster processing time we chosed a 0.5 m resolution, but this is likely to have affected detection possibilities for individual small canopy sizes.

The diameter of the Local Maxima filter may have a significant influence on the smoothed CHM. Chen *et al*. (2006) recommends a filter size no larger than the smallest tree crown within the study area. Barnes et al. (2017) suggests the following LM 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). We smoothed our CHMs with a Local Maxima (LM) filter size of 3 m in diameter (equal to 6 pixels). This may have under-segmented trees < 30 m.

Clearly, the segmented data should be validated with field measurements of the tree canopy height and volume. So far, we have only validated the segmented tree canopy data from 2017 with the tree point database (managed by the Oslo BYM). Approximately 70 % of the control trees coincided spatially with our segmented tree crowns (it should however be noted that the control trees do not cover all trees in Oslo). Comparing the XY coordinates of the control trees with the XY coordinates of their nearest segmented tree top, shows a mean deviation of 4.7 m, a minimum deviation of 0,0046 m and a maximum deviation of 35.1 m. Even though our segmented tree top points may not have accurate position, it should be noted that the location of the control points probably have some GPS- offsets. For the future, a minimum required detection range precision level should be defined.

6.2 Reliability

The input LIDAR-data for the years 2014 and 2017 is missing a vegetation classification. We have tried to make the segmentation result data from 2011-2014-2017 as comparable as possible using the same segmentation procedure corrected with the TGI vegetation mask and filtered with the FKB mask for building and technical infrastructure.

6.2.1 Permanent infrastructure

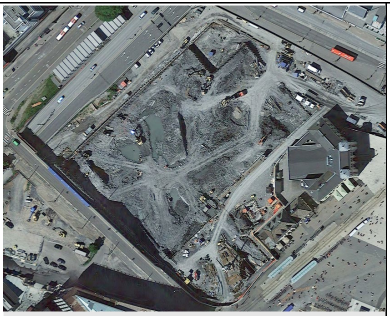
The TGI vegetation mask cannot completely remove all false signals caused by mistaken tree-segmentation of vertical man-made structures. To correct for these false signals the segmented trees for 2011, 2014 and 2017 were masked with a vegetation mask and FKB building polygons dated from mid-2017. Other technical infrastructure such as buildings, traffic and railway installations, statues and power lines/telecommunication cables (including poles) are masked out in the 2017 tree segmentation data using buffered vector data on technical infrastructure from FKB. We were not able to mask out technical infrastructure in the 2011 and 2014 tree segmentation data because we did not have access to FKB-masks for these years.

The greatest segmentation overestimate occurs in 2014 when Lidar data were not classified for vegetation, combined with our lack of masking infrastructure. This tend to overestimate the amount of trees for 2014 relative to 2011 and 2017. This suggests that for the city as a whole the increase in taller trees between 2011 and 2014 may be smaller, and for 2014-2017, larger than what we have modelled (Figure 26). For the Småhusplan area the decrease in large trees 2011-2014 is larger and for 2014-2017 smaller (Figure 29) than what we have modelled. For this reason, we place greater confidence in the overall change 2011-2017 than for intermediate periods.

6.2.2 Temporary infrastructure, construction equipment

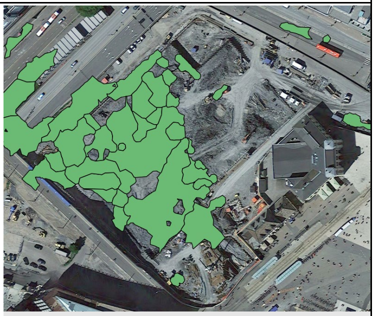
In addition, there are some false segmentations due to the presence of larger vehicles, bulk-containers, mobile cranes, construction sites and newly constructed buildings/infrastructures that are not yet registered in FKB (Box 1).

Box 1 LiDAR returns at construction sites and segmentation bias



National museum construction site October 2016

Construction cranes at national museum



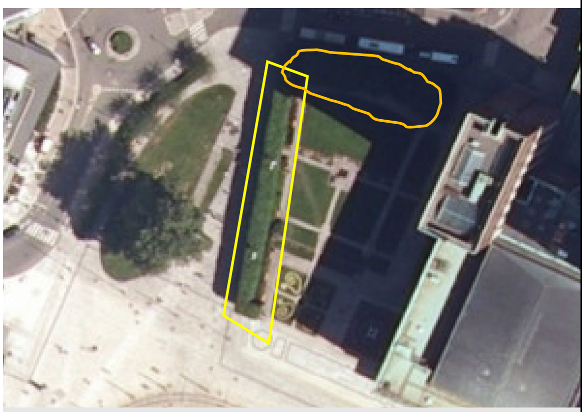
ALS estimated canopy cover 2017 due to construction crane activity on construction site

Construction sites in Oslo during the analysis period 2011-2017 present a challenge. At construction sites cranes are identified as trees while there may not exist a completed building polygon with which to mask them out. A possible solution for compilation of urban tree statistics may be apply a mask for planned construction sites based municipal building permits. We did not have this data available for our analysis. The problem would be localised and more serious around urban densification nodes.

6.2.3 Unidentified effects of tree management measures

Figure 27 shows that between 6m and 12m the distribution of tree canopy heights is flat – there is an equal number of trees across the city with heights between 6 and 12 m. This may represent the effects of tree planting and management. Other tree management effects are illustrated in Box 2.

Box 2 Sources of classification and segmentation error in managed urban trees



Orthophoto 29. September 2011. Note the vegetation identified in the yellow triangle are pruned tree canopies (>5 m). The orange polygon in shade from city hall indicates un-pruned tree crowns.

"Leaf-off" orthophoto 6. May 2017 and tree segmentation based on 2011 LiDAR dataset.

Box 2 illustrates that our canopy segmentation (1) groups several trees with pruned flat canopy into a single tree (observe "leaf off" shadows of individual tree trunks), and (2) LiDAR data does not identify part of the flat pruned canopy. Also, only one of the line of Japanese cherry trees to the west is identified - this may be due to canopy height near cut-off limit and thinning of canopy.

The image in Box 2 also indicates that building shading may have been an issue for the triangular greenness index. We have not controlled for this error, but it would be more likely in central Oslo. It is more easily corrected for because most trees in central Oslo near tall buildings are street trees managed by the municipality.

6.2.4 Unknown sources of segmentation error

Due to other unknown errors in the segmentation routine some trees lack canopy height information or have a suspicious canopy height > 50 m which is the height of the tallest known tree in Norway (see table 12).

Year	Segmented trees	No Canopy height	Canopy height > 50 m
2011	365956	3041 (0.83 %)	1819 (0.49 %)
2014	404365	24674 (6.10 %)	202 (0.040 %)
2017	393386	2812 (0.71 %)	106 (0.026 %)

Table 12: Relative number (%) of segmented trees in Oslo having invalid tree canopy height

In summary, segmenting tree crowns using remote sensing within an urban environment has a number of sources of error. Some of these can be corrected for in future. In our present results they limit the extent to which results can be used for localized accounting at tree and neighbourhood level. At larger units of spatial analysis such as city districts, and for longer time periods such as 2011-2017, random errors will cancel out, while systematic errors will be a smaller proportion of the total. Oslo municipality can also improve the data input by requiring LIDAR data suppliers to classify raw data for vegetation.

7 Approaches to municipal reporting of changes in urban tree canopy at city level

For the built-up zone in Oslo, changes in the tree canopy surface area for different tree canopy height bands were calculated between 2011 and 2017. Different ecosystem reporting units can be chosen, such as statistical units of 0.25 square km^2 from Statistics Norway (figure 42)[18], census districts ("grunnkretser") (figure 43), and city district ("bydeler") (figure 44). Only tree heights up to 30m are mapped here due to identification errors with infrastructure for taller height classes (see section 5.3).

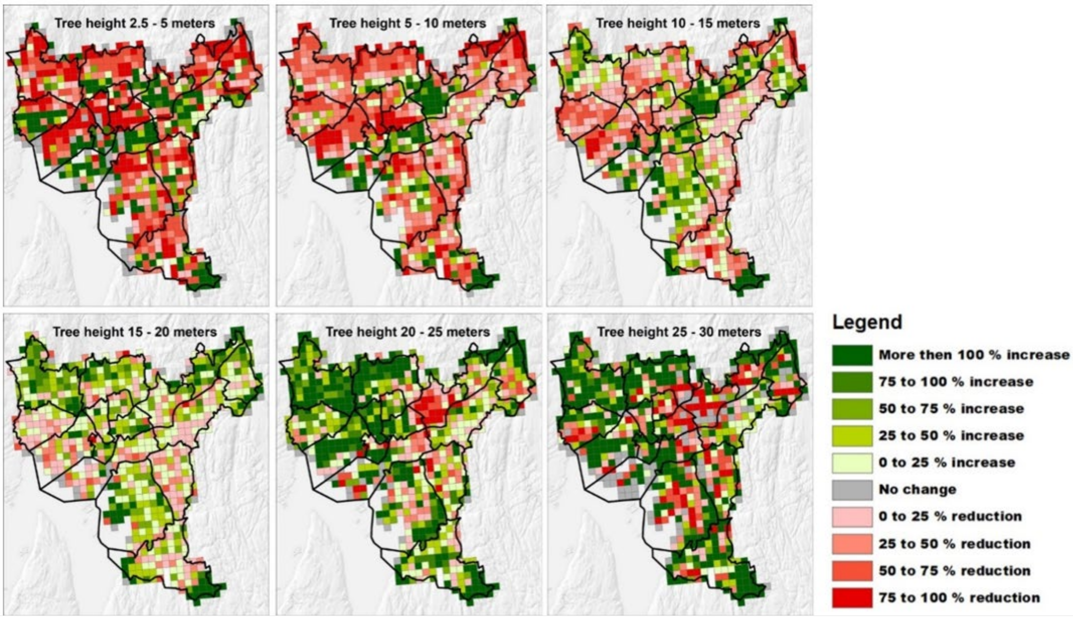


Figure 42: Changes in the tree canopy surface area for different height bands (2011 and 2017) using Statistical units of 0.25 square km2 from Statistics Norway.

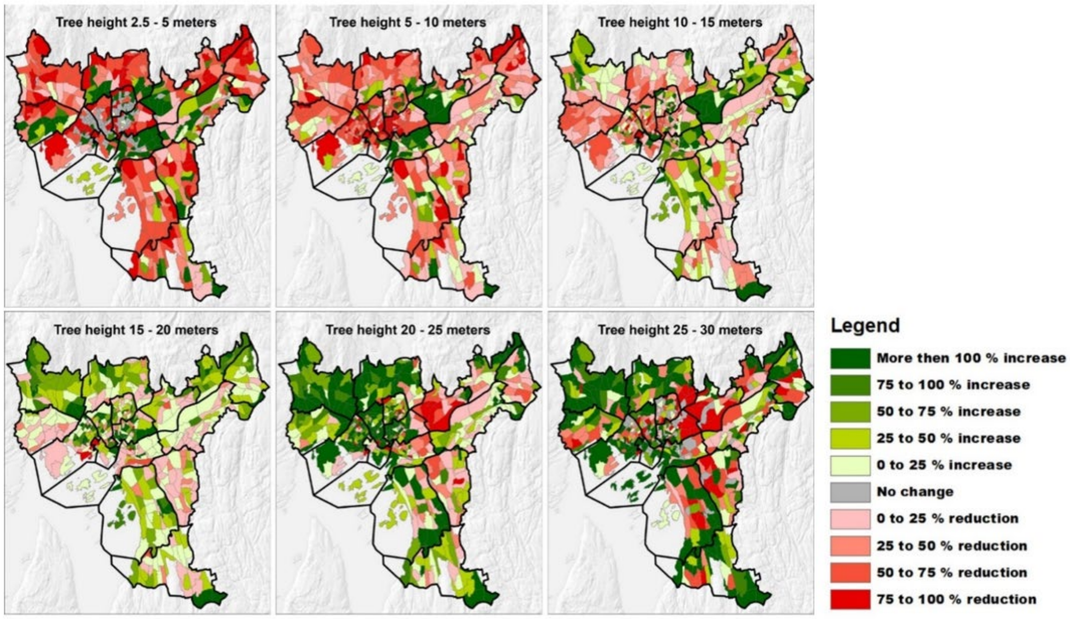


Figure 43: Changes in the tree canopy surface area for different height bands (2011 and 2017) using Basic Statistical units.

[18] https://www.ssb.no/natur-og-miljo/artikler-og-publikasjoner/statistical-grids-for-norway

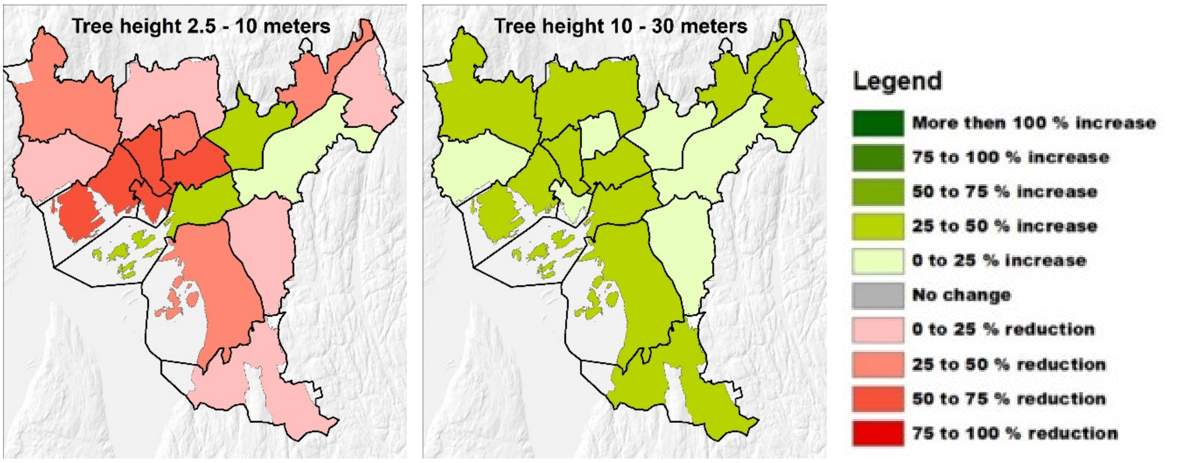


Figure 44. Changes in the tree canopy surface area for different height bands (2011 and 2017) using City regions.

Mapping of changes is one of the principle characteristics of ecosystem accounting. The choice of statistical reporting unit resolution in mapping ecosystem accounting data is not trivial. Using statistical reporting units with different spatial resolution emphasises different "narratives", and policy options.

The Småhusplan area is a focus area for tree conservation policy in Oslo, with permits required to cut down large trees. Tables 12-13 illustrate contrast changes in tree canopy for Oslo's built area as a whole versus the Småhusplan area, recording both additions and losses to the "tree crown cover assets" during the accounting periods.

Table 12: Accounting table - the Oslo built-up zone

	Tree height									
Crown cover	**2.5-5M**	**5-10M**	**10-15M**	**15-20M**	**20-25M**	**25-30M**	**30-35M**	**35-40M**	**40-45M**	**45-50M**
Total 2011 (daa)	257.79	4814.76	8385.30	12537.70	9568.47	3288.69	523.03	78.39	40.89	33.52
Additions (daa)	47.82	241.37	771.33	1916.48	1887.60	917.22	240.71	8.22	0.00	0.00
Losses(daa)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-28.64	-23.46
Total 2014 (daa)	305.61	5056.13	9156.63	14454.18	11456.06	4205.90	763.74	86.61	12.25	10.06
Additions (daa)	40.03	17.21	0.00	0.00	368.59	299.56	82.29	15.89	0.59	0.00
Losses (daa)	0.00	0.00	-39.15	-47.56	0.00	0.00	0.00	0.00	0.00	-4.52
Total 2017 (daa)	345.64	5073.34	9117.48	14406.63	11824.65	4505.46	846.03	102.50	12.84	5.54

Table 13: Accounting table – the Småhusplan area (policy focus)

	Tree height									
Crown cover	**2.5-5M**	**5-10M**	**10-15M**	**15-20M**	**20-25M**	**25-30M**	**30-35M**	**35-40M**	**40-45M**	**45-50M**
Total 2011 (daa)	65.26	1150.11	1821.78	2494.59	1884.17	660.50	122.57	14.79	9.38	5.21
Additions (daa)	67.38	738.94	102.23	9.57	0.00	0.00	0.00	0.00	0.00	0.00
Losses(daa)	0.00	0.00	0.00	0.00	-224.49	-313.23	-71.12	-7.33	-8.59	-4.86
Total 2014 (daa)	132.65	1889.05	1924.01	2504.16	1659.67	347.27	51.45	7.46	0.79	0.36
Additions (daa)	15.73	8.50	80.67	0.00	25.51	8.31	0.45	1.51	0.00	0.00
Losses (daa)	0.00	0.00	0.00	-82.11	0.00	0.00	0.00	0.00	-0.52	-0.36
Total 2017 (daa)	148.38	1897.55	2004.68	2422.04	1685.18	355.58	51.90	8.97	0.27	0.00

The overall story of increasing cover of large trees in Oslo, with a decreasing cover for smaller trees, is reversed when focusing only on the "Småhusplan" area. Our modelling shows a loss of large trees(> 15 m) while small trees (< 15 m) have increased between 2011-2017.

8 Summary and recommendations

8.2 Method

The purpose of the study has been to demonstrate the use of airborne laser scanning data to inventory and account for changes in all urban tree canopies on public and private land in the built zone. Furthermore, we aimed to evaluate existing ALS data for Oslo municipality against other methods for detecting urban tree canopy. Finally, we evaluate what municipal policy and planning purposes ALS segmented tree canopy can serve, given accuracy and reliability of the data.

Due to the voluminous amount of data, we divided the ALS data point cloud into numerous data tiles defined by the data provider. The purpose of this first step was to optimize the data prior to the tree canopy segmentation process. For this purpose, we created a map index that referenced all the data tiles and their associated surface characteristics.

ALS data purchased by Oslo Municipality for 2014 and 2017 were not classified for vegetation, as they were in 2011. Because ALS data were not consistently classified into vegetation signals, we first created a vegetation mask using a triangular greenness index (TGI) based on light bands from aerial photography. The purpose of this step is to compensate for unclassified vegetation points in the 2014 and 2017 data.

We identified the treetops and tree canopies of all trees in Oslo above 2.5 m. We utilized a tree canopy model (CHM) that assumes that the shape of an upside-down tree crown resembles a drainage basin, and that the treetop resembles its drainage point. We calculated the height of the tree canopy, given by the elevation difference between the Digital Terrain Model and the Digital Surface Model. We then invert the CHM to imitate a drainage basin, and calculated the internal flow direction between each cell within the imitated drainage basin resembling the tree canopy. The method next detects the drainage points (treetops) and delineates the drainage basin (tree crowns). ALS data was available with average point densities per m2 ranging from 10 (2017), to 25 (2014) to 43 (2011). To reduce raster processing time we chosed to interpolate at 0.5 m, but this is likely to have affected detection possibilities for individual small canopy sizes.

We chosed a Local Maxima filter of 3 meter in diameter for smoothing the CHM, appropriate for larger trees > 30 m. This means that smaller trees < 30 m have been under- estimated. Finally, we removed objects (buildings and technical infrastructure) that are incorrectly segmented as trees.

The tree canopy volume is useful because, combined with tree species information, it can be used to estimate the Leaf Area Index (LAI) as a condition indicator and input to the i-Tree Eco model for calculating regulating services of city trees.

The TGI-corrected infrastructure-masked Lidar data identified approximately 393 000 individual canopies taller than 2.5 m in Oslo's built zone. For Oslo as a whole the number of large trees increased (> 10 m height), while the number of smaller trees declined. For the area in the "small house plan" the number of large trees declined, while small trees increased.

The TGI-corrected segmentation method used in this report overestimates tree canopy area relative to a vegetation classification of the ALS raw data by 95.2 % and underestimates the number of individual trees by 72.9 % (2011). The reason for the smaller number of segmented trees from 2011 is probably that several crowns are detected as one tree. This is probably an underestimating effect of the fixed kernel size of the Local Maxima for trees < 30 m. The reason for the larger tree canopy estimation in our segmented tree canopies from 2011 could mainly be related to misdetection of other structures and that tree crowns are detected larger than they are. It would be necessary to know more about the process used for the segmentation of the PBE ALS 2011 tree data in order to draw further conclusions on the deviating results.

Our TGI-corrected Lidar method probably underestimates the total number of trees in Oslo. Our analysis of direction of change in tree canopy is more reliable, but also contains error. We were unable to mask out technical infrastructure for 2011 and 2014. Taken together changes in crown cover of tall trees in 2014 is likely to be overestimated relative to 2011 and 2017. We therefore place greater confidence in our identification of change in canopy for 2011-2017.

Comparing to the use of Sentinel-2 satelite imagery, the ALS based approach is best for urban areas with canopy densities of approximately less than 20%, while for canopy densities above 20%, satellite optical remote sensing data is sufficient and more cost-efficient for canopy extent accounting.

8.3 Recommendations

In the preceding pages we have identified a number of limitations in the ALS data used for our analysis, methodological choices and data processing assumptions which determine the accuracy of our tree canopy inventory and accounting of change over time. Table 14 summarises our recommendations for use of the tree segmentation data identified in this report.

Table 14 Spatial scale of accounting and confidence levels.

Scale	Policy and management applications	Notes on limitations and uncertainty
Single tree level	Monitoring (i) conservation of large private trees circumference > 90 cm in “Småhusplan” area, (ii) preservation of large trees > 100 cm	Uncertainty with indirect measurement using allometric equations for tree height and canopy width
Property level	Calculating number of trees and canopy cover for blue-green factor (BGF) Prediction of shading and insolation	Identifies canopy area on property better than number of trees Misidentification of construction cranes
Public parks, streets	Inventory of managed trees’ canopy surface and volume for ecosystem service estimation	Higher confidence for open areas and streets in low building areas.
City sub-district level	Green accounts. Change in neigbourhood level access to greenviews per capita	Higher confidence
City level	Green citywide accounts identifying change in tree canopy area	Highest confidence

Broadly speaking we would not recommend using our data for monitoring presence/absence of individual trees, or the number of trees at property/tree level. In order to use ALS data for monitoring protection of large trees in the Småhusplan area, for example, the following conditions should be met:

- classification of vegetation points in the LIDAR point cloud is essential for tree canopy segmentation. This classification can be performed by the data provider or internally if resources are available.

- interpolate digital surface and terrain models at the maximum resolution provided by the input data

For inventorying tree canopy in public green spaces and accounting for change in canopy at aggregate city district level we are confident that the approach demonstrated here provides useful additional information to Oslo municipality's "green cover" accounts.

From a cost-effectiveness perspective we would recommend continuing using ALS data for areas of the city with canopy density < 20%. For areas with higher than 20% canopy density satellite data offers equal or better accuracy and is free of charge.

For estimation of ecosystem services of urban trees using i-Tree Eco, it would be desirable to have as accurate estimates as possible of tree canopy area and volume. The importance of correct segmentation of individual trees would seem to be more important in GIS-based modelling of visual impacts of tree crowns, than for regulating services where the exact shape and location of tree crown matters less than the total leaf area. In order to increase the accuracy of canopy area measurements it is therefore important to choose a smoothing algorithm for the canopy height model that segment tree canopy for tree size classes typical of Oslo's the built zone (trees < 30 m tall).

For the future, a similar segmentation could be done in Google Earth Engine using available point clouds or pre-processed high-resolution DTMs and DSMs (at minimum 0.5 to 1 m resolution) from Digital Norway[19]. In Google Engine a Gaussian softening kernel algorithm would be implemented in combination with pit-filling alghoritms. To overcome the problem of using a fixed kernel size, the tree-tops (the local maxima) would be identified using a dynamic kernel size that changes over the region of interest so that it is most appropriate for "local" average tree height and tree canopy diameter. Instead of using a watershed algorithm (which is currently not available in Google Engine), a focal mode smoothing function would be iterated multiple times over the CHM to segment the individual tree canopies. The accuracy of this approach would also need to be validated with ground-truth data or some manually digitized tree canopies. The advantages of Google Earth Engine are that most of the parrellisation and big data handling is managed by Googles infrastructures. This means that one could theoretically scale the analysis to segment trees over multiple cities or whole counties. The disadvantages of using Google Engine in tree canopy segmentation is that some GIS- algorithms (such as e.g. the watershed algorithm) are not available and thus alternatives have to be used. However, because the Google Engine computation environment allows the user to perform large computations on the fly and visualize results quickly, one can test a range of other methods that otherwise would be cumbersome to test using ESRI products like for example ArcGIS.

[19] https://hoydedata.no/LaserInnsyn/

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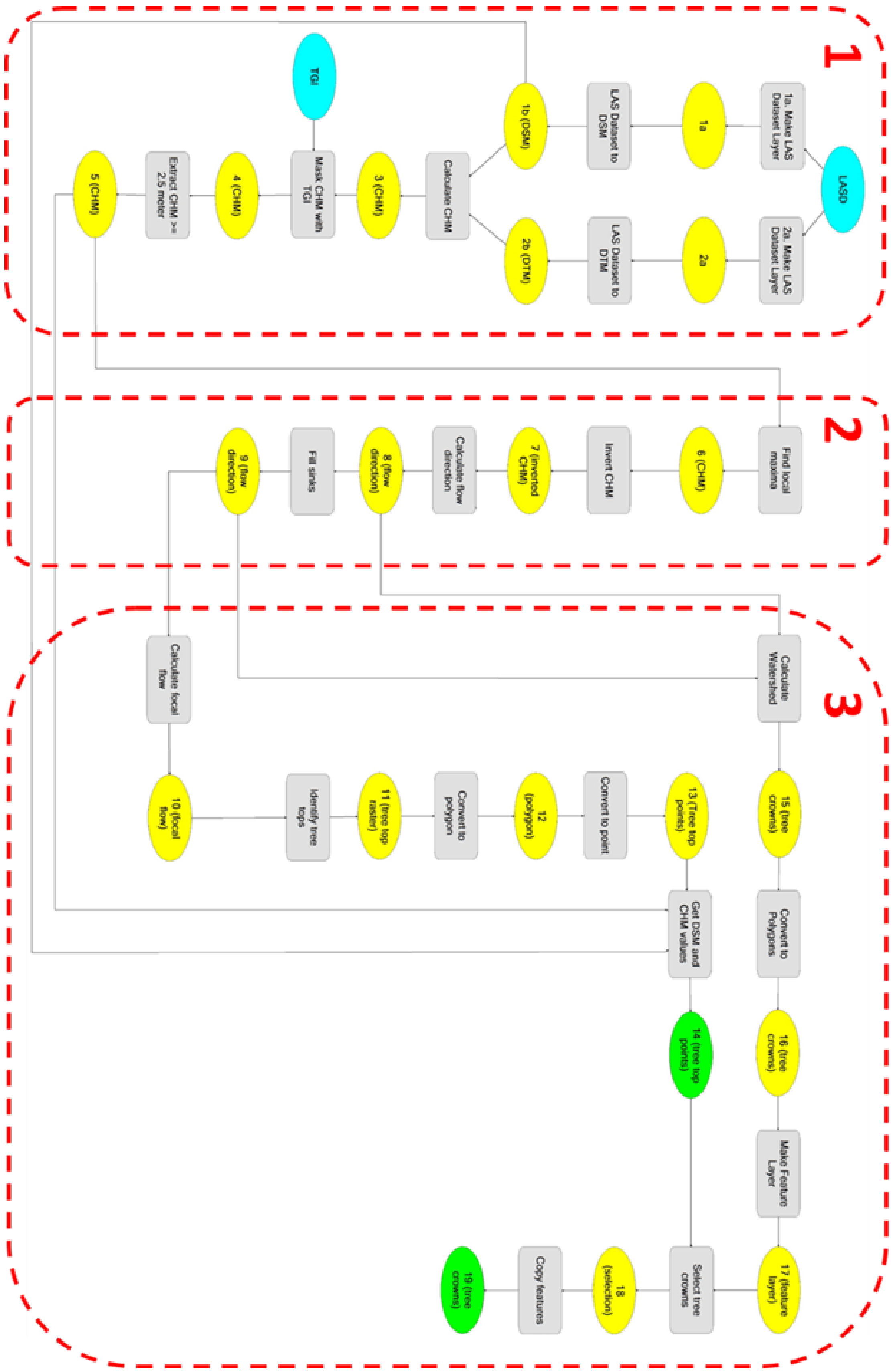
7 Appendix


1
LASD
1a. Make LAS Dataset Layer
1a
LAS Dataset to DSM
1b (DSM)
2a. Make LAS Dataset Layer
2a
LAS Dataset to DTM
2b (DTM)
Calculate CHM
3 (CHM)
TGI
Mask CHM with TGI
4 (CHM)
Extract CHM >= 2.5 meter
5 (CHM)
2
Find local maxima
6 (CHM)
Invert CHM
7 (inverted CHM)
Calculate flow direction
8 (flow direction)
Fill sinks
9 (flow direction)
3
Calculate Watershed
15 (tree crowns)
Convert to Polygons
16 (tree crowns)
Make Feature Layer
17 (feature layer)
Calculate focal flow
10 (focal flow)
Identify tree tops
11 (tree top raster)
Convert to polygon
12 (polygon)
Convert to point
13 (Tree top points)
Get DSM and CHM values
14 (tree top points)
Select tree crowns
18 (selection)
Copy features
19 (tree crowns)

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