



The potential of geospatial analysis and Bayesian networks to enable i-Tree Eco assessment of existing tree inventories



Zofie Cimburova^{a,b,*}, David N. Barton^a

^a Norwegian Institute for Nature Research (NINA), Sognsveien 68, NO-0855, Oslo, Norway

^b Department of Architecture and Planning, Faculty of Architecture and Design, NTNU—Norwegian University of Science and Technology, NO-7491, Trondheim, Norway

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ABSTRACT

Valuing the ecosystem services of urban trees is important for gaining public and political support for urban tree conservation and maintenance. The i-Tree Eco software application can be used to estimate regulating ecosystem services provided by urban forests. However, existing municipal tree inventories may not contain data necessary for running i-Tree Eco and manual field surveys are costly and time consuming. Using a tree inventory of Oslo, Norway, as an example, we demonstrate the potential of geospatial and machine learning methods to supplement missing and incomplete i-Tree Eco attributes in existing municipal inventories for the purpose of rapid low-cost urban ecosystem accounting. We correlate manually surveyed stem diameter and crown dimensions derived from airborne laser scanning imagery to complete most structural attributes. We then use auxiliary spatial datasets to derive missing attributes of trees' spatial context and include differentiation of air pollution levels. The integration of Oslo's tree inventory with available spatial data increases the proportion of records suitable for i-Tree Eco analysis from 19 % to 54 %. Furthermore, we illustrate how machine learning with Bayesian networks can be used to extrapolate i-Tree Eco outputs and infer the value of the entire municipal inventory. We find the expected total asset value of municipal trees in Oslo to be 38.5–43.4 million USD, depending on different modelling assumptions. We argue that there is a potential for greater use of geospatial methods in compiling information for valuation of urban tree inventories, especially when assessing location-specific tree characteristics, and for more spatially sensitive scaling methods for determining asset values of urban forests for the purpose of awareness-raising. However, given the available data in our case, we question the accuracy of values inferred by Bayesian networks in relation to the purposes of ecosystem accounting and tree compensation valuation.

1. Introduction

More than half of the world's population lives in cities. The proportion is predicted to rise to 68 % by 2050 globally and from 75 % in 2020 to nearly 84 % in 2050 in Europe (UN, 2018), leading to increased demand for living space. This results in the conversion of natural vegetation cover to artificial surfaces and soil sealing (European Environment Agency (EEA, 2006). Urban green infrastructure comprising all types of vegetation provides ecosystem services (ES) to urban populations (European Commission, 2013; Gomez-Baggethun and Barton, 2013). Urban forests and individual trees are the major components of urban green infrastructure, delivering provisioning, cultural and regulating services (Mullaney et al., 2015; Nesbitt et al., 2017;

Nowak et al., 2008; Song et al., 2018) with social, economic, health and visual aesthetic benefits to humans (Roy et al., 2012). For example, the health benefits of trees and forests in the coterminous US were valued at 1.5–13 billion USD, mostly occurring in urban areas (Nowak et al., 2014).

The population of Oslo municipality, Norway, is predicted to grow from 673 000 in 2018 to 850 000 by 2030 (Oslo municipality, 2018). Oslo's Municipal Plan focuses on the growth within the existing built zone, following a strategy of densification and urban transformation. This poses a threat to the city's green infrastructure. Trees within the city's built zone are a substantial ecosystem asset (Barton et al., 2015). Oslo currently has twice as much tree canopy as roof area (Hanssen et al., 2019), ranks high in international comparisons of city greenview

Abbreviations: ALS, Airborne laser scanning; BN, Bayesian networks; CD, Crown diameter; CA, Crown area; CLE, Crown light exposure; DB, Direction and distance to building; DBH, Stem diameter at breast height; DSM, Digital surface model; DTM, Digital terrain model; ES, Ecosystem services; H, Total tree height; HCB, Height to crown base; HLT, Height to live top; LU, Land use; PCM, Percent crown missing; TLS, terrestrial laser scanning

* Corresponding author at: Norwegian Institute for Nature Research (NINA), Sognsveien 68, NO-0855, Oslo, Norway.

E-mail address: zofie.cimburova@nina.no (Z. Cimburova).

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index (MIT Senseable City Lab, 2020) and was awarded the European Green Capital 2019 (European Commission, 2020). Trees' importance for stormwater management and air pollution removal is recognised in Oslo's Strategy for City Trees (Urban Environment Agency (BYM, 2014). The Municipal Plan calls for establishing rules for protection of large trees within the urban core. The city's climate accounts lack documentation of urban trees' contribution to the city's carbon storage and sequestration (Søgaard and Bjørkelo, 2018). Oslo currently implements a series of methods that directly or indirectly map and value urban trees using both biophysical and monetary methods (Agency for Planning and Building Services (PBE, 2018a, 2018b; Barton et al., 2015; Hanssen et al., 2019; Lauwers et al., 2017). However, none of these methods combines a city-wide mapping of individual trees with tree specific quantification and valuation of regulating ES. In site-specific development, lacking quantification of benefits of individual trees can lead to tree removal and inadequate compensation in terms of regulating ES. Quantification of the benefits of individual street trees is also a component of urban ecosystem accounting for municipal decision-support (UN, 2017; Wang et al., 2019). ES mapping for policy-support has been limited by lacking documentation of data and modelling uncertainty, lacking assessment relative to different purposes, and where necessary for decision-making, lacking approaches to reduce that uncertainty (Hou et al., 2013; Schulp et al., 2014).

In Oslo, the i-Tree Eco model – a software application intended for quantification and valuation of regulating ES provided by urban tree inventories, developed by the United States Department of Agriculture Forest Service (“i-Tree Eco v.6,” n.d.) – could provide the municipality with a means for both (i) site-specific service quantification and benefit valuation and (ii) ecosystem accounting of city-wide tree populations that are currently only partially inventoried. I-Tree Eco has been identified as a modelling tool that can meet different municipal policy-support needs of Oslo, including awareness-raising and funding support, ecosystem accounting, spatial priority-setting, instrument design, economic liability and compensation (Barton et al., 2015; Gomez-Baggethun and Barton, 2013).

The main input to i-Tree Eco analysis is a database of individual trees and their attributes comprising tree species, dimensions, condition or spatial context measures. In the standard approach recommended by the i-Tree Eco Field Guide (i-Tree Eco Field Guide v6.0, 2019), the tree database is obtained through a field survey in which tree attributes are measured manually and individually. Depending on the sampling intensity and spatial extent of the study, this can be time consuming and expensive. The cost of manual surveys is a major limitation in valuing regulating ES of urban trees – a third of respondents in a study of UK i-Tree projects reported time taken to complete surveys as a significant barrier to implementation (Raum et al., 2019).

Municipalities often maintain a tree inventory for tree management purposes. In Oslo, the Urban Environment Agency maintains a database of nearly 30 000 geolocated street and park trees, used to manage and monitor private tree maintenance contracts. Municipal tree inventories can be used as a source of individual tree data for i-Tree Eco analysis instead of investing in specialized manual field surveys. However, missing and incomplete tree attributes in these inventories relative to the needs of i-Tree Eco can lead to low numbers of analysed trees and/or lower accuracy of results. In the worst case, municipal tree inventories do not contain even minimum data required to run i-Tree Eco.

Rapid technological advances have enabled the application of geospatial technologies in automated urban forest surveying. In a review of urban tree inventorying methods, Nielsen et al. (2014) found manual field surveys to be more accurate than remote sensing-based surveys, calling for further technological development and scientific testing before these methods can replace manual surveys. Recently, however, increased accuracy and availability of high-resolution airborne laser scanning (ALS) or terrestrial laser scanning (TLS) and hyperspectral imagery allowed for partial or complete substitution of manual surveying of locations, species and structural attributes of trees in urban environments (Fassnacht et al., 2016; Gu and Townsend, 2016; Heo et al., 2019; Herrero-Huerta et al., 2018; Liew et al., 2018; Mozgeris et al., 2018; Saarinen et al., 2014; Zagoranski et al., 2018). Alonzo et al. (2016) demonstrated that species-level canopy cover estimates from remote sensing methods had generally smaller uncertainty compared to field-plot methods. Furthermore, new approaches to virtual ground-based tree inventorying using Google Street View are sufficiently accurate to complement and verify remote sensing data (Berland and Lange, 2017).

These advances suggest a greater role of remote sensing in automated surveying of individual tree structural attributes and species for i-Tree Eco. Furthermore, attributes of tree's spatial context, i.e. expressing the relationship between a tree and its surrounding structures and phenomena (buildings, other trees, land use), can more rapidly, consistently and at low cost be estimated using geospatial analysis methods from digital terrain models, cadastral maps or land use maps. To our knowledge, these new approaches are scarcely used in i-Tree Eco studies. Zhao et al. (2018) used geospatial technologies to create an urban tree inventory in Nantong City, China. They employed mobile TLS to automatically detect location, height, crown width and stem diameter of individual street trees for evaluation of carbon sequestration and PM_{2.5} removal. We found only two studies exploring the integration of spatial data with existing municipal tree inventories for calculating missing tree attributes; both use spatial data to estimate attributes of spatial context. Scholz et al. (2018) used a high-resolution digital surface model to estimate trees' crown light exposure (for estimation of carbon sequestration) in Duisburg, Germany. Similarly, at University of Pennsylvania, US, Bassett (2015) measured trees' distance and direction to buildings (for estimation of building energy savings by temperature regulation due to trees) in GIS; buildings were represented by their footprints in a cadastre map.

For ecosystem accounting, a further step of extrapolation of i-Tree Eco valuation results from partially inventoried municipal trees to the whole population of municipally owned trees is required. This task can be tackled by Bayesian networks (BN), a generic machine learning method for representing a correlation structure in a causal network and for decision analysis under conditions of missing data and uncertainty (Kjærulff and Madsen, 2008). Expert systems such as BN have been used successfully in several environmental management fields to infer unobserved characteristics across a population (Barton et al., 2012). BN have been identified as potentially useful for generalizing modelling results from study areas to ecosystem wide accounting (Barton et al., 2019). The ability of BN to explicitly consider data and modelling uncertainty also address the uncertainty documentation gap identified in the ES mapping and modelling literature (Hou et al., 2013; Schulp et al., 2014).

Compared to the wide adoption of i-Tree Eco, these few examples suggest that the community of i-Tree Eco practitioners makes limited

use of new geospatial and machine learning methods to replace or supplement manual field surveys of urban forests. Developing further the approaches started by Bassett (2015); Scholz et al. (2018) and Zhao et al. (2018), in this article we aim to demonstrate the potential of geospatial and machine learning methods to both supplement missing tree attributes and increase the number of trees suitable for i-Tree Eco analysis by filling data gaps in existing municipal tree inventories. We will show how spatial data from ALS imagery and auxiliary spatial datasets were integrated with existing municipal tree inventory of Oslo to supplement a range of missing and incomplete tree attributes. Subsequently, we will demonstrate how machine learning with BN enabled inferring the value of the entire municipal urban forest from partially overlapping samples of tree attributes.

2. Methods

2.1. Study area and used software

The study area is the city of Oslo built zone regulated for urban development, where the analysed tree inventory is located. Oslo built zone covers 147 km², of which 47 % was covered by vegetation in 2017, 27 % of which was regulated green space (Agency for Planning and Building Services (PBE, 2018a). The population was 640 902 in 2015, which is the reference year in this study (Statistics Norway (SSB, 2019).

For analysis of tree inventory of Oslo, we used i-Tree Eco v.6., a part of the i-Tree suite of software which quantifies urban forest structure, estimates the supply of and benefits from regulating ES provided by trees in terms of annual ES indicators and associated monetary values and enables forecast modelling and management support. Estimated ES indicators included in this study were air pollution removal, avoided runoff, carbon sequestration and building energy savings. Supply of oxygen production and volatile organic compound emissions is estimated, but these services/disservices are not valued (Nowak, 2019). To quantify ES, i-Tree Eco uses peer-reviewed model equations based on long-term research. Required input information to the model is species and stem diameter at breast height (DBH) of individual trees, recorded in random sample plots or complete inventory. Optional tree attributes (condition, structure, spatial context) increase model accuracy and enable quantifying additional ES (Use of Direct Measures by i-Tree Eco (v6.0), 2018). Table S4 in Supplementary Material provides an overview of i-Tree Eco attributes. Further input to the model is location information including weather and air pollution concentration data (used to estimate air pollution removal) and benefit prices of ES indicators. The resulting estimates of annual ES indicators and associated monetary values are provided as aggregates across the analysed tree inventory or disaggregated to individual tree level (for complete inventory). I-Tree Eco has been extensively used for valuation of urban trees in both small inventories and regional scale assessment projects, initially in the US and recently in Canada, Australia, Mexico and several European countries, particularly the UK (i-Tree International, 2020; i-Tree Reports, 2020).

We further used ESRI ArcMap 10.6 (ESRI, 2018) for geospatial analysis, The R Project for Statistical Computing (R Core Team, 2018) for statistical analysis and Expert Learning tool in Hugin Expert® software for BN modelling (Madsen et al., 2003).

2.2. Input data

2.2.1. Municipal tree dataset

Within the built zone, the Urban Environment Agency manages approximately 30 000 park and street trees, which are the subject of this study. The tree inventory of the Urban Environment Agency, hereafter the “municipal dataset”, contains trees recorded over several years of the agency’s sub-contracted planting and management. Trees in the dataset are represented as points with associated attributes (stem coordinates, species, stem diameter and/or circumference and condition indicators) (Fig. 1A), however, many of these attributes are incomplete. As of August 2018, the dataset contained 30 237 records, reduced to 29 928 after removing records with identical locations.

Before further analysis, we corrected gross errors (i.e. mistakes in measurement, recording or digitization errors and mistakes). Stem diameter or circumference was recorded for 6 313 trees (21.1 %). We calculated diameter from the circumference, assuming a circular stem cross-section, and considered it an estimation of DBH. Tree species (Norwegian or Latin name) was recorded for 17 044 trees (57.0 %) and we matched it to predefined species from the i-Tree database (i-Tree Database, 2020). Recorded condition indicators were not used, because they did not match the condition indicators used in i-Tree Eco. The resulting municipal dataset contains 5 782 trees with recorded DBH (19.3 %) and 16 989 trees with recorded species (56.8 %).

2.2.2. ALS tree dataset

Using ALS imagery, Hanssen et al. (2019) identified individual trees taller than 2.5 m on both private and public land in Oslo’s built zone in 2011, 2014 and 2017. We use the 2014 dataset containing 402 610 records. In this dataset, hereafter the “ALS dataset”, each recorded tree is represented by a polygon of 2D crown geometry (Fig. 1A). An additional attribute of each tree is crown diameter, approximated as a diameter circle circumscribed to the crown polygon. The ALS dataset represents a complete tree population of Oslo built zone regardless of management practices and ownership and is therefore suitable for accounting of urban tree canopy at an aggregate level. However, due to lacking information about tree species and lower accuracy at individual tree level caused by lower point density of ALS point clouds (Hanssen et al., 2019), the dataset cannot be directly used in i-Tree Eco analysis.

2.2.3. Auxiliary spatial datasets

We used a vector map of Land use in urban settlements in reference scale 1:5 000 (Statistics Norway, 2015) (Fig. 1B), hereafter “Land use map”, and a vector FKB-AR5 Land resource map in reference scale 1:5 000 (Norwegian Institute for Bioeconomy Research (NIBIO, 2015) (Fig. 1C), hereafter “Land resource map”, for information about local land use. The Land use map provides detailed information about land use classes of built-up areas but does not cover all unbuilt space, whereas the Land resource map is seamless, but with lower information resolution. Vector FKB-Buildings map in reference scale 1:5 000 (Norwegian Mapping Authority, 2015) (Fig. 1D), hereafter “Building map”, was used for information about building footprints. A non-negative difference raster of digital surface (DSM) and terrain (DTM) model in 1-meter resolution (Norwegian Mapping Authority, 2014), hereafter “DSM-DTM raster”, was used to derive tree and building heights (Fig. 1E).

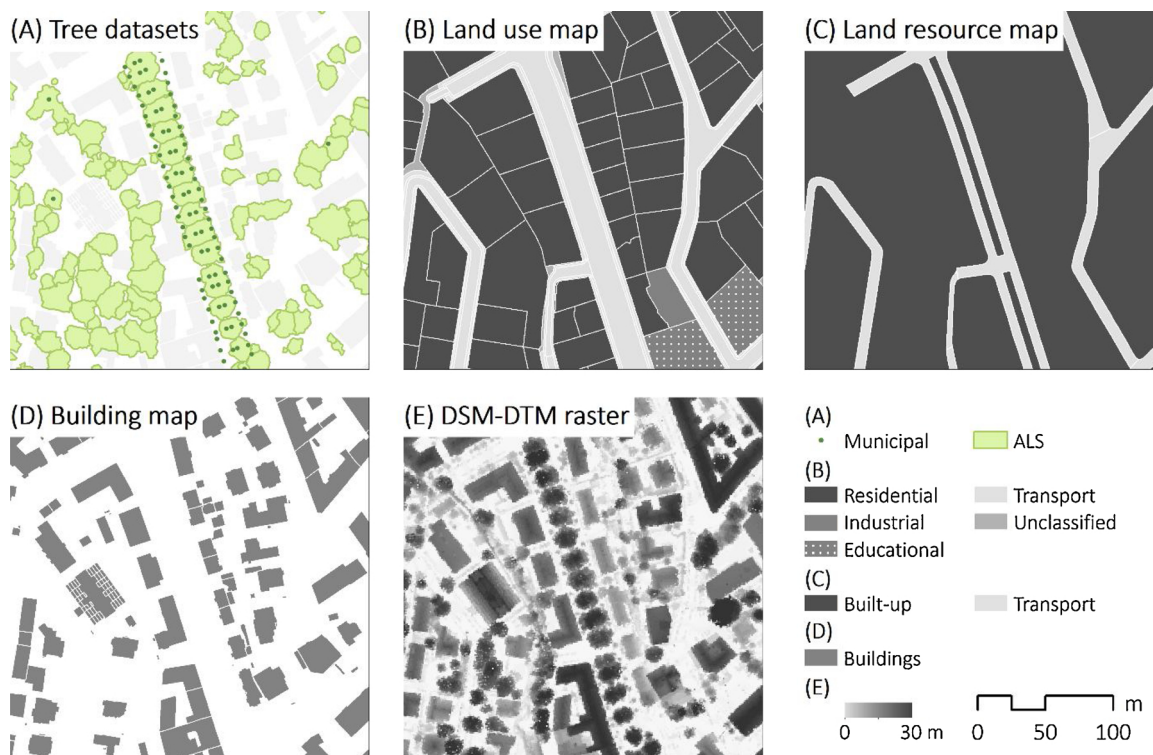


Fig. 1. Used spatial datasets.

2.2.4. Location information

For the reference year 2015, i-Tree Eco v.6 stores weather data including annual hourly precipitation levels provided by NOAA’s National Climatic Data Centre (NCDC), as well as air pollution levels of nitrogen dioxide (NO2), particulate matter 2.5 micrometres or less in diameter (PM2.5), carbon monoxide (CO), ozone (O3) and sulphur dioxide (SO2) provided by the U.S. Environmental Protection Agency. For Oslo, both weather and air pollution data are stored for a single monitoring station Oslo-Blindern.

The precipitation totals in i-Tree Eco were considerably different from values recorded by the Norwegian Meteorological Institute (Norwegian meteorological institute (MET, 2015) at a corresponding monitoring station in 2015 (NCDC: 55.77 mm, MET: 921.1 mm), implying missing observations in the NCDC data. Therefore we replaced the stored precipitation levels by annual hourly precipitation levels recorded by MET for the Oslo-Blindern station.

Air pollution in Oslo varies significantly, depending mainly on distance from a pollution source (Schneider et al., 2017). To account for heterogeneity in air pollution levels and thus enable more precise estimation of air pollution removal by trees, we replaced the stored air pollution data by air pollution levels spatially disaggregated to three zones, defined by limits for daily, winter and annual means of NO2 and PM10 (NILU and MET, 2015). In 2015, there were 12 stations monitoring hourly air pollution levels in Oslo (Norwegian Institute for Air Research (NILU, 2015). Levels of PM2.5 and NO2 in each zone were represented as medians of levels recorded by monitoring stations within

each zone. Levels of CO, O3 and SO2 were recorded by one station only and were considered constant across all three zones.

We used local Oslo and Norwegian data sources to determine benefit prices for ES indicators (see Supplementary Material for more information). All values are in 2014 prices.

2.3. Methodology workflow

The methodology workflow is illustrated in Fig. 2. In Steps 1 and Step 2, missing and incomplete attributes in the existing municipal tree inventory are supplemented by associating stem points with crown geometry from the ALS dataset (Step 1) and with auxiliary spatial datasets (Step 2) using geospatial analysis. Only attributes influencing the included ES indicators are calculated (Table S4 in Supplementary Material, Use of Direct Measures by i-Tree Eco (v6.0), 2018). Furthermore, attributes which cannot be calculated from available spatial data (crown health) are omitted. Steps 1 and 2 result in a final tree dataset. Trees with a complete attribute set from the final dataset, together with location information, are the input to i-Tree Eco analysis. The outputs are processed in i-Tree Eco emulation using BN to estimate the total asset value of the complete municipal inventory.

2.4. Step 1: associating stem points with crown geometry

To enable associating crown geometry attributes from the ALS dataset to stem points from the municipal dataset, we handled four

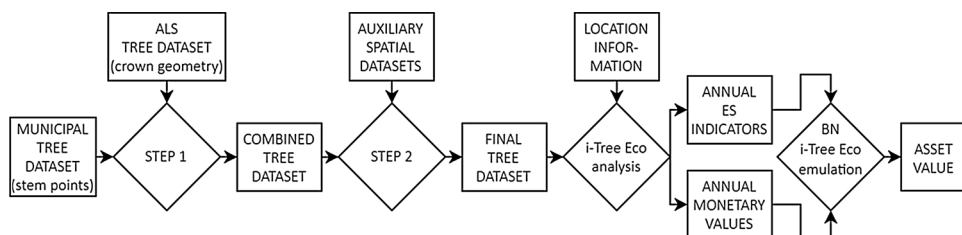


Fig. 2. Methodology workflow of i-Tree Eco implementation in Oslo.

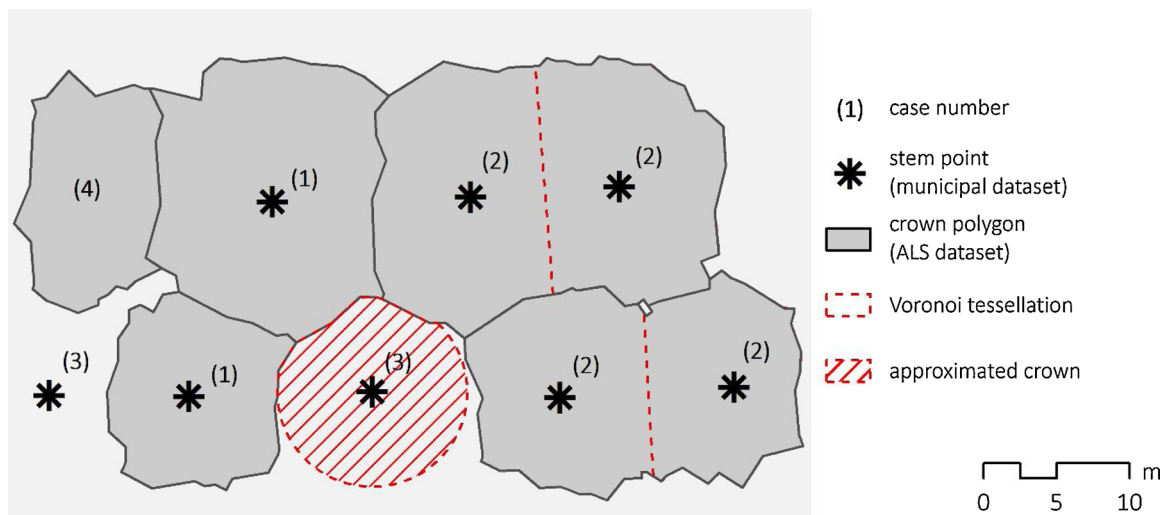


Fig. 3. Four cases of geometrical relationship between stem points (municipal dataset) and crown polygons (ALS dataset).

general cases of geometrical relationship between stem points and crown polygons (Fig. 3). In Case 1 (18 % of records in the municipal dataset), one crown polygon contains exactly one stem point and we directly joined crown polygons to corresponding stem points. In Case 2 (51 % of records in the municipal dataset), one crown polygon contains more than one stem point. We split the concerned crown polygons by Voronoi tessellation, frequently used in tree crown segmentation (Heinimann and Breschan, 2012; Novotny et al., 2011). We then recomputed crown diameter (CD) of the new crown polygons, defined by the closest stem point, and joined them to corresponding stem points. In Case 3 (13 % of records in the municipal dataset), a stem point is not overlapped by any crown polygon. We used an inverse allometric equation suggested by Jucker et al. (2017) to predict CD from measured DBH if it was available (see Supplementary Material for further details on model fitting). We then approximated crown geometry as a circle centred at stem point with a diameter equal to predicted CD, adjusted for the geometry of neighbouring crowns. In Case 4 (18 % of records in the municipal dataset), a crown polygon contains no stem point. These records of the ALS dataset were utilized when adjusting the geometry of approximated tree crowns from Case 3 and when modelling crown light exposure.

2.5. Step 2: integrating auxiliary spatial datasets

We used geospatial analysis and statistical methods to integrate auxiliary spatial datasets and calculate missing and incomplete tree attributes. The developed methods follow attribute definition according to the *i-Tree Eco Field Guide* (*i-Tree Eco Field Guide v6.0, 2019*) where possible.

2.5.1. Species

In the municipal dataset of Oslo, tree species were manually recorded for 56.8 % of trees. In the diverse urban environment, the combination of airborne optical imagery and airborne ALS imagery seems promising for automatic tree species classification to replace manual field surveys (Wang et al., 2018). However, we did not carry out additional automatic species classification because none of the available auxiliary datasets was suitable for this task.

2.5.2. Stem diameter at breast height (DBH)

In manual surveys, DBH is measured at 1.37 m above the ground. If DBH is not recorded, it can be either predicted from other structural attributes using allometric equations (Jucker et al., 2017), measured directly from TLS imagery (Cabo et al., 2018; Moskal and Zheng, 2011)

or predicted indirectly from metrics calculated from ALS imagery (Tanhuanpää et al., 2014). To calculate DBH of municipal trees whose stem diameter or circumference was not recorded, we predicted DBH from derived total tree height (H) using an allometric equation suggested by Jucker et al. (2017) (69 % of records in the municipal dataset; see Supplementary Material for further details on model fitting).

2.5.3. Crown width (CD)

Crown diameter in *i-Tree Eco* is expressed as crown width in two cardinal directions – north-south and east-west, measured perpendicularly to the stem. Allometric equations to predict CD from other structural attributes have been developed (Jucker et al., 2017; Nowak, 2019). Furthermore, direct measurement of CD from TLS imagery (Herrero-Huerta et al., 2018; Zhao et al., 2018) or ALS imagery (Alonzo et al., 2016; Zhang et al., 2015) is common. As described in Step 1: Associating stem points with crown geometry, we both utilized the direct measurement of CD from the ALS dataset (Cases 1 and 2) and predicted CD from DBH using allometric equations (Case 3). We derived crown width in cardinal directions as the width and length of minimum bounding envelope of the crown geometry.

2.5.4. Total tree height and Height to live top (H, HLT)

In manual surveys, H is measured as the distance from the ground to treetop (alive or dead) along the stem. If H is not recorded, it can be either predicted from other structural attributes using allometric equations (Jucker et al., 2017; Nowak, 2019; Scholz et al., 2018) or measured directly from ALS (Alonzo et al., 2016; Saarinen et al., 2014; Zhang et al., 2015) or TLS (Martí et al., 2018; Moskal and Zheng, 2011) imagery. We derived H from DSM-DTM raster at stem location. To account for inaccuracies in recorded stem location and cases where treetop does not align with stem location, we recorded the maximum value in a 3×3 Rook's neighbourhood of the stem point. If the recorded value was smaller than 0.5 m, suggesting a tree was cut before or planted after the DSM-DTM dataset was created, we predicted H from DBH using in-built *i-Tree Eco* species-specific allometric equations. We approximated HLT, i.e. the height from ground to live treetop, as equal to H.

2.5.5. Height to crown base (HCB)

Defined as the height from ground to live crown base, apart from manual surveys, HCB can be measured from ALS imagery (Alonzo et al., 2016; Zhang et al., 2015) or TLS imagery (Herrero-Huerta et al., 2018; Wu et al., 2013). Because HCB was not recorded in the ALS dataset, we predicted it from DBH using in-built *i-Tree Eco* species-specific

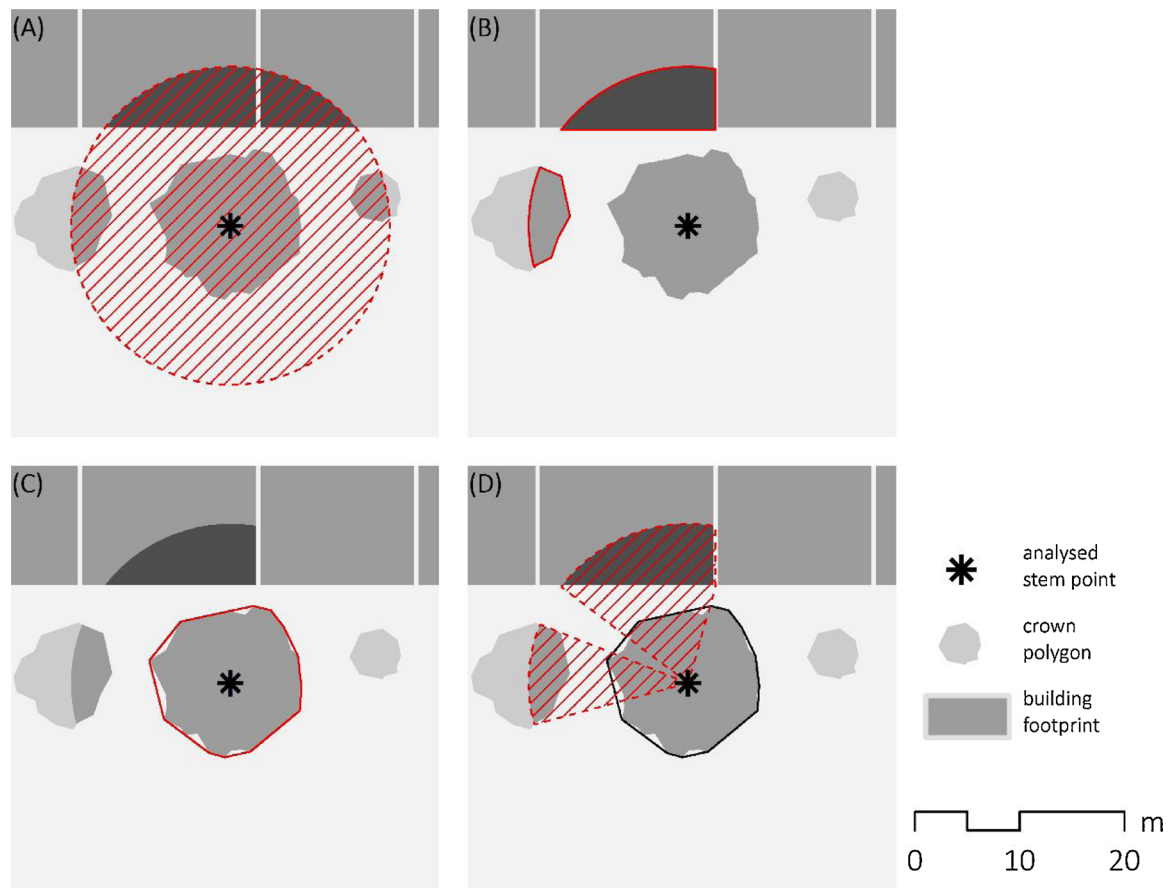


Fig. 4. Modelling crown light exposure. (A) a buffer of radius equal to the crown diameter and objects within this buffer, (B) selected objects taller than the analysed tree, (C) convex hull of the analysed tree crown, (D) tangents between stem point and edges of extracted objects define parts of crown perimeter not receiving light. In these hypothetical settings, 70 % of the analysed crown perimeter receives light, corresponding to crown light exposure class 3.

allometric equations.

2.5.6. Crown light exposure (CLE)

The i-Tree Eco Field Guide defines crown light exposure as “the number of sides of the tree’s crown receiving light from above or the side” where obstructions for light are “any parts of an adjacent tree crown or building that are a) overtopping any part of that crown side, or b) within one average crown width away from the measured tree’s stem and the object is at least as tall as the measured tree”. CLE is expressed by a score from 0 (tree does not receive light from any side) to 5 (tree receives light from all directions and from above). Several geospatial analysis methods for deriving CLE have been developed. Scholz et al. (2018) estimate CLE by observing whether digital surface model pixels in four compass directions from the tree’s centre are located higher (casting a shadow on the tree) or lower (permitting the sun to reach the tree) than the tree’s height. Alternatively, Pace et al. (2018) estimate CLE from a competition index computed in the Single-tree-based stand simulator SILVA (Pretzsch et al., 2002) and using a fixed distance buffer to account for shading by buildings and other trees. We estimated CLE in a GIS processing routine as the percentage of crown perimeter exposed to open light (Fig. 4). Following the i-Tree Eco Field Guide, we first selected all adjacent buildings and tree crowns, i.e. all pixels from the DSM-DTM raster within a buffer around stem point with radius equal to CD (Fig. 4A). We then extracted all pixels with a value equal to or larger than recorded H (Fig. 4B). To minimize the effect of concavities in the crown perimeter, we approximated the crown geometry by its convex hull (Fig. 4C). Finally, we calculated the proportion of crown’s perimeter receiving light by constructing tangents between stem point and edges of extracted objects (Fig. 4D). To match the

calculated proportion to i-Tree Eco scores, we classified the proportion of crown’s perimeter receiving light as follows: 0–12.5 %: CLE = 1, 12.6–37.5 %: CLE = 2, 37.6–62.5 %: CLE = 3, 62.6–87.5 %: CLE = 4, > 87.6 %: CLE = 5. Due to the origin of the ALS dataset, no overlaps exist between detected crowns and we assumed light from above for all trees, although in reality overlaps between crowns are common in dense tree stands.

2.5.7. Distance and direction to building (DB)

To estimate building energy savings, distance and direction to the three nearest residential buildings can be measured in a manual survey. Distance and direction measurement between geometrical features (stem points and building footprints) is a simple geospatial analysis task, for i-Tree Eco analysis used for example by Bassett (2015). Following the i-Tree Eco Field Guide, we measured distance and direction from stem points of trees taller than 6 m to three nearest residential building footprints selected from the Building map, lower than four storeys and closer than 18.3 m to the analysed stem point.

2.5.8. Land use (LU)

In manual surveys, one of 13 default land use classes at tree location is recorded. We combined the Land use and Land resource maps to create a seamless LU map covering the study area and reclassified it to match LU classes used by i-Tree Eco. To determine each tree’s LU class, we intersected each stem point with the seamless LU map in GIS. Following the definition of Transportation class, trees intersected by minor road classes were classified according to the nearest adjacent LU.

2.5.9. Percent crown missing (PCM)

Percent crown missing is the proportion of tree crown volume not occupied by branches and leaves. In manual surveys, it is estimated by comparing the tree's crown shape to a natural crown shape for particular species. No studies addressing PCM estimation using geospatial analysis methods were found and therefore we used i-Tree Eco default value 15%–20% for all trees.

2.6. i-Tree Eco analysis

The final dataset was split by air pollution zones and we ran an i-Tree Eco model for each zone. Trees with complete attribute set were imported into i-Tree Eco v.6 together with location information. The output from the models – estimates of annual ES indicators and associated monetary values – were linked back to individual trees in the final dataset. Estimated ES indicators were: air pollution removal, avoided runoff, carbon sequestration and building energy savings.

We furthermore estimated asset value per tree based on the annual monetary value of ES indicators as calculated by i-Tree Eco, current tree age estimates and tree life expectancy based on simple allometric equations (Lauwers et al., 2017) and a 1.4% discount rate (Stern, 2007). The asset value was calculated as the present value of the discounted flow of annual monetary value of the ES indicator for the expected lifetime of the tree.

2.7. i-Tree Eco emulation and model assessment

The final dataset was incomplete with regards to DBH and species required by i-Tree Eco, while CD and H were calculated for almost all trees (Fig. 5). Based on i-Tree Eco outputs for the final dataset and tree location characteristics (air pollution level), we therefore used BN to emulate ES indicators and asset values for all 29 928 trees from the municipal dataset. For inference of asset value, we used crown area (CA) instead of CD. While CD and CA are close proxies, CA is a direct measure derived from ALS segmentation. Area-based asset values are also the unit of measure for ecosystem accounting.

Hugin Expert® software uses expectation maximization (Lauritzen, 1995) to learn conditional probability tables in the presence of missing data. It is a nonparametric approach. We used the necessary path condition algorithm, which allows users to guide learning using a causal structure with a limited number of variables. In effect, the BN is a reduced form emulation model (Castelletti et al., 2012) for the complex i-Tree Eco model. We also used the mutual information index to evaluate the information value of observing derived tree attributes (CA, H) relative to observing attributes usually measured in manual field surveys (DBH, species). We scaled the estimated asset value per tree from the final dataset to the total 29 926 trees of the municipal dataset to estimate the expected total asset value of municipally managed trees. We assessed how the robustness of the resulting total asset value

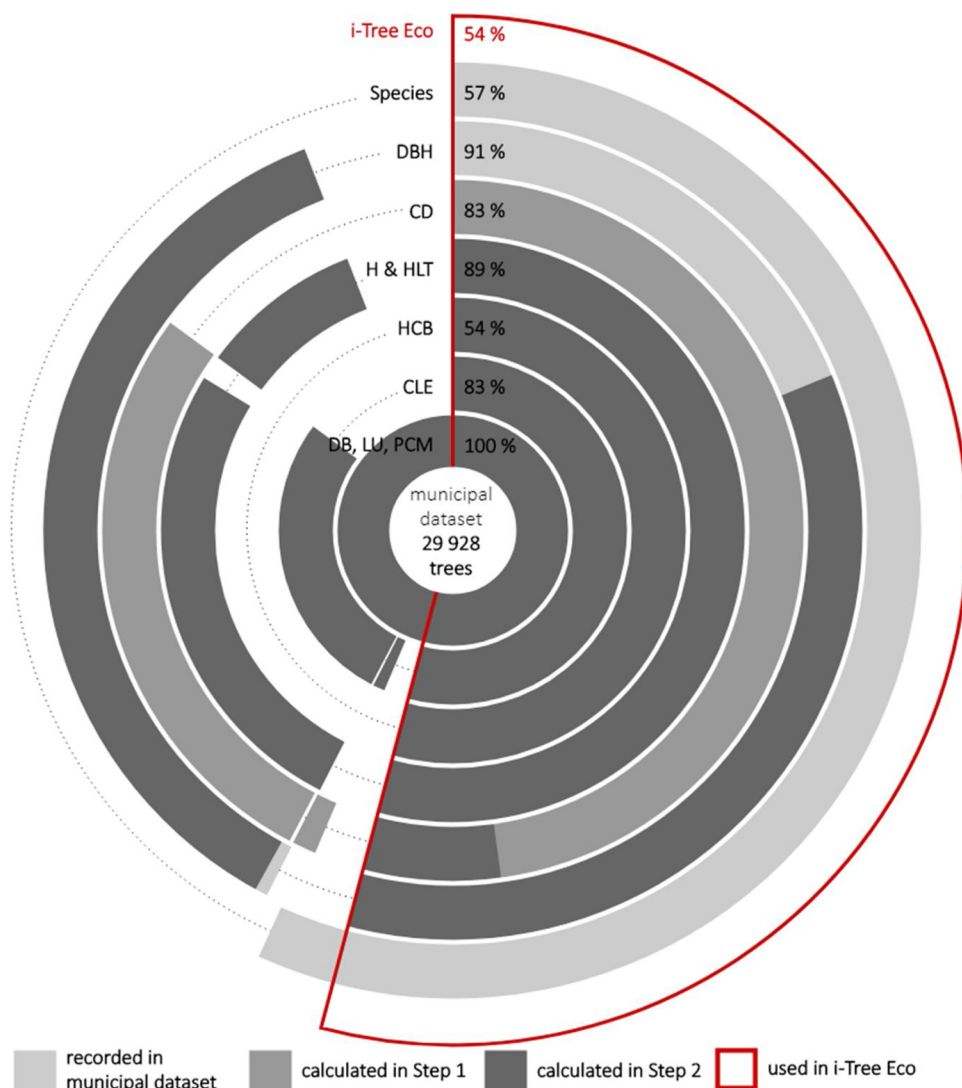


Fig. 5. Information gain from integrating municipal tree dataset with available spatial data. Each concentric circle symbolizes one attribute. Arc size is proportional to the percentage of trees with that attribute in the final dataset. Arc colour represents the origin of the attribute – the original Municipal dataset, Step 1 (Associating stem points with crown geometry) or Step 2 (Integrating auxiliary spatial datasets). pie wedges illustrate the combinations of recorded, calculated or missing attributes for subsamples of trees in the final dataset. The pie wedge outlined in red depicts the proportion of trees with complete attribute set used in the final i-Tree Eco analysis.

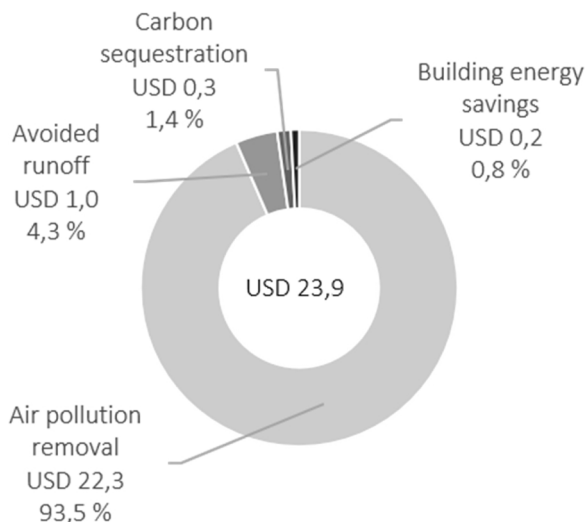


Fig. 6. Per-tree average annual monetary value distributed per ES indicator.

depends on assumptions about the non-parametric probability distribution of all trees. Using the Hugin Expert spatial data processing module we estimated the Bayesian credible interval of the asset value, and discuss it relative to different decision-support requirements. (See Supplementary Material for further details.)

3. Results

3.1. Information gain from integrating municipal tree dataset with available spatial data

Information gain, i.e. the proportion of trees with calculated attributes after each step, is visualized in Fig. 5 and summarised in Table S4 in Supplementary Material. The basis for i-Tree Eco analysis in Oslo was a municipal dataset containing 29 928 recorded trees. Species were recorded for 57 % and DBH for 19 % of trees. Furthermore, GPS coordinates were recorded for each tree. I-Tree Eco analysis of the municipal dataset is possible for 19 % of trees, i.e. all trees with both species and DBH recorded.

Integrating crown geometry from the ALS dataset (Step 1) enabled calculating CD for 76 % of trees. The number of trees suitable for i-Tree Eco analysis remains constant. Calculating CD from the ALS dataset instead of predicting it using allometric equations in i-Tree Eco is however expected to increase the reliability of estimated annual ES indicators and associated monetary values because it relies on direct measurement of tree crowns rather than modelling.

Integrating auxiliary spatial datasets (Step 2) enabled supplementing incomplete attributes for DBH (71 % of trees) and CD (6% of trees). Furthermore, seven missing attributes were calculated, namely H, HLT, HCB, CLE, CD, LU and PCM. The integration of auxiliary spatial datasets enabled estimating additional ES indicator (building energy savings) and increased the number of trees suitable for i-Tree Eco analysis from 19 % to 54 % of trees. Supplementing missing attributes is also expected to increase the reliability of estimated annual ES indicators and associated monetary values.

Fig. 5 also enables summarizing the effectivity of calculation methods representing the municipal tree population, i.e. the proportion of final tree dataset with calculated attributes. Methods requiring only tree coordinates and auxiliary spatial datasets on the input were highly effective (100 % for DB and LU). The effectivity of methods for calculating H, HLT, CD, CLE and DBH was lower, mainly due to the methods' dependency on other attributes such as DBH. The method used to calculate HCB has the lowest effectivity due to species-specific allometric equation used to calculate this attribute. The low percentage of trees with recorded species (57 %) is the main cause of only 54 % of trees from the final dataset included in the i-Tree Eco analysis

3.2. Ecosystem services of individual municipal trees

The outputs from i-Tree Eco analysis – annual ES indicators and associated monetary values for individual trees – are visualized in an interactive map (link in Supplementary Material). Fig. 6 presents the per-tree average annual monetary value, distributed per individual ES indicators. The average value of air pollution removal constitutes the largest proportion (93.5 %) of the annual monetary value of an average tree, highlighting the importance of correct estimation of air pollution at tree location, here addressed by air quality zonation. The proportions of values associated with other ES indicators (avoided runoff, carbon sequestration and building energy savings) are considerably smaller. Fig. 7 illustrates the distribution of per-tree average annual monetary value for the most common genera and CD classes. Much of variation in ES supply from individual trees can be explained by tree size, represented here by CD. Observation of tree species, here summarised by genus, provides further insight into the variation.

3.3. Asset value of all municipal trees

The mean asset value per tree, estimated by BN i-Tree Eco emulation model using all information available about all 29 928 trees from the municipal dataset, is 1 443 USD/tree. The spatial variation in the ES indicators, particularly in air pollution removal, is large and leads to the mean asset value dropping to 893 USD/tree in the lowest air pollution zone and rising to 2 347 USD/tree in the highest air pollution zone.

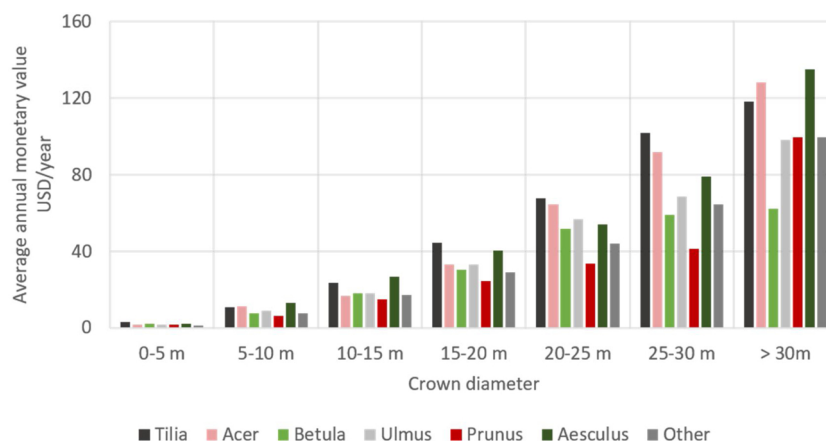


Fig. 7. Distribution of per-tree average annual monetary value for the most common genera and crown diameter classes.

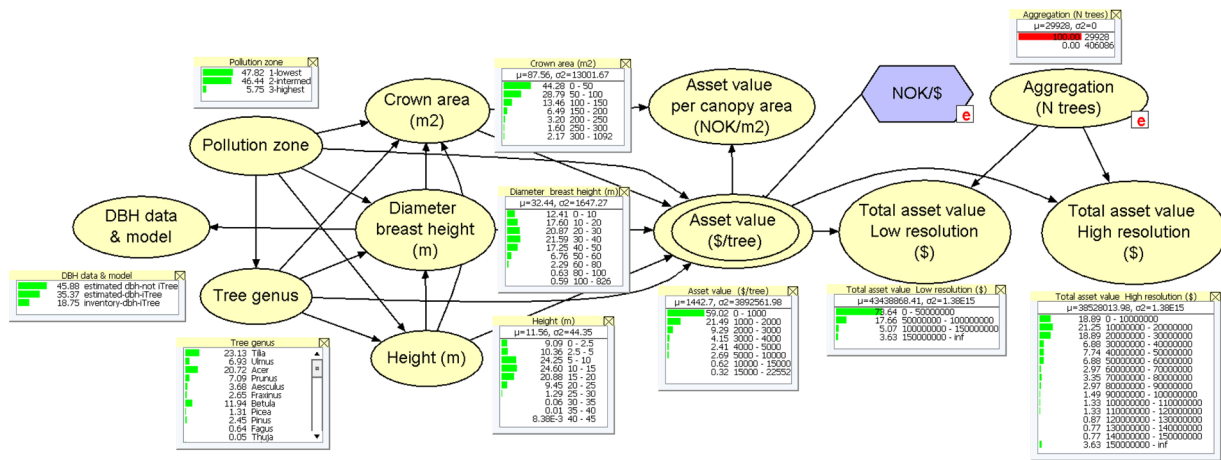


Fig. 8. A Bayesian network emulating tree asset value based on i-Tree Eco and a selection of attributes from the final dataset. Variable windows show probability distributions for categorical variables and continuous variables discretized into intervals. Mean (μ) and variance (σ^2) of continuous variables is reported at the top of each window.

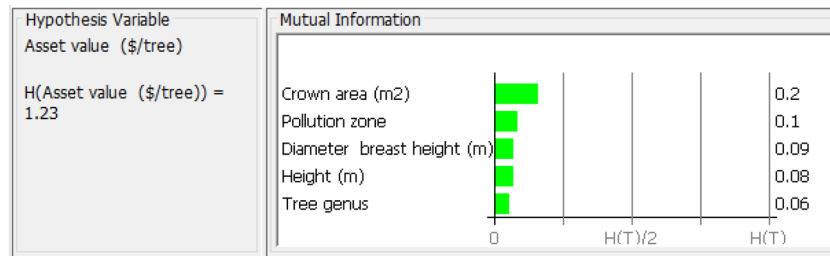


Fig. 9. Index of mutual information between asset value and tree attributes.

Value of information analysis using Hugin Expert® software (Fig. 9) shows that observation of CA provides more information about the asset value than other variables. Air pollution zone, DBH and H are relatively similar in predictive power. Field observations of tree genus do not provide as much information as structural tree attributes (CA, DBH, H). Structural tree attributes - in particular crown area - are better predictors of regulating ES estimated by i-Tree Eco.

Structural attributes of individual trees and ES indicators are not normally distributed, with many small trees and a few tall large-canopy trees with exceptional asset values (> 10 000 USD/tree). When scaling individual asset value predicted by the model to the population, total asset values are sensitive to assumptions about the shape and resolution of the probability distribution of the tree population. The two panels on the far right of Fig. 8 show that a non-parametric probability distribution with low resolution (top right panel) produces a higher aggregate asset value than a probability distribution with high resolution (bottom right panel). If individual tree asset values are inferred using the Hugin Spatial Processing Tool, the aggregate asset values are yet more conservative. The expected total asset value with these different inference approaches is 33.1–43.8 million USD (see Supplementary Material for further details).

4. Discussion

In this paper, we demonstrated the potential of geospatial and machine learning methods to fill data gaps in existing tree inventories and enable i-Tree Eco analysis. By integrating the tree inventory of Urban Environment Agency of Oslo, Norway, with available spatial data, we were able to both supplement missing i-Tree Eco attributes and increase the proportion of tree records suitable for i-Tree Eco analysis from 19 % to 54 %. Integrating spatial data enabling species recognition into the processing chain would further increase the proportion to 91 %, which is the current proportion of inventoried trees with recorded

DBH. Furthermore, we illustrated how machine learning with BN can be used to extrapolate i-Tree Eco outputs and infer the value of the entire municipal inventory.

These are the first steps towards a full substitution of manual field surveys by geospatial methods-based surveys. Advances in the availability and combination of high-resolution ALS and hyperspectral imagery have already enabled detection of individual trees and their attributes, including crown dimensions, species and condition (Fassnacht et al., 2016; Gu and Townsend, 2016; Heo et al., 2019; Herrero-Huerta et al., 2018; Liew et al., 2018; Mozgeris et al., 2018; Saarinen et al., 2014; Zagoranski et al., 2018). There is an opportunity for the i-Tree community to actively use this data and tailor the detection methods to fit i-Tree Eco requirements. I-Tree practitioners have started to use geospatial analysis methods to generate selected field measurements such as CLE and DB (Bassett, 2015; Scholz et al., 2018), but we show in this paper that there is scope for more.

The i-Tree Eco Field Guide puts a strong focus on the measurement procedures of individual attributes in manual field surveys to calculate reliable estimates of ES indicators. Implementing i-Tree Eco on top of tree inventories that are not carried out in accordance with these guidelines and substituting manual field measurements of input attributes with automatic methods may increase the uncertainty of resulting ES indicators, depending on the functional dependency between tree attributes and respective ES indicators. While e.g. structural attributes (H, PCM) or tree species are used for estimating several ES indicators, CLE or DB are used for single ES indicator only (lower part of Table 1).

The reliability of tree attributes estimated here varies with the methods used (upper part of Table 1), i.e. statistical or geospatial methods. The reliability of statistical methods, applied to estimate DBH and a small portion of CD, might be negatively affected by heterogeneity in tree species, growing conditions or management practices, which interfere with the observed functional relationship between tree dimensions (see Supplementary Material for details of the regression

Table 1
Input data and methods for tree attribute estimation and use of tree attributes in estimating respective ecosystem service indicators by i-Tree Eco.

	Species*	DBH*	CD	H & HLT	HCB	CLE	DB	LU	PCM
Input data and methods for tree attribute estimation									
Geospatial methods	ALS dataset		✓						
	DSM-DTM			✓		✓			
	Building map					✓	✓		
	Land use/Land resource map							✓	
Statistical methods	~ DBH		✓	✓	✓				
	~ H	✓							
	~ CD	✓							
	~ species			✓	✓				
Constant									✓
Ecosystem service indicators (adapted from Use of Direct Measures by i-Tree Eco (v6.0) (2018))									
Air pollution removal	✓		✓	✓	✓				✓
Avoided runoff	✓		✓	✓	✓				✓
Carbon sequestration	✓	✓		✓		✓		✓	✓
Building energy savings	✓			✓			✓		✓

* Tree species and DBH are required attributes used by i-Tree Eco to estimate missing attributes.

models). This is reflected in the relatively low R² value of the respective prediction models used in this study (0.46 for CD, 0.51 for DBH). Accounting for these factors might lead to more reliable estimates (Vaz Monteiro et al., 2016). Similarly, the in-built i-Tree Eco allometric equations, used in this study to predict H and HCB, are fitted on datasets from numerous cities and might not be representative for the conditions of Oslo. Finally, our regression models lead to underestimation of CD and DBH, because these were estimated without applying a correction factor for logarithmic transformation bias. This underestimation means that the resulting ES indicators and associated monetary value are conservative for 77 % of trees suitable for the i-Tree Eco analysis. When using allometric equations, it is important to always apply a bias correction term when back-transforming prediction on a logarithmic scale to prediction on the original scale (Baskerville, 1972; Clifford et al., 2013; Smith, 1993). In a further use of the municipal tree dataset, this bias correction will be applied.

Geospatial methods on the other hand often have a potential to decrease the uncertainties of manual field measurements which might occur due to local conditions, access rights or subjective perceptions of the survey crew, especially when the position of the tree towards other structures is assessed – such as CLE, DB or LU. The reliability of attributes derived using geospatial methods is in that case affected by the precision and accuracy of the spatial datasets used, and by accuracy in the measured location of tree stems. Employing detailed national spatial datasets, such as those used here (DSM-DTM raster, maps of buildings, land use and land resources), increases reliability. As mentioned before, the ALS dataset might lead to less reliable estimates of CD due to inaccuracies in individual crown delineation. In addition to the reliability of estimated tree attributes, validity assessment should be applied when the routines to model tree attributes from spatial data do not strictly follow the i-Tree Eco guidelines (i-Tree Eco Field Guide v6.0, 2019). We diverged when modelling CLE, but discussed the methodology with i-Tree Eco developers who confirmed the suitability of the method. The impact of uncertainties in modelled attributes on the reliability of ES indicators estimated by i-Tree Eco remains to be explored in further research.

In addition to complementing manual field measurements, geospatial methods open possibilities for estimating tree attributes which are difficult to measure in the field, and thereby enable valuation of benefits which are unevenly distributed in space. Across urban areas, the supply of regulating ES such as air pollution removal by urban trees has been shown to vary and may be limited relative to total air pollution emissions of cities (Baró et al., 2015). Escobedo and Nowak (2009) documented the importance of micro-scale meteorological data for assessing air pollution removal by trees. Yet, the i-Tree Eco model does not enable spatial differentiation of air pollution levels and requires

practitioners to assign average levels to all trees. In this study, we have demonstrated the importance of taking of air pollution into consideration. Air pollution removal constitutes the largest proportion (93.5 %) of the annual monetary value of an average tree. Air pollution level at tree location is one of the main determinants of trees' asset value.

To estimate ES provided by the entire urban forest with i-Tree Eco, sample inventory is usually adopted due to high costs of complete inventories (i-Tree Eco Field Guide v6.0, 2019). However, the sampling approach only enables estimating ES indicators and associated monetary values at an aggregate level and prevents from utilizing the outputs e.g. for detailed urban planning purposes where individual trees need to be assessed. Complete substitution of manual field surveys with geospatial methods-based surveys enables quantifying ES of the entire urban forest while maintaining the possibility for spatially disaggregate outputs. In places where high-resolution remote sensing and auxiliary spatial data are not available to identify all tree attributes required by empirical ES models like i-Tree Eco, practitioners can nevertheless infer the likelihood of individual tree attributes and monetary values with available data and methods using BN. We observed that CA, here derived from the ALS dataset, explains a large part of the variation in annual monetary values across genera (Fig. 7). Using the value of information analysis in the BN (Fig. 9) we also found indications that attributes derived directly from ALS (CA) and auxiliary spatial datasets (H) or derived indirectly from other attributes (DBH) (upper part of Table 1) can be better proxies of asset value than tree species (measured in a manual survey) and may be therefore sufficient for aggregate valuation of municipalities trees for awareness-raising and accounting purposes. For individual tree appraisal purposes using tools like VAT03 (Randrup et al., 2003), manual surveying of tree species is still needed, but we argue that it may not be necessary when answering questions at a population level. The most accurate total asset value could be obtained by inferring each tree's asset value using BN with observable attributes of each tree from a GIS platform. BN models implemented in GIS are becoming available in commercial software (Landuyt et al., 2015). In Oslo, the ALS dataset represents the entire urban forest. Due to missing spatial data enabling species recognition we however utilized only a small fraction of the total 402 610 tree records. With a more representative sampling of all trees on both private and public land combined with a BN model implemented in GIS, it should be possible to obtain individual estimates of regulating ES for each tree in the city. Further research should address how inferring ES indicators for individual trees based on the sample modelled in i-Tree Eco could complement ground-based tree valuation methods of structural and amenity values such as VAT, CAVAT and CTLA.

We have tested a low-cost desk-based approach to estimating the

aggregate asset value of all municipal trees using machine learning methods. The interactive map and the BN show that there is a large variance in individual tree asset value, depending most on CA, and secondarily on DBH and H, as well as tree's location in different pollution zones. Tree sizes and asset values in urban forests are not normally distributed. In our testing of the BN model, the expected total asset value varies between 38.5–43.4 million USD depending on modelling assumptions about the shape and resolution of the probability distribution of asset value. Assuming normally distributed tree size and asset value, a simple multiplication of mean asset value from the sample over all municipal trees would lead to expected total asset value of about 51.7 million USD. This reflects a more general challenge in ecosystem accounting when inferring value from a sample of a spatially heterogeneous ecosystem with non-normally distributed attributes used for ES quantification. Varying allometric relationships have been shown to be a general challenge in forest inventorying at tree level using remote sensing data (Zapata-Cuartas et al., 2012).

Our analysis contributes to a gap in the literature on uncertainty assessment in ecosystem accounting (Barton et al., 2019). The estimated aggregate asset value of all municipal trees is probably a useful first estimate for awareness-raising purposes in cities that have no previous valuation of regulating services from urban trees. This is the case of Oslo. However, the estimated ES indicators and aggregate monetary asset values are not sufficiently accurate and reliable to meet the accounting need for detecting trends in the asset value of trees. The differences in aggregate asset value under different modelling assumptions are greater than the 4-year change in urban canopy cover (Hanssen et al., 2019). We also tested inferring the asset value of individual non-municipal trees using a Bayesian network emulating i-Tree Eco, based on a sample of municipal trees. We find that the credible intervals of individual asset value are not sufficiently accurate for assessing individual trees.

5. Conclusions

The results of this study support greater use of spatial data and geospatial analysis methods in i-Tree Eco implementation and more spatially sensitive scaling methods for determining the asset values of urban forests for awareness-raising purposes. To ensure broader adoption of these new methods by the i-Tree Eco community, further studies should assess the impact of uncertainties in modelled tree attributes on the reliability of ES indicators estimated by i-Tree Eco compared to manual field surveys. At the same time, this study revealed that iterated updating of location information and implementing i-Tree Eco with atypical input such as spatially disaggregated pollution data is laborious because it requires technical support from the i-Tree Eco team for every new model run. Allowing for running i-Tree Eco locally would provide more flexibility in customisation of input data, opening up possibilities for using i-Tree Eco for more advanced research such as climate or air pollution scenario assessment.

The majority of attributes modelled using auxiliary spatial datasets (CLE, DB, LU) express trees' spatial context, recognizing that trees' location mediates the ecological function of a tree. We have furthermore highlighted the importance of considering tree location for realization of trees' potential for air pollution removal. A variety of other measures of tree's spatial context influence ecological function and delivery of ES from trees – for example, planting density and proximity to noise source influences noise attenuation (Davies et al., 2017; Gómez-Baggethun et al., 2013). The integration of geospatial analysis into ES valuation of individual trees opens a possibility for rapid and consistent estimation of spatial context attributes which are otherwise costly or impossible to measure manually. Further research should assess these possibilities as well as the impact of tree location on ES delivery.

CRedit authorship contribution statement

Zofie Cimburova: Conceptualization, Methodology, Formal analysis, Data curation, Writing - original draft, Visualization. **David N. Barton:** Methodology, Formal analysis, Writing - original draft, Writing - review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors report no declarations of interest.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:<https://doi.org/10.1016/j.ufug.2020.126801>.

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