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Testing different remote sensing products for observing urban tree canopy and their implications for valuation of regulating ecosystem services in monetary ecosystem accounts

David N. Barton and Zander S. Venter

Norwegian Institute for Nature Research

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Barton, D.N. & Venter, Z.S. 2023. Testing different remote sensing products for observing urban tree canopy and their implications for valuation of regulating ecosystem services in monetary ecosystem accounts. NINA Report 2261. Norwegian Institute for Nature Research

Oslo, February 2023

ISSN: 1504-3312
ISBN: 978-82-426-5058-0

AVAILABILITY
Open

PUBLICATION TYPE
Digital document (pdf)

QUALITY CONTROLLED BY
Willeke A'Campo

SIGNATURE OF RESPONSIBLE PERSON
Research director Kristin Thorsrud Teien (sign.)

CLIENT(S)/SUBSCRIBER(S)
Statistics Norway

CLIENTS/SUBSCRIBER CONTACT PERSON(S)
Jørn Kristian Undelstvedt

COVER PICTURE
Oslo's most valuable tree © David N. Barton

KEY WORDS
- Oslo
- urban forestry
- urban nature
- ecosystem accounting
- uncertainty
- iTree Eco
- ecosystem services
- LiDAR
- TerraSAR-X
- Sentinel-2

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Abstract

Barton, D.N. & Venter, Z.S. 2023. Testing different remote sensing of urban tree canopy and implications for valuation of regulating ecosystem services in monetary ecosystem accounts. NINA Report 2261. Norwegian Institute for Nature Research

This report assesses regulating ecosystem services (ES) from urban trees in an accounting pilot area in a subset of Oslo's built zone for which different remote sensing data were available (TerraSAR-X, Sentinel-1, Sentinel-2, LiDAR; LiDAR-canopy segmentation. We tested ecosystem service estimates derived from these sources of remote sensing data. We used i-Tree Eco to model ecosystem services from individual trees. We used a non-parametric Bayesian network to generalize the regulating services calculated by i-Tree Eco for municipal trees managed by Oslo's Urban Environment Agency, to all trees in the accounting study area. For 108 000 tree canopy objects within the study area, we find that monetary estimates for carbon storage vary between 77 – 176 million NOK, and annual flows of carbon sequestration, air pollution mitigation and run-off regulation vary between 6 – 11 million NOK / year. The variation in these estimates is explained by two factors: (i) the difference in the remote sensing data sources that are used to identify tree canopy heights, and (ii) the increasing overestimation of canopy area with a decreasing spatial resolution of remote sensing data. For future urban ecosystem accounts, we recommend building an emulation model for value generalization purposes using a parametric regression model, to avoid the loss of precision due to the discretization of the data required by the non-parametric approach of Bayesian Networks used in this study. I-Tree Eco is not open source model code. Testing the open-source INCA-Tool (Buchhorn et al., 2022) on bespoke LiDAR data of vegetation structure collected by municipalities seems a promising way forward. Given the periodicity of LiDAR data updating in Oslo of approximately 4 years, and the correspondence with the municipal planning cycle, we would recommend that any urban ecosystem physical accounts for Oslo are updated every 4 years as well. In future research, optimal reporting periods for change detection could also be evaluated.

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Sammendrag

Barton, D.N. & Venter, Z.S. 2023. Testing different remote sensing of urban tree canopy and implications for valuation of regulating ecosystem services in monetary ecosystem accounts. NINA Report 2261. Norwegian Institute for Nature Research

Rapporten beregner regulerende økosystemtjenester fra bytrær i et pilotområde innenfor Oslo's byggesone der vi hadde tilgang til fjernmålingsdata for det samme området (TerraSAR-X, Sentinel-1, Sentinel-2, LiDAR; LiDAR-trekrone-segmentering). Vi beregnet økosystemtjenester fra enkelt-trær basert på ulike typer fjernmålingsdata ved hjelp av i-Tree Eco modellen. Vi brukte en ikke-parametrisk Bayesiansk nettverksmodell for å generalisere de fysiske økosystemtjenestene beregnet på bytrær forvaltet av Oslo Kommunes Bymiljøetat til alle trær i studie-området. For de 108 000 trekrone-objektene vi identifiserte i studie-området, beregnet vi krone-verdien av karbonlagring til mellom 77 – 176 million NOK totalt, og samlet årlig verdi av karbonopptak, luftrensing og overvannsregulering til mellom 6- 11 millioner NOK/år. Usikkerheten i disse estimatene skyldes to forhold: (i) forskjellen i fjernmålingsdata i identifisering av trekronehøyder, og (ii) økende over-estimering av trekrone-areale ved reduksjon i romlig oppløsning av ulike fjernmålingsdata. I fremtidige beregninger for bynaturregnskap, anbefaler vi å bruke en parametrisk simuleringsmodell for å generalisere økosystemtjenester fra et utvalg til hele regnskapsområder. Dette vil unngå tap av nøyaktighet som i denne studien skyldes diskretisering av data som gjøres ved å bruke en ikke-parametrisk Bayesiansk modell. I-Tree Eco modellen er ikke åpen-kildekode. Uttesting av INCA-Tool modellene (Buchhorn et al., 2022) – en EU-standardisert modellpakke med åpen kildekode for å beregne økosystemtjenester - sammen med kommunale LiDAR data for vegetasjonsstruktur virker lovende. Gitt et omløp hittil på omtrent 4 år på LiDAR data i Oslo, som også samsvarer med periode for kommunevalg, anbefaler vi bytre-regnskap som også oppdateres hvert 4 år. I fremtidig utviklingsarbeid bør man også teste hva som er optimale regnskapsperiode i forhold til deteksjon av endring i trekrone-dekket.

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Contents

Foreword

This work was conducted for the URBANECO project coordinated by Statistics Norway under EUROSTAT Grant 2020-NO-URBANECO (101023580).

We thank Lars Hein and Kristin Thorsrud Teien for their comments and suggestions on an earlier draft, and Frode Thomassen Singsaas and Willeke A'Campo for assistance with editing and quality assurance.

17th February 2023, David N. Barton

1 Introduction

We assessed regulating ecosystem services (ES) in an accounting pilot area in a subset of Oslo's built zone for which different remote sensing data were available for the summer of 2022 (TerraSAR-X, Sentinel-1, Sentinel-2, LiDAR; LiDAR-canopy segmentation). Since the periodicity of the data did not match, monetary ecosystem service change accounts between two years comparing different sensors for the same two years could not be generated. This report, therefore, produces monetary flow tables for a single year based on a comparison of the different sensors with imagery acquired in different years (2015-2017-2021) and discusses biases.
We tested ecosystem service estimates derived from these sources of remote sensing data. For 108 000 tree canopy objects within the study area, we find that monetary estimates for carbon storage vary between 77 – 176 million NOK, and annual flows of carbon sequestration, air pollution mitigation and run-off regulation vary between 6 – 11 million NOK / year. The variation in these estimates is explained by two factors: (i) the difference in the remote sensing data sources that are used to identify tree canopy heights, and (ii) the increasing overestimation of canopy area with a decreasing spatial resolution of remote sensing data.

Canopy area and ecosystem service estimates based on Sentinel-2 100m^2 canopy pixels were the highest. Combining findings from Venter et al. (2022) and this study we find that the higher the resolution of the remote sensing data, the more conservative the urban tree canopy estimate is. Venter et al. (2022) recommend using the high-resolution LiDAR-1m^2 approach for extent-condition accounts, which is expected to also produce more conservative area-based ecosystem service estimates.

We recommend using a combination of LiDAR extent-condition classification at 1m^2 pixels and LiDAR canopy segmentation to predict ecosystem services requiring the identification of individual trees. The LiDAR-canopy segmentation algorithm is expected to have improved accuracy with higher point density and classification of vegetation strata. The most recent LiDAR data for Oslo for summer 2021 has these features. This data was unfortunately not available to this project, but when analysed is expected to show a better convergence with the canopy area estimates from LiDAR-1m^2.

We used i-Tree Eco to model ecosystem services from individual trees. For ecosystem service assessment purposes that do not depend on modelling individual trees – such as aggregating ecosystem accounting purposes - we recommend using a canopy-area based approach to predict physical ecosystem services. In future, rather than i-Tree Eco's ecosystem service algorithms fixed by the licensed software, we recommend using individual ecosystem service functions that can be (re)programmed in open-source code using e.g. Python for greater transparency and updatability. Testing the INCA-Tool (Buchhorn et al., 2022) on bespoke LiDAR data of vegetation structure collected by municipalities seems a promising way forward.

At the property level, which requires higher spatial resolution and more accurate data, ecosystem services should be computed based on field data identifying individual trees in order to ground-truth remote sensing data for greater accuracy.

We used a non-parametric Bayesian network to generalize the regulating services calculated by i-Tree Eco for municipal trees, to all trees in the accounting area. In summary, we observe the following cumulating sources of error in the ecosystem service estimates due to combining different methods, listed by importance:

1) Source of remote sensing data. Differences in the resolution of basic spatial units used for accounting. The higher the resolution, the more conservative the estimates. Consequence: affects aggregate estimates.
2) Modelling of canopy area. The canopy segmentation algorithm leads to higher estimates than all pixel-based measures of canopy area except for Sentinel-2 data.

3) Relative differences in detection of canopy area by tree height (a bias towards the detection of large trees, which in turn biases carbon storage estimates upwards relative to regulating services depending only on leaf area).
4) Resolution of statistics for basic spatial units as reflected in the discretization of continuous variables in the Bayesian network emulation model. The lower the resolution, the wider the intervals, the more it will tend to overestimate canopy cover, given that the population distribution is heavily skewed to the left (many smaller than larger trees).

On balance, we would recommend building an emulation model for value generalization purposes using a parametric regression model, to avoid the loss of precision due to the discretization of the data required by the non-parametric approach of Bayesian Networks used in this study.

Norwegian municipalities need not be constrained by any EU member state level requirements for reporting extent-condition and physical ecosystem services. Given the periodicity of LiDAR data updating in Oslo of approximately 4 years (similar to LiDAR periodicity in other Norwegian cities), and the correspondence with the municipal planning cycle, we would recommend that any urban ecosystem physical accounts for Oslo are updated every 4 years as well. In future work, optimal reporting periods for change detection could also be evaluated.

Municipal level ecosystem accounts are not constrained by SEEA EA national statistical standards to use accounting prices based on SNA-compatible exchange values. Complementary accounting approaches for municipal policy purposes should explore options for using welfare values as a basis for accounting prices.

2 Objectives

The objectives of this study for the URBANECO project were as follows:

- Demonstrate value transfer / generalization from a sample of ground-truthed trees to a population of trees identified using different remote sensing products.

- Assess the sensitivity of the economic value of regulating services from urban tree canopy - using the i-Tree Eco model with different sources of remote sensing for tree canopy extent-condition mapping.

- Assess differences in accuracy of monetary accounts using different remote sensing sources for the extent-condition of an urban tree canopy.

- Discuss the different policy applications that can be addressed given the robustness of the combined data.

- Discuss the EUROSTAT regulation on ecosystem accounting considering the modelling results; highlight the importance of making ecosystem service models consistent with and sensitive to reported condition variables.

3 Study concept

This research note tests methods from “values transfer” or “value generalization” (NCAVES and MAIA, 2022) in the context of urban ecosystem accounting. Value transfer involves extrapolating model estimates from a study site where ground-truthed data is available to calibrate a valuation model, to a “policy site” where only a few site features are known (Figure 1.1.).

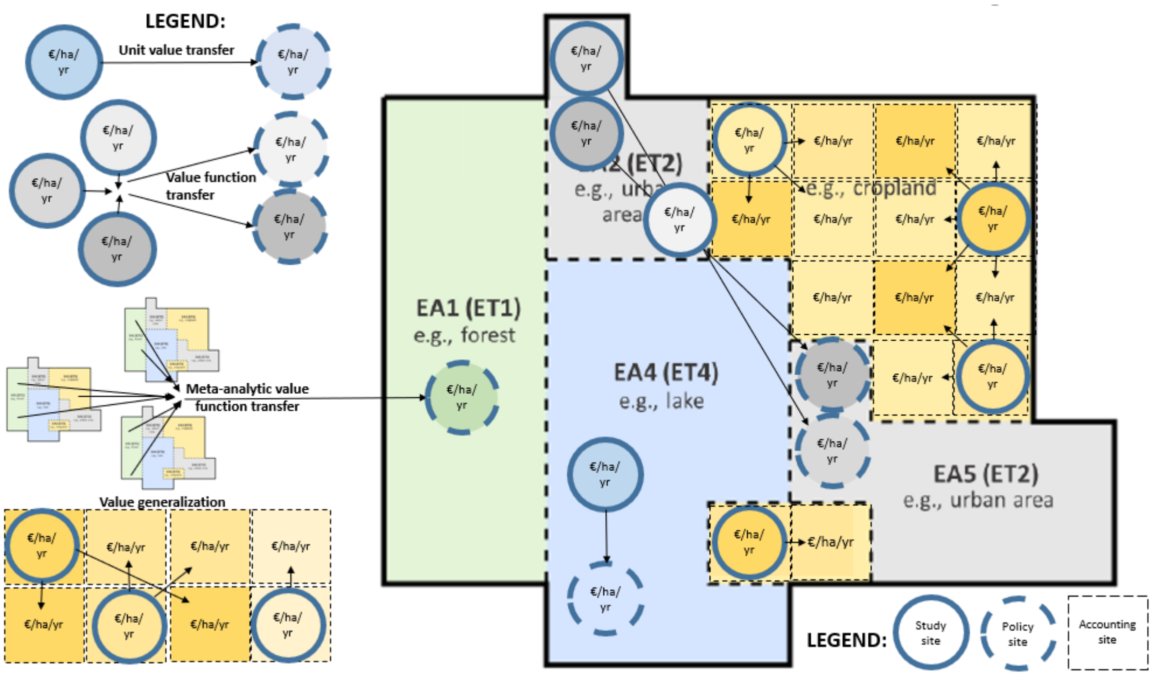


Figure 1.1 *Value generalization and other value transfer methods.*

Value transfer is often discussed in the context of monetary valuation, but it is employed in any setting where a model calibrated on a sample of sites is used to predict ecosystem services for other sites. Value generalization is simply applying value transfer to predict physical ecosystem services and their monetary values for all assets of an accounting area. Figure 1.1 illustrates the conceptual similarities.

In this study, we apply value generalization to urban trees in Oslo. The ‘study site sample’ with ground-truthed field recorded data on tree species and stem diameter was available for roughly 16 000 municipal trees. The assets of the accounting area are all trees whether on public or private land. The limited characteristics that can be observed for trees outside the field sample – tree canopy area and height – depend on different sources of remote sensing data (Figure 1.2).

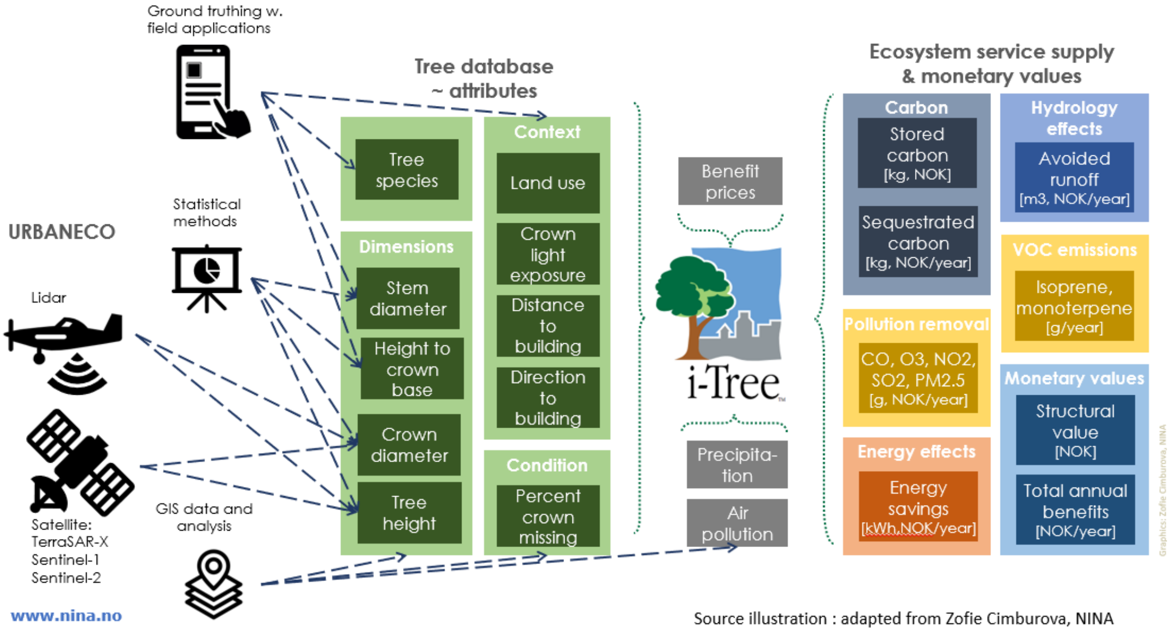


Figure 1.2 *Generalizing i-Tree Eco model results from a sample of municipal trees to all urban trees using different remote sensing data inputs.*

The valuation model employed in this note is i-Tree Eco (Nowak, 2020a) which predicts regulating ecosystem services for individual trees. I-Tree Eco has high temporal resolution using daily rainfall and air pollution monitoring data, and specification of the leaf-on period for the specific location. However, i-Tree spatial resolution of air pollution data in its default application uses air quality monitoring data from only one 'representative' monitoring site. While this may be acceptable for aggregate city-wide estimates, it leads to both under and overestimates at specific tree locations. We based our results on an upgraded approach where air pollution zones are estimated explicitly for each tree based on interpolation between all available monitoring station data in Oslo (Cimburova and Barton, 2020a).

The results of this model are generalized from municipal trees to all trees using a non-parametric statistical method called Bayesian networks (Madsen et al., 2013). The non-parametric approach is well suited for urban trees where tree characteristics are not normally distributed. Bayesian networks were also chosen for their ease in visualizing the probability distributions to aid with the diagnostics of the models.

4 Methodology

4.1 Assessment of individual trees, ecosystem services and aggregation

A Bayesian network (BN) emulates the i-Tree Eco model computed with measurements from Oslo municipality's tree inventory (grey fields, Figure 2; (Cimburova and Barton, 2020a)). We compute ecosystem services using this BBN for individual tree polygons and pixels depending on the remote sensing source (green fields, Figure 2).

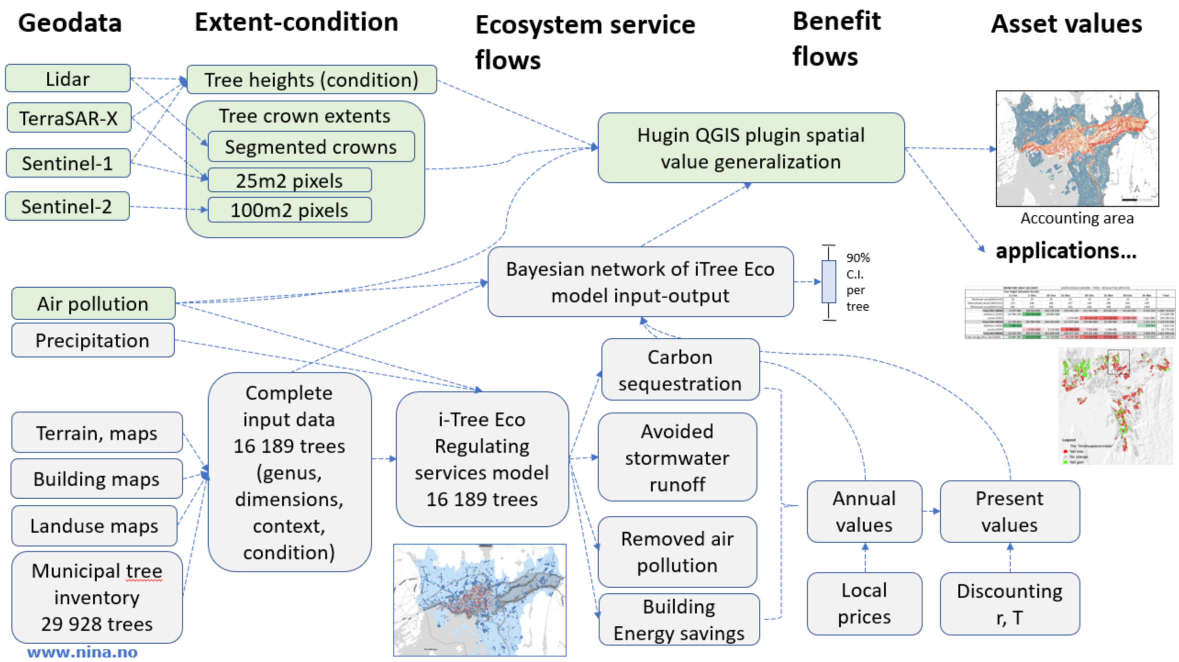


Figure 2. *The Hugin QGIS plugin emulates the i-Tree Eco model to value regulating ecosystem services of trees. Source: adapted from Barton (One Ecosystem under review). Note: Daily air pollution and precipitation data are used by i-Tree Eco. Air pollution time series are assigned to air pollution zones based on interpolation between available monitoring stations.*

We assess results for model runs with and without tree height and the pollution zone variable; the latter is the most sensitive variable for (air filtration) ecosystem service value in the ii-Tree model (Cimburova and Barton, 2020a). This provides the basis for discussing the advantage of identifying ecosystem condition that is consistent with ecosystem service models used in ecosystem accounting.

The input data of the Hugin QGIS plugin model emulating the i-Tree Eco model is shown in Figure 3. The parameters derived from the remote sensing products are limited to the crown area and tree height.

For unspecified nodes, the model uses the probability distribution of known municipal trees in Oslo in place of a determined value. For example, the species distribution of municipal trees is assumed to be the same on private and public land. The reason to use a non-parametric Bayesian network model is to include an estimate of modelling uncertainty in the prediction of individual tree ecosystem services (ES). (In future work for municipalities that are not interested in uncertainty assessments, the workflow can be more streamlined to make a deterministic regression equation of the i-Tree input and outputs and implement it as Python code in QGIS).

For modelling, the non-parametric probability distribution of ecosystem services provided across the tree population, the ecosystem service estimates from i-Tree Eco model runs have been discretized. Discretization sets the accuracy/resolution of the extrapolation. This should be done considering the resolution of other variables in the monetary accounts, notably prices. In a first proof of principle model, we use a low-resolution model with few discrete intervals, corresponding to the low accuracy of the pricing data (which varies by order of magnitude). We use Hugin's built-in algorithm to discretize ES to intervals minimizing classification noise /entropy (Hugin, 2014), and rounding to the nearest 100 ES measurement units. For population-level aggregates and using the accounts for awareness-raising purposes that may be sufficient accuracy.

Figure 3.1 shows the structure of the model used to generalize the i-Tree Eco estimates of regulating services from municipal trees to the accounting window of this report. The input variables (pollution zone, crown area and tree height) are the three variables that most explain variation in ecosystem services among those observable from remote sensing and GIS data (Cimburova and Barton, 2020a). The regulating services selected from the model output for this study are ecosystem services with positive benefits (prices). For example, i-Tree Eco predicts the reduction of Ozone (O3) and carbon monoxide (CO), but they are not considered air pollution problems in Oslo, Norway, priced to zero, and therefore not reported further in this note (see Annex 2 for further explanation).

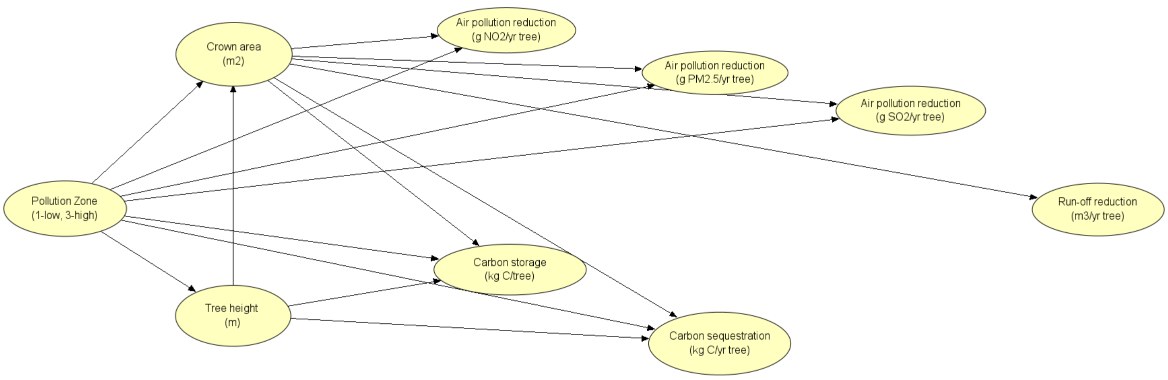


Figure 3.1.- *i-Tree Eco emulation model used to extrapolate ecosystem services from municipal trees to all trees in the urban accounting area*

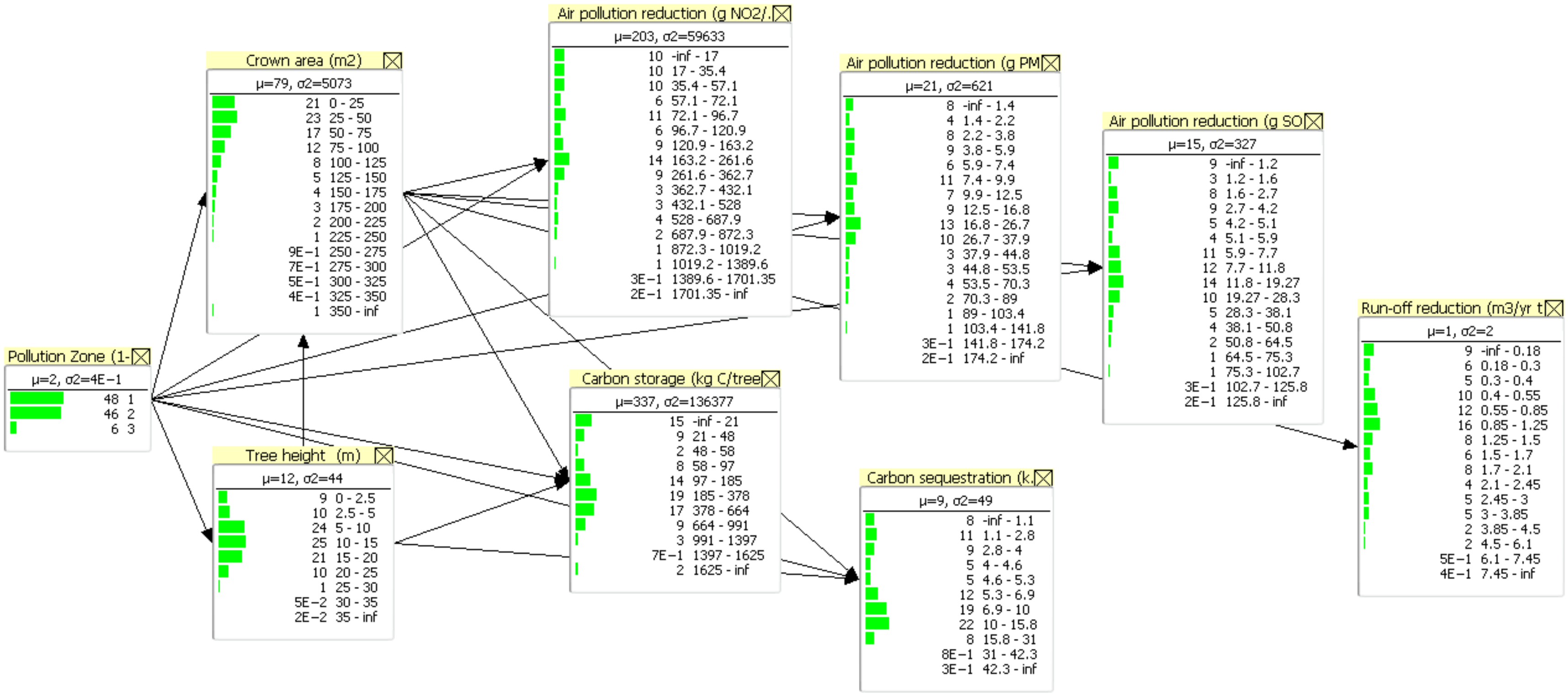


Figure 3.2 *Bayesian network with the conditional probability distributions for municipal tree characteristics and selected i-Tree Eco regulating services*

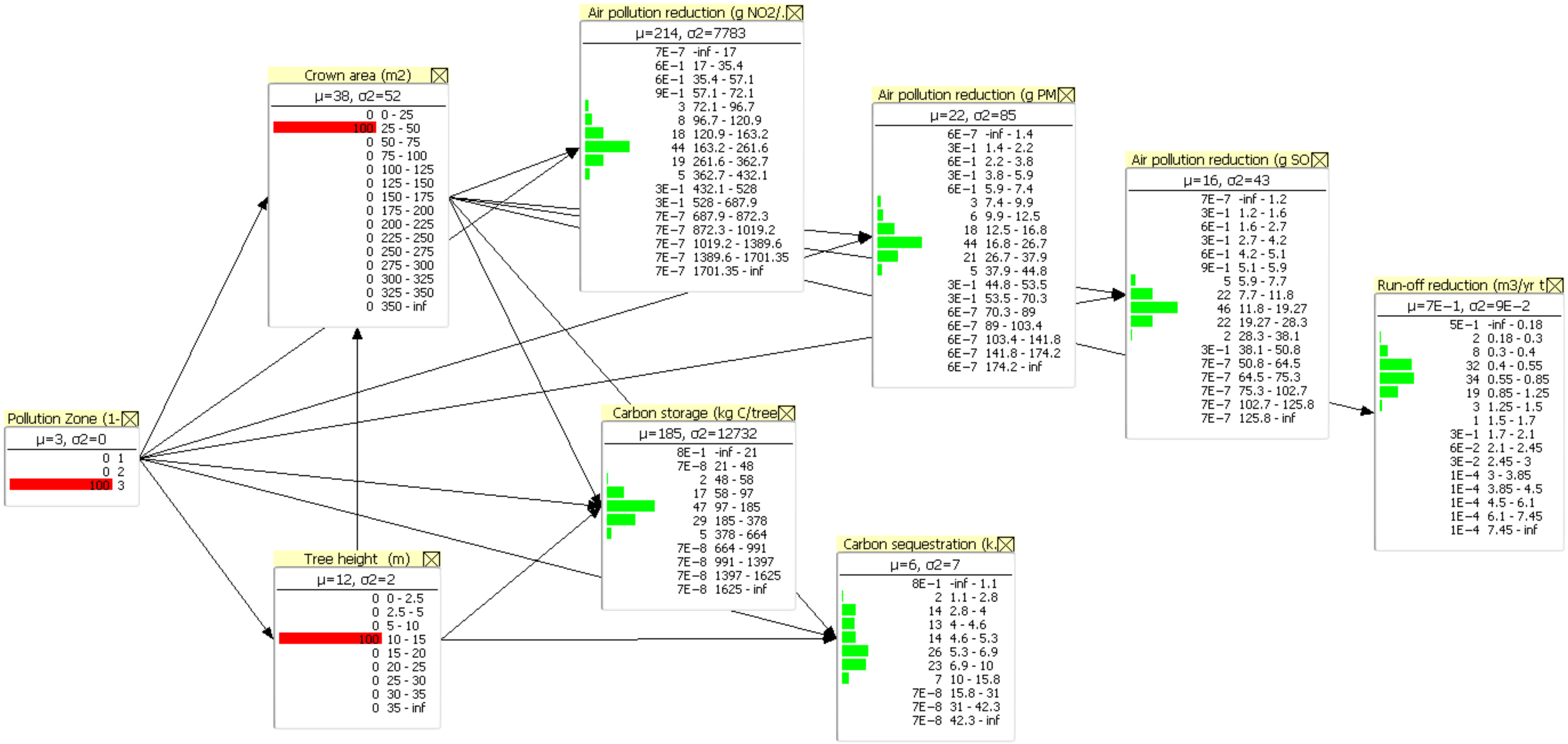


Figure 3.3 *Example estimation: for a tree 10-15m high with a canopy of 25-50m² in pollution zone 3 (high) the Bayesian network predicts probability distributions for each regulating service based on the range of estimates of similar municipal trees.*

4.2 Remote sensing data – study area

We carried out a comparison of regulating ecosystem service provision for the tree canopy identified in “Window 2” (Figure 5) used in the note by Venter et al. 2022 to compare Sentinel-1 data to other remote sensing products The following data were available from 2015 to 2021: one TerraSAR-X image; processed Sentinel-2 imagery for 2015 and 2021; one processed composite Sentinel-1 image for March-November 2021; and one LiDAR-canopy segmentation product for 2017 (Venter et al. 2022). Since the periodicity of the data did not match, LiDAR regulating ecosystem services are calculated for a single year based on a comparison of different sensors with imagery acquired in different years (2015-2017-2021), the relative biases are discussed.

Radar data can be processed to different spatial resolutions, in this case, the Sentinel-1 images were processed to 5x5 m spatial resolution. . This spatial resolution is required for urban ecosystem accounting but requires consideration of a series of radar images to improve the resolution to this level (compared to what is more usual for Sentinel-1, i.e.,15 to 25m).

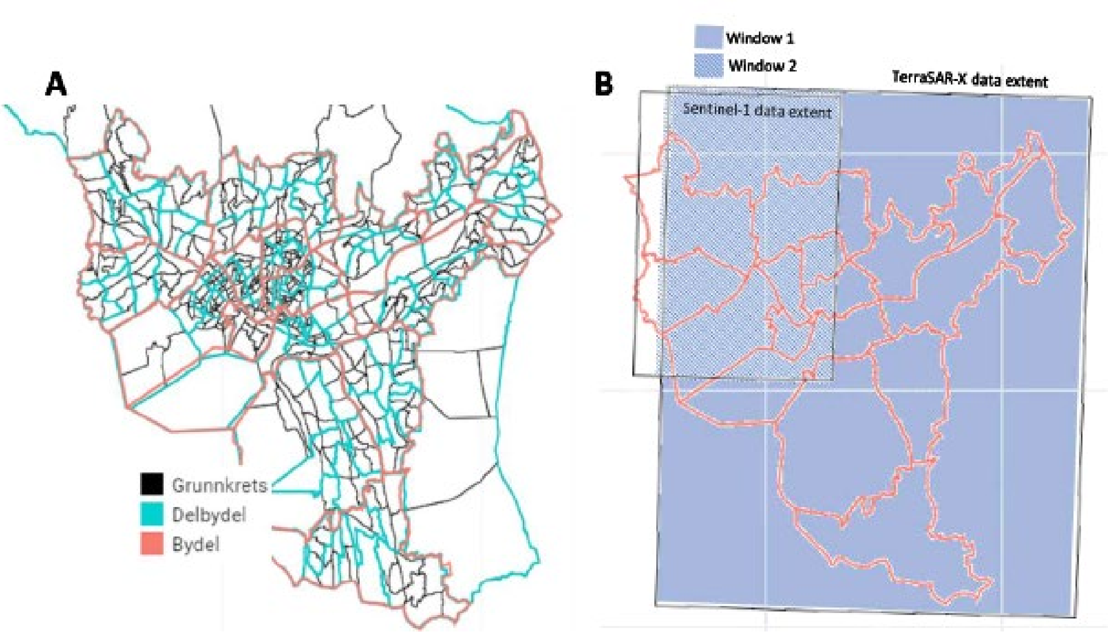


***Figure 4**. Outlines of different municipal units used for spatial aggregation of tree canopy height and areas (A). Extent and coverage of tree height data derived from TerraSAR-X and Sentinel-1 sensors with overlapping windows identified with shaded blue (B). Source: Venter et al. 2022*

Venter et al. (2022) compared the bands illustrated in Figure 5.1. to compile extent-condition tables for urban tree canopy.

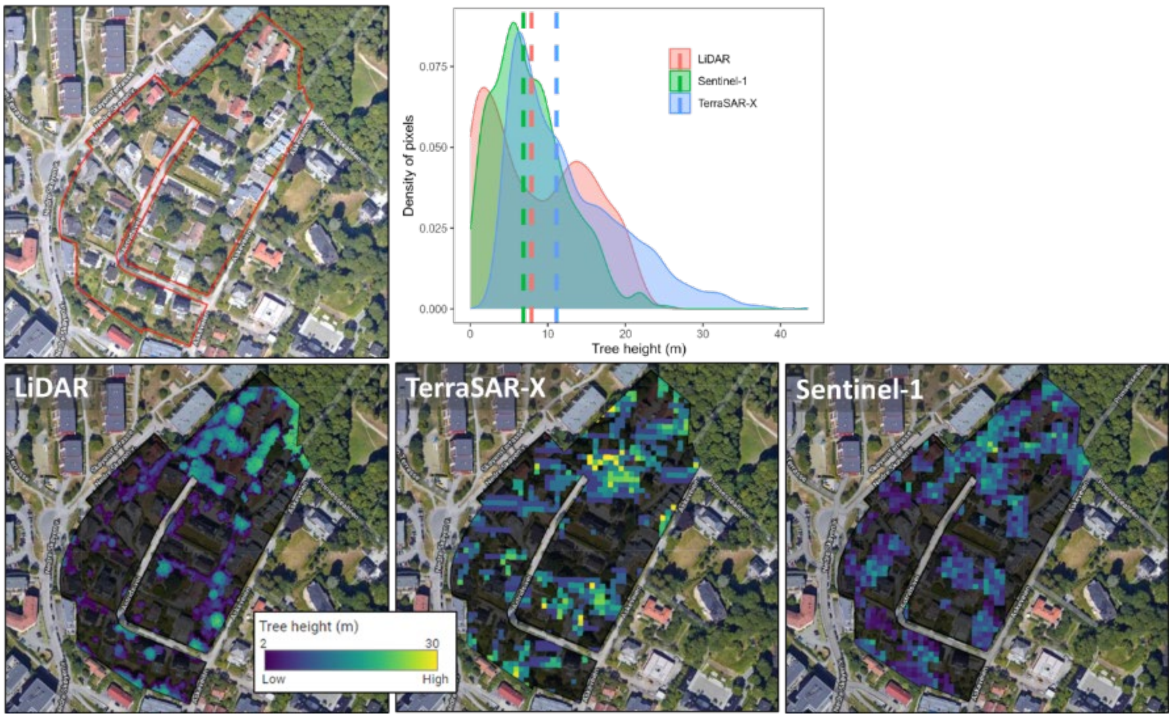


Figure 5.1. *LiDAR, TerraSAR-X and Sentinel-1.   Note: Pixel resolutions of TerraSAR-X (25m²) and Sentinel-1 (25m²), LiDAR (1m²).   Source. Venter et al. (2022)*

We make two additional comparisons of tree canopy data to model regulating services illustrated in Figure 5.2. In addition to TerraSAR-X and Sentinel-1, we compare Sentinel-2 tree canopy classification (NINA, n.d.) to segmented tree crowns based on August 2017 LiDAR.

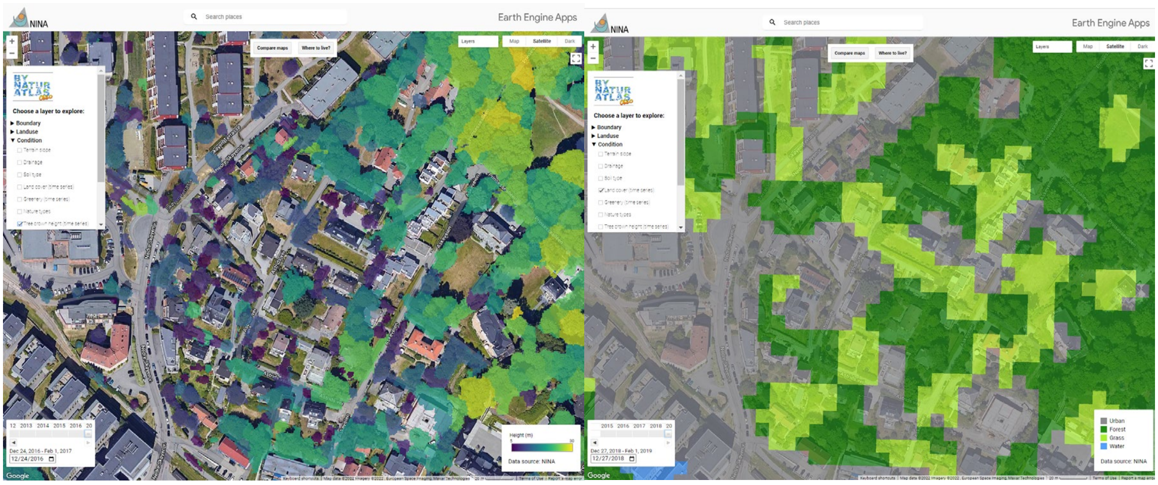


Figure 5.2*. Tree crown polygons segmented based on LiDAR and pixels based on Sentinel-2 Note: Pixel resolution of Sentinel-2 (10x10m). Source: (NINA, n.d.)*

The method for segmenting LiDAR data into tree canopies necessitates that a single height value (maximum LiDAR height) be reported for the entire tree canopy. In contrast, when the LiDAR data is left in 1x1m pixel form, each pixel is assigned a high value. When summing tree extents across different height classes using these two methods, it is expected that the resulting total will be different. Indeed, there is a substantial difference between the canopy area computed using these two interpretations of the LiDAR data (Table 1). The canopy segmentation overestimates total canopy area by 31% relative to LiDAR 1m². This is more than the 20% overestimate of Sentinel-1 25m² pixel data compared to LiDAR 1m² pixels found in Venter et al. 2022. The tree canopy segmentation algorithm produces large underestimates of canopy area for trees <10m and overidentifies canopy area for trees taller than 15m.

Table 1. *Comparison of tree crown area for 1m² pixel classification of tree height and maximum tree height per segmented tree crown. Source LiDAR 1m²: Venter et al. 2022. Source LiDAR segmented tree crowns maximum heights (Hanssen et al., 2021) for "Window 2" in Figure 4.*

Tree height		3–5 m	5–10 m	10–15 m	15–20 m	20–25 m	25–30 m	30–35 m	35–40 m	3–40 m
LiDAR (Sum segmented tree crowns)	daa	120	1671	2656	4563	4793	1903	326	52	16084
LiDAR (Sum 1 m2 pixels)*	daa	2631	3360	3057	2194	852	142	12	1	12249
% difference		-95 %	-50 %	-13 %	108 %	463 %	1240 %	2617 %	5100 %	31 %

The differences in canopy areas with the LiDAR 1m²-pixel benchmark are carried into the estimates of the regulating ecosystem services.

In the rest of the report, our benchmark for comparing the estimation of regulating services for all other remote sensing data is the dataset of segmented tree crowns (Hanssen et al., 2021). The segmented tree crown data was chosen as a benchmark because it was the basis for geospatial analysis to determine the individual tree characteristics required as input to the i-Tree Eco model (Cimburova and Barton, 2020). i-Tree Eco computes based on characteristics of individual trees rather than 2D tree rasters, e.g. requiring a minimum data input to run both 'tree species' and 'diameter at breast height' (DBH) per tree. Neither species nor DBH is observed in the LiDAR point cloud data.

Other biases are expected in trying to generalize regulating services computed "per tree canopy" to estimates "per pixel canopy". The distribution of crown area sizes (Figure 6) covers the different raster pixel sizes of the raster data (25m2, 100m²). This means that the machine learned model has experience data from actual trees in the range of 25m² and 100m² which are used to calculate the regulating services of the artificial rasterized trees.

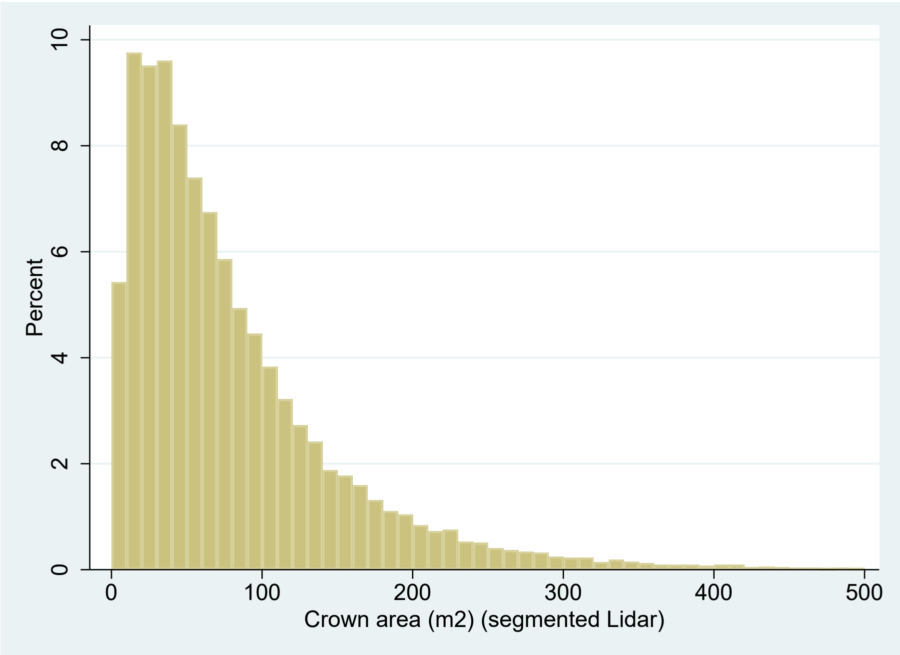
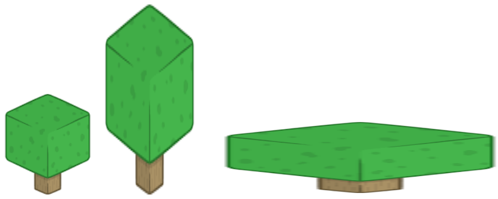


Figure 6. *Crown area distribution in LiDAR segmented canopies.*

Note: the median segmented tree canopy area is 82 m².

With TerraSAR-X and Sentinel-1 pixel data we are in effect computing regulating services for pixelated trees of a fixed canopy area and variable height - cubic “Minecraft” like trees. With Sentinel-2 data, the trees are all compressed to 2D surfaces with no height (illustration).



The allometric relationships between tree stem height and diameter and tree crown area (as a proxy for total Leaf Area) will be more distorted the further the fixed pixel size is from the tree canopy area of the tree to which the pixel belongs. This is expected to lead to a deviation between the estimates of ecosystem services depending on the leaf area (e.g. run-off regulation, carbon sequestration) and carbon storage which depends on the allometric relationship between the crown and the stem.

We know in advance that these remote sensing datasets will lead to differences – the objective of this study is to assess how large the difference turns out to be and discuss them relative to possible error tolerance levels of urban ecosystem accounting and possible decision-support contexts.

4.3 Accounting prices

For the monetary valuation of benefits, we use recommendations for accounting compatible prices (NCAVES and MAIA, 2022). For air pollution, these are marginal costs of compliance and/or material damages. Marginal costs of compliance for air pollution are based on the amount of the Norwegian tax on NOx emissions, approximately equivalent to the marginal costs of measures. Marginal compliance costs for PM2.5 in Norway are not available - national Norwegian guidelines for impact assessment recommend an arbitrary price set equal to that of NOx. SO2 is valued at the marginal damage costs to buildings and materials.

To the extent that the accounting prices are based on Norwegian norms for pricing externalities that are accounting compatible, the choice of accounting price is not arbitrary. However, it should be recognized that the accounting prices is determined by the regulatory institutional context (NCAVES and MAIA, 2022), as much as a physical-economic cause-effect.

Accounting prices used here are lower than avoided cost-of-illness estimates used by Cimburova and Barton (2021). For stored carbon, we use the social cost of carbon and for carbon sequestration the cost of emissions trading in the compliance market. For run-off regulation, we use the avoided costs of additional sewage treatment caused by combined sewage overflow. Assumptions and alternatives are explained in Appendix 3.

5 Results

Table 2 presents the total tree canopy areas estimated for each remote sensing product and the sum of regulating services across tree heights 0-40m estimated using the i-Tree Eco emulation model. Total estimates for the accounting area deviate by as much as an order of magnitude. Results for the individual remote sensing products and different tree heights are presented in Appendix 2.

***Table 2** Differences between estimated regulating services of individual trees based on different remote sensing products.*

Tree heights	Data sources	Crown area daa	Carbon storage kg	Carbon sequestr. kg/yr	Run-off reduction m3/yr	NO2 reduction g/yr.	PM2.5 reduction g/yr.	SO2 reduction g/yr.
	Lidar (segmented)	16 085	52 820 572	1 226 197	241 667	23 094 847	2 381 337	1 706 337
	TSX	12 870	117 419 817	2 893 573	104 898	10 878 207	971 533	783 879
	Difference Lidar-TSX	3 215	- 64 599 245	- 1 667 376	136 769	12 216 640	1 409 804	922 458
	% difference	20 %	-122 %	-136 %	57 %	53 %	59 %	54 %
	Sentinel-1	14 835	51 249 954	2 104 623	120 915	12 622 779	1 129 737	910 079
	Difference Lidar-S1	1 250	1 570 618	- 878 426	120 752	10 472 068	1 251 600	796 258
	% difference	8 %	3 %	-72 %	50 %	45 %	53 %	47 %
	Sentinel-2	30 322	106 887 732	2 737 250	449 794	41 086 774	4 251 972	3 124 269
	Difference Lidar-S2	- 14 237	- 54 067 160	- 1 511 053	- 208 127	- 17 991 927	- 1 870 635	- 1 417 932
	% difference	-89 %	-102 %	-123 %	-86 %	-78 %	-79 %	-83 %

Differences are dominated by the differences carried over from the canopy area estimates (Table 1, Venter et al. 2022). However, in some cases, they are compounded or cancelled out by the effects of trying to generalize service estimates from the probability distribution of individual tree canopies in LiDAR to fixed area tree canopy pixels of TerraSAR-X, Sentinel-1 and Sentinel-2. This is particularly the case for carbon storage and sequestration which in the emulation model are conditional on canopy area and tree height, whereas the other regulating services are only conditional on canopy area.

How can carbon storage be lower for Sentinel-1 than TSX when the total crown area is greater? The Sentinel-1 canopy area model observes 5491 decar of tree canopy <5 m, which is not observed for TerraSAR-X data. While this low vegetation constitutes a large area, it stores less carbon than tree sizes >5 meters, where TerraSAR-X consistently predicts more canopy area than Sentinel-1. One m^2 of canopy area for larger trees represents disproportionately more stored carbon than the same canopy area close to the ground due to the mass of the woody part of the tree.

The monetary values of individual ecosystem service values per year reflect the differences in physical estimates shown in Table 3.

Table 3. *Differences between estimated regulating services of individual trees based on different remote sensing products.*

Remote sensing data source	Carbon storage		Carbon sequestr.		Run-off reduction		NO2 reduction		PM2.5 reduction		SO2 reduction		Total annual value (NOK/yr.)
Lidar crown segmented	52 820 572	kg	1 226 197	kg/yr	241 667	m3/yr	23 094 847	g/yr.	2 381 337	g/yr.	1 706 337	g/yr.	
	79 230 858	NOK	2 778 562	NOK/yr	1 885 003	NOK/yr	508 087	NOK/yr	52 389	NOK/yr	37 539	NOK/yr	5 261 580
TerraSAR-X	117 419 817	kg	2 893 573	kg/yr	104 898	m3/yr	10 878 207	g/yr.	971 533	g/yr.	783 879	g/yr.	
	176 129 726	NOK	6 556 836	NOK/yr	818 204	NOK/yr	239 321	NOK/yr	21 374	NOK/yr	17 245	NOK/yr	7 652 980
Sentinel-1	51 249 954	kg	2 104 623	kg/yr	120 915	m3/yr	12 622 779	g/yr.	1 129 737	g/yr.	910 079	g/yr.	
	76 874 931	NOK	4 769 076	NOK/yr	943 137	NOK/yr	277 701	NOK/yr	24 854	NOK/yr	20 022	NOK/yr	6 034 790
Sentinel-2	106 887 732	kg	2 737 250	kg/yr	449 794	m3/yr	41 086 774	g/yr.	4 251 972	g/yr.	3 124 269	g/yr.	
	160 331 598	NOK	6 202 609	NOK/yr	3 508 393	NOK/yr	903 909	NOK/yr	93 543	NOK/yr	68 734	NOK/yr	10 777 188

The monetary values are a rescaling of the physical values using fixed accounting prices. The differences in carbon storage values are due to the differences in whether remote sensing picks up low or high tree canopy with associated woody biomass. The total value per year for annual flows of regulating ecosystem services is more similar because variations tend to cancel one another out.

The monetary values in the table represent approximately 108 000 individuals (LiDAR segmented) trees within the accounting area (Window 2, Figure 4). This equates to an average monetary value per tree of about 48 NOK/year. Although the value per individual tree varies greatly with size, the magnitude in aggregate for individual trees suggests that annual accounting values for urban trees cannot be expected to have a large awareness-raising effect when comparing to relevant decision contexts.

6 Discussion

6.1 Segmented tree canopies or canopy pixels?

A comparison of tree canopies segmented using LiDAR data and LiDAR points interpreted at 1m^2 pixel resolution show a 31% greater canopy area identified for the former. The segmentation method used by Hanssen et al. (2021) had to use a combination of NDVI and LiDAR data points to identify vegetation signals in the 2017 LiDAR data for Oslo. More recently LiDAR data collected by the Planning and Building Agency (PBE) summer 2021 has been classified for vegetation structure and has a higher point density than in 2017. This raises expectations that the upward bias of the tree canopy segmentation algorithm used by Hanssen et al. (2021) will be reduced.

Different methods can complement one another. Identification of individual trees is not necessary for aggregate accounting purposes, in which case area-based (i.e. pixel-based) approximations of regulating services are sufficient for calculating the order of magnitude ecosystem service value for awareness-raising purposes. For monitoring the extent-condition of the urban tree canopy, classification at 1m^2 pixels requires fewer estimation assumptions and seems more robust to variation in point density.

For the estimation of ecosystem services use of the i-Tree Eco method requires obtaining data for individual trees (e.g. species, DBH, tree crown radius, tree crown condition, light exposure, and distance to buildings). Identification of individual trees is necessary for property-level analysis, e.g. for calculating Blue-Green Factor, VAT compensation value and compensation measures. Future work should compare ecosystem service estimates of canopy-based versus individual tree measures.

We, therefore, recommend that a combination of LiDAR extent-condition classification at 1m^2 pixels is complemented by both area-based and tree-based models of ecosystem services. The two approaches should converge for crown area-dependent ecosystem services as the LiDAR data increases in resolution and points are classified for vegetation versus other topographical features. At property level resolution requiring higher accuracy, ecosystem services should be computed based on field data identifying individual trees.

For cities without periodic LiDAR data, Sentintel-1 and Terra-SAR-X data both provided more accurate estimates than Sentinel-2 data, but these data require image purchase and/or processing multiple images which is are more costly to implement (Venter et al. 2022). Conversely, Sentinel-2 has the lowest costs, but the poorest accuracy.

6.2 Pros and cons of the value transfer approach using Bayesian networks

We tested a Bayesian network (BN) software and built a non-parametric “emulation model” to represent the key input-output relationships of the i-Tree Eco model. We simplified the model to only use input variables that can be observed with remote sensing data and to only use a selection of regulating services with positive accounting prices.

The choice of a BN non-parametric approach has certain advantages and disadvantages for value generalization, especially compared to an alternative parametric regression approach.

Advantages

- A non-parametric approach takes non-normal tree canopy area and height distributions into account.
- Uncertainty of ecosystem service outputs relative to the variation in tree characteristics is explicit.

- Bayesian networks allow for visual inspection of conditional probability tables in the model to carry out diagnostics and understand the data surfaces produced by the underlying model.
- Discretization of the input-output data for the model allows the modeller to determine the resolution of the model, helping policy-science discussions about the minimum resolution required relative to purpose.

Disadvantages

- i-Tree Eco modelling assumptions for each ecosystem service is well documented, but the software does not allow users to make any changes to the functions. As such i-Tree Eco is a "black box" (even though the functions and parameters can be found in the i-Tree manuals).
- The emulation model is another "black box" relative to the algorithms being used by i-Tree Eco. The selection of i-Tree Eco variables to include in the emulation is a subjective decision, although it was made based on prior research on the main predictors of ES.
- The non-parametric model requires subjective determination of the discretization of the input and output data. Discretization of continuous variables of tree canopy and height leads to a loss of precision. The resulting probability distributions of the ecosystem service outputs are a combination of the variability in the tree population, and the resolution set by the modeller.
- Bayesian networks represent a specialized type of model used in a smaller research community and require a commercial license.
- BN software such as Hugin and Netica have relatively rudimentary GIS integration, which is surpassed by GIS-based platforms for accounting coming online such as AIRIES and the INCA-Tool.

On balance, we would recommend building an emulation model using a regression model to avoid the loss of precision due to the discretization of the data required by the non-parametric BN.

For ecosystem services assessment purposes not dependent on modelling individual trees – such as aggregate ecosystem accounting purposes - we recommend using a canopy-area based approach to predicting physical ecosystem services. Individual ecosystem service functions are to be programmed in opensource code (e.g. Python) for greater transparency.

6.3 Robustness of physical ecosystem service estimates to different sources of remote sensing data

The accounting of changes in the flow of regulating ecosystem services in an accounting period depends on comparable remote sensing data for years at the beginning and end of the accounting period. In this project there was only enough data for a single map output between 2015 and 2021 for TerraSAR-X; Sentinel-2 was processed for 2015 and 2021; a composite of Sentinel-1 data was processed for March-November 2021; while LiDAR-canopy segmentation was only available for 2017 (Venter et al. 2022). For this reason, monetary ecosystem service change accounts within two years, and comparing different sensors for the same years was not possible. This report has therefore produced monetary ecosystem service tables for a single year based on a comparison of different sensors with imagery acquired in different years (2015-2017-2021), discussing relative biases.

For the extent-condition accounts, Venter et al. (2022) found that aggregate estimates of tree canopy cover were almost the same for LiDAR-1m^2-pixels and TerraSAR-X for the largest accounting areas encompassing nearly the whole of Oslo. Nevertheless, the aggregates reveal differences in the tree height detectable, with LiDAR detecting smaller canopy areas, and TerraSAR-X overestimating canopy area and heights. Sentinel-1 data also overestimated the canopy area compared to LiDAR-1m^2, conversely detecting more small canopy trees than LiDAR-1m^2. All these differences would carry on over to area-based ecosystem service models. Venter et al. (2022) recommend using the high resolution LiDAR-1m^2 data which is also expected to produce more accurate area-based ecosystem service estimates.

For the LiDAR-canopy segmentation model, the converse is true relative to both TerraSAR-X and Sentinel-1. The LiDAR-canopy data overestimates the canopy area relative to all the remote sensing approaches assessed by Venter et al. (2022). Sentinel-2 with 100m^2 pixels represents the largest canopy area overestimated relative to LiDAR-1m. Broadly speaking, the higher the resolution of the data - the more conservative the canopy estimate.

Individual tree canopy segmentation is required to associate LiDAR tree height data to individual tree objects in the i-Tree Eco model. Canopy height and area are used to infer DBH which is a remotely 'unsensed' variable,but required input in i-Tree Eco. The ecosystem service model in this case requires canopy modelling of the remote sensing input data. The BN emulation model works around this limitation of i-Tree, but the BN model requires a series of subjective modelling decisions (choice of omitted variables, network model structure, discretization) which adds potential bias to the estimate of ecosystem services.

Our study is limited to regulating services estimated by i-Tree Eco. Local climate regulation and recreation (Venter et al., 2020; Venter et al., 2020) are significant ecosystem services in Oslo which have not been addressed in this work. Urban heat island mitigation of trees has been successfully modelled using area-based canopy estimates classified as part of urban morphologies correlated with ground temperature profiles. Estimates of green exposure to tree canopy - as part of everyday mobility as well as active recreation - require the identification of tree canopy as 2.5 or 3 D objects (Cimburova, 2022). Future research will need to explore the biases on green exposure of canopy area overestimates due to LiDAR-segmentation. Modelling green exposure to 1m^2 canopy pixels seems feasible.

6.4 Robustness of monetary accounts

We have calculated ecosystem service monetary values using prices that would be compatible with ecosystem accounts. In some important cases, these are more conservative than marginal values either used as default prices in i-Tree Eco or potentially:

- Health benefits of avoided air pollution. Estimates of health benefits are three orders of magnitude higher than the "marginal compliance cost" we used in this report.

- Stormwater run-off regulation. The definition of the avoided run-off service only includes avoided sewage treatment, as in the i-Tree Eco default, but does not include avoided flooding. We did not account for how municipal regulations requiring run-off mitigation measures on-property affect the accounting price of the stormwater run-off regulation service. Run-off regulation requirements for new property developments may raise compliance costs by as much as three orders of magnitude relative to the prices we use. All of these factors lead to a conservative marginal value of every m3 of run-off reduction provided by each tree.

6.5 Policy implications given robustness of the assessment

Aggregate monetary accounting values for a whole urban accounting area may appear surprising at first view, as they are substantially higher than the zero monetary value accorded regulating services in traditional planning and project assessment (Barton et al., 2015). However, the annual monetary exchange-based value of regulating services per tree is substantially lower than e.g. city tree maintenance costs (Lauwers et al., 2017). Beyond awareness raising about the significant positive (non-zero) economic contribution of trees' regulating services to the urban economy, the policy application of the partial monetary values reported here is limited.

The use of monetary valuation of ecosystem services for feasibility analysis requires more complete coverage of ecosystem services which are known to contribute to benefits of both recreation and human health.

A proposal for amendment of EU Regulation 691/2011 for member states reporting of ecosystem accounts has indicated reporting of extent and condition every 3 years, while ecosystem services are to be reported every year (EUROSTAT, 2021). In the eventuality that this becomes a member state reporting requirement and local governments want to follow these national level reporting requirements, it seems unnecessary to report ecosystem services on years when extent-condition accounts are not updated. In the case of regulating services calculated by i-Tree Eco, factors that may change demand for regulating services include changes in prices (e.g. in the compliance market price for carbon credits), changes in urban infrastructure (e.g. new buildings close to trees increasing energy savings, increased downstream sewage treatment measures). In principle increased population density may increase the demand for air quality. However, if air pollution costs are based on marginal compliance costs, they will not be sensitive to changes in population.

Annual accounts of 2D tree canopy are feasible using Sentinel-1 and Sentinel-2 data, but the reliability of canopy classification in Norway is currently unknown (Venter et al., 2022). We do not recommend annual urban ecosystem service accounts for the same reasons as we would not recommend them at the national level. The additional information of relevance for policy and planning applications of annual ecosystem service accounts is minor. Except for carbon prices, statistics reflecting changes in demand for other regulating services would not be compiled on an annual basis and/or minor experience changes. In our modelling, changes in the supply of regulating ecosystem services are driven largely by tree canopy area, and to a lesser extent by tree canopy height (condition).

Municipalities will not be constrained by eventual member state reporting requirements for extent-condition and physical ecosystem services. Municipal level ecosystem accounts are not constrained by SEEA EA national statistical standards to use accounting prices based on SNA-compatible exchange values. Given the periodicity of LiDAR data updating in Oslo of approximately 4 years, and the correspondence with the municipal planning cycle, we would recommend that any urban ecosystem physical accounts for Oslo are updated every 4 years as well.

7 Conclusions and recommendations

We assessed regulating ecosystem services in an accounting pilot area in a subset of Oslo's built zone for which all remote sensing data were available (TerraSAR-X, Sentinel-1, Sentinel-2, LiDAR-1m^2 and LiDAR-canopy segmentation). We tested ecosystem service estimates for different sources of remote sensing data. For 108 000 tree canopy objects within the study area, we find that monetary estimates for carbon storage vary between 77 – 176 million NOK, and annual flows of carbon sequestration, air pollution mitigation and run-off regulation to vary between 6 – 11 million NOK/yr (carbon sequestration 2.7 - 6.6 million NOK/yr; run-off regulation 0.8-3.5 million NOK/yr; NO2 reduction 0,2-0,9 million NOK/yr; PM2.5 0,02-0,09 NOK/yr; SO2 reduction 0,02-0,07 million NOK/yr).

Variation in estimates is driven by the differences in the remote sensing data to identify different tree canopy heights and overestimates of canopy area with decreasing resolution. Future work could evaluate the difference in ecosystem services estimates of relative biases in canopy height estimation.

Combining findings from Venter et al. (2022) and this study we find that the higher the resolution of the remote sensing data, the more conservative the urban tree canopy estimate is. Venter et al. (2022) recommends using the high-resolution LiDAR-1m^2 approach for extent-condition accounts, which would also be expected to produce more conservative area-based ecosystem service estimates.

We recommend using a combination of LiDAR extent-condition classification at 1m^2 pixels and LiDAR canopy segmentation to predict ecosystem services requiring the identification of individual trees. The two approaches should converge for crown area-dependent ecosystem services as LiDAR data increases in resolution.

We used i-Tree Eco to model services from individual trees. For ecosystem services assessment purposes that do not depend on modelling individual trees – such as aggregate ecosystem accounting purposes - we recommend using a canopy-area based approach to predicting physical ecosystem services. In future, rather than i-Tree Eco's ecosystem service algorithms fixed by the licensed software, we recommend using individual ecosystem service functions that can be (re)programmed in open-source code using Python for greater transparency and updatability. Testing the INCA-Tool (Buchhorn et al., 2022) on bespoke LiDAR data of vegetation structure collected by municipalities seems to be a promising way forward.

At property level resolution requiring higher accuracy, ecosystem services should be computed based on field data identifying individual trees to ground-truth remote sensing data for greater accuracy.

We used a non-parametric Bayesian network to generalize the regulating services calculated by i-Tree Eco for municipal trees to all trees in the accounting area. In summary, we observe the following cumulating sources of error in the ecosystem service estimates combining different methods, listed by importance:

- Source of remote sensing data. Differences in the resolution of basic spatial units used for accounting. The higher the resolution, the more conservative estimates. Consequence: Affects aggregate estimates.
- Modelling of canopy area. The canopy segmentation algorithm leads to upwards bias.
- Relative differences in detection of canopy area by tree height (a bias towards detection of large trees, biases carbon storage estimates upwards relative to regulating services depending only on leaf area).
- Resolution of statistics for basic spatial units is reflected in the discretization. The lower the resolution, the wider intervals, the more it will tend to overestimate canopy cover,

given that the population distribution is heavily skewed to the left (many small than large trees).

On balance, we would recommend building an emulation model using a parametric regression model to avoid the loss of precision due to the discretization of the data required by the non-parametric Bayesian Network.

Municipalities are not constrained by EUROSTAT reporting requirements for reporting extent-condition and physical ecosystem services. Municipal level ecosystem accounts are not constrained by SEEA EA national statistical standards to use accounting prices based on SNA-compatible exchange values. Given the periodicity of LiDAR data updating in Oslo of approximately 4 years, and the correspondence with the municipal planning cycle, we would recommend that any urban ecosystem physical accounts for Oslo are updated every 4 years as well.

8 References

Barton, D.N., E. Stange, S. Blumentrath, N. Vågnes Traaholt, 2015. Economic valuation of ecosystem services for policy. A pilot study on green infrastructure in Oslo [NINA Report 1114, 77p]. http://www.openness-project.eu/node/78.

Barton, D.N., Venter, Z.S., Sælthun, N.R., Skumlien Furuseth, I., Seifert-Dähnn, I., 2021. Brukerfinansiert klimaberedskap? En beregningsmodell for overvannsgebyr i Oslo. Vann 18.

Buchhorn, M., Smets, B., Danckaert, T., Loo, M. van, Broekx, S., Peelaerts, W., 2022. Establishing a reference tool for ecosystem accounting in Europe, based on the INCA methodology. One Ecosystem 7, e85389. https://doi.org/10.3897/oneeco.7.e85389

Cimburova, Z., 2022. Capturing the context: Developing GIS methods for modelling the ecosystem services of urban trees. Ph.D: thesis. NTNU.

Cimburova, Z., Barton, D.N., 2020a. The potential of geospatial analysis and Bayesian networks to enable i-Tree Eco assessment of existing tree inventories. Urban Forestry & Urban Greening 55, 126801. https://doi.org/10.1016/j.ufug.2020.126801

Cimburova, Z., Barton, D.N., 2020b. The potential of geospatial analysis and Bayesian networks to enable i-Tree Eco assessment of existing tree inventories. Urban Forestry & Urban Greening 55, 126801. https://doi.org/10.1016/j.ufug.2020.126801

EUROSTAT, 2021. Proposal for amendment of Regulation 691/2011: ecosystem accounts. May 2021 (No. ENV/EA-MESA/WG/18 (2021)). European Commission.

Hanssen, F., Barton, D.N., Venter, Z.S., Nowell, M.S., Cimburova, Z., 2021. Utilizing LiDAR data to map tree canopy for urban ecosystem extent and condition accounts in Oslo. Ecological Indicators 130, 108007. https://doi.org/10.1016/j.ecolind.2021.108007

Hugin, 2014. Manual. Hugin Release 8.0, March 2014. Hugin Expert A/S.

Ibenholt, K., Magussen, K., Navrud, S., Skjelvik, J.M., 2015. Marginale eksterne kostnader ved enkelte miljøpåvirkninger. VISTA Rapport nummer 2015/19.

Lauwers, L., Barton, D.N., Blumentrath, S., Nowell, M.S., 2017. Accounting for urban trees. Updating the VAT03 Compensation Value Model. NINA Report 1453.

Madsen, A.L., Karlsen, M., Barker, G.C., Garcia, A.B., Hoorfar, J., Jensen, F., 2013. A Software Package for Web Deployment of Probabilistic Graphical Models.

NCAVES and MAIA, 2022. Monetary valuation of ecosystem services and ecosystem assets for ecosystem accounting: Interim Version 1st edition. United Nations Department of Economic and Social Affairs, Statistics Division, New York.

NINA, n.d. Land Cover (time Series /Condition. Oslo Urban Nature Atlas.

Nowak, D.J., 2020a. Understanding i-Tree: Summary of programs and methods (No. NRS-GTR-200). U.S. Department of Agriculture, Forest Service, Northern Research Station, Madison, WI. https://doi.org/10.2737/NRS-GTR-200

Nowak, D.J., 2020b. Understanding i-Tree: Summary of programs and methods (No. NRS-GTR-200). U.S. Department of Agriculture, Forest Service, Northern Research Station, Madison, WI. https://doi.org/10.2737/NRS-GTR-200

Paus, A.K.H., Høylie, S.S., Bjørnsen, S.L., Nilsen, V., Nordheim, L.-G., Friborg, T., 2022. Samfunnsøkonomisk analyse av sjablongmessige krav til fordrøyning av overvann. Vann 02, 13.

Rødseth et al., K.L., 2019. The external costs of transport – External cost estimates for passenger and freight transport in Norway. TØI Rapport 1704/2019.

SSB, 2021. Stor variasjon i effektive karbonpriser [WWW Document]. SSB. URL https://www.ssb.no/natur-og-miljo/miljoregnskap/artikler/stor-variasjon-i-effektive-karbonpriser (accessed 8.31.22).

Statens Vegvesen, 2021. Konsekvensanalyser. V712 i Statens vegvesens håndbokserie.

Venter, Z., Barton, D., Gundersen, V., Figari, H., Nowell, M., 2020. Urban nature in a time of crisis: recreational use of green space increases during the COVID-19 outbreak in Oslo, Norway. Environ. Res. Lett. https://doi.org/10.1088/1748-9326/abb396

Venter, Z.S., Barton, D.N., Chakraborty, T., Simensen, T., Singh, G., 2022. Global 10 m Land Use Land Cover Datasets: A Comparison of Dynamic World, World Cover and Esri Land Cover. Remote Sensing 14, 4101. https://doi.org/10.3390/rs14164101

Venter, Z.S., Krog, N.H., Barton, D.N., 2020. Linking green infrastructure to urban heat and human health risk mitigation in Oslo, Norway. Science of The Total Environment 709, 136193. https://doi.org/10.1016/j.scitotenv.2019.136193

Appendix 1 - Remote sensing data input to i-Tree emulation model

Four data sets for each of the remote sensing products clipped to the boundaries of Oslo's built zone/bydeler.

LiDAR tree canopy data:
- CROWN_ID from tree segmentation
- Coordinates lat, long
- TerrasarX_Window: 1/0
- Sentinel-1_Window: 1/0
- Crown area: polygon
- Crown height
- Pollution zone used in (Cimburova and Barton, 2020a). Data on URBAN EEA geonode: http://urban.nina.no/layers/?limit=100&offset=0&title__icontains=Air%20pollution%20zones%20in%20Oslo,%202015

TerraSAR-X data
- Pixel ID TerraSAR-X
- TerrasarX_Window: 1/0
- Sentinel-1_Window: 1/0
- Crown area: constant pixel size 25m^2
- Crown height
- Pollution zone

SENTINEL-1 data
- Pixel ID Sentinel-1
- TerrasarX_Window: 1/0
- Sentinel-1_Window: 1/0
- Crown area: constant pixel size 25 m^2
- Crown height:
- Pollution zone:

SENTINEL-2 data
- Pixel ID Sentinel-2
- TerrasarX_Window: 1/0
- Sentinel-1_Window: 1/0
- Crown area: constant pixel size 100 m^2
- Crown height: no data
- Pollution zone

Appendix 2 – Regulating ecosystem services extrapolated to the common test window

The following are the generalizations of the i-Tree Eco model outputs using a Bayesian network to generalize the values from known municipal trees to the different remote sensing products within the test window (intersect of Sentinel-1 and TerraSAR-X data area). Table A2.0 shows the absolute and percentage differences for each ecosystem service per tree height band comparing the different remote sensing models. The table is compiled using the services per remote sensing model provided in Tables A2.1-4.

Table A2.0 *Regulating services comparison across tree heights and remote sensing models of tree canopy*

Tree height m	Differences	Crown area daa	Carbon storage kg	Carbon sequestr. kg/yr	Run-off reduction m3/yr	NO2 reduction g/yr.	PM2.5 reduction g/yr.	SO2 reduction g/yr.
3 - 5.0	Lidar-TSX	na	na	na	na	na	na	na
	Lidar-S1	- 2 300	- 1 978 800	- 200 500	- 18 000	- 1 920 300	- 169 700	- 138 100
	% difference	-1917 %	-2461 %	-3250 %	-913 %	-1136 %	-979 %	-1102 %
5 - 10	Lidar-TSX	- 4 500	- 8 023 000	- 770 200	- 22 800	- 2 725 700	- 208 400	- 191 000
	% difference	-269 %	-355 %	-652 %	-83 %	-108 %	-80 %	-102 %
	Lidar-S1	- 3 800	- 6 887 600	- 672 000	- 17 200	- 2 189 000	- 161 500	- 152 600
	% difference	-227 %	-305 %	-569 %	-62 %	-87 %	-62 %	-82 %
10 - 15	Lidar-TSX	- 300	- 12 277 700	- 443 600	18 500	1 522 700	191 500	117 400
	% difference	-11 %	-208 %	-243 %	44 %	38 %	46 %	40 %
	Lidar-S1	- 100	- 11 238 200	- 407 500	19 900	1 656 800	203 300	127 000
	% difference	-4 %	-190 %	-223 %	47 %	42 %	49 %	43 %
15 - 20	Lidar-TSX	2 700	- 17 095 900	- 220 800	54 700	5 154 100	552 700	383 500
	% difference	59 %	-115 %	-63 %	79 %	77 %	80 %	78 %
	Lidar-S1	3 600	- 1 944 000	49 800	61 700	5 872 400	616 600	435 200
	% difference	75 %	-10 %	13 %	89 %	87 %	89 %	87 %
20 - 25	Lidar-TSX	3 600	- 10 590 700	- 75 300	59 100	5 715 000	602 700	423 400
	% difference	75 %	-57 %	-20 %	86 %	85 %	87 %	85 %
	Lidar-S1	4 700	15 592 400	332 200	68 100	6 643 700	685 600	490 300
	% difference	98 %	84 %	88 %	99 %	98 %	99 %	99 %
25 - 30	Lidar-TSX	1 400	- 6 731 700	- 14 400	22 400	2 157 800	227 600	159 800
	% difference	74 %	-69 %	-9 %	86 %	85 %	87 %	85 %
	Lidar-S1	1 900	9 304 400	160 600	26 000	2 528 500	260 400	186 500
	% difference	100 %	95 %	97 %	99 %	100 %	100 %	100 %
30 - 35	Lidar-TSX	100	- 9 168 900	- 130 400	2 900	231 900	26 100	17 400
	% difference	31 %	-817 %	-639 %	66 %	60 %	66 %	61 %
	Lidar-S1	300	1 089 600	19 900	4 400	384 400	39 700	28 300
	% difference	92 %	97 %	98 %	100 %	100 %	100 %	100 %
>=35	Lidar-TSX	-35	-791772	-18767	-46	-8086	205	-473
	% difference	-67 %	-425 %	-772 %	-7 %	-13 %	3 %	-10 %
	Lidar-S1	52	185878	2418	662	63427	6537	4671
	% difference	100 %	100 %	100 %	100 %	100 %	100 %	100 %

Tree heights	Data sources	Crown area daa	Carbon storage kg	Carbon sequestr. kg/yr	Run-off reduction m3/yr	NO2 reduction g/yr.	PM2.5 reduction g/yr.	SO2 reduction g/yr.
	Lidar (segmented)	16 085	52 820 572	1 226 197	241 667	23 094 847	2 381 337	1 706 337
	TSX	12 870	117 419 817	2 893 573	104 898	10 878 207	971 533	783 879
	Difference Lidar-TSX	3 215	- 64 599 245	- 1 667 376	136 769	12 216 640	1 409 804	922 458
	% difference	20 %	-122 %	-136 %	57 %	53 %	59 %	54 %
	Sentinel-1	14 835	51 249 954	2 104 623	120 915	12 622 779	1 129 737	910 079
	Difference Lidar-S1	1 250	1 570 618	- 878 426	120 752	10 472 068	1 251 600	796 258
	% difference	8 %	3 %	-72 %	50 %	45 %	53 %	47 %
	Sentinel-2	30 322	106 887 732	2 737 250	449 794	41 086 774	4 251 972	3 124 269
	Difference Lidar-S2	- 14 237	- 54 067 160	- 1 511 053	- 208 127	- 17 991 927	- 1 870 635	- 1 417 932
	% difference	-89 %	-102 %	-123 %	-86 %	-78 %	-79 %	-83 %

Table A2.1 *Ecosystem services based on LiDAR (tree height data, segmented tree canopies)*

Tree height	stats	Measured crown area	Carbon storage	Carbon sequestr.	Run-off reduction	NO2 reduction	PM2.5 reduction	SO2 reduction
m		daa	kg	kg/yr	m3/yr	g/yr.	g/yr.	g/yr.
3 - 5	sum	120	80415	6169	1971	168977	17328	12528
	N	2530	2530	2530	2530	2530	2530	2530
5-10	sum	1671	2259983	118179	27596	2515094	260129	186680
	N	22370	22370	22370	22370	22370	22370	22370
10 - 15	sum	2656	5907771	182912	42237	3991655	412304	295321
	N	21554	21554	21554	21554	21554	21554	21554
15 - 20	sum	4563	14927022	351793	69554	6684965	689193	493801
	N	27966	27966	27966	27966	27966	27966	27966
20 - 25	sum	4793	18576791	378724	69122	6747165	694804	497721
	N	23779	23779	23779	23779	23779	23779	23779
25 - 30	sum	1903	9759754	165592	26135	2538741	261334	187237
	N	8666	8666	8666	8666	8666	8666	8666
30 - 35	sum	326	1122395	20398	4392	384747	39701	28373
	N	1525	1525	1525	1525	1525	1525	1525
>=35	sum	52	186441	2430	662	63502	6545	4677
	N	228	228	228	228	228	228	228
Total	sum	16085	52820572	1226197	241667	23094847	2381337	1706337
	N	108618	108618	108618	108618	108618	108618	108618

Table A2.2 *Ecosystem services based on Sentinel-2 (no tree height data, 100m2 pixels)*

Tree height	stats	Crown area	Carbon storage	Carbon sequestr.	Run-off reduction	NO2 reduction	PM2.5 reduction	SO2 reduction
m		daa	kg	kg/yr	m3/yr	g/yr.	g/yr.	g/yr.
n.a.	sum	30322	106887732	2737250	449794	41086774	4251972	3124269
	N	303527	303527	303527	303527	303527	303527	303527

Table A2.3 *Ecosystem services based on Sentinel-1 (tree height data, 25m² pixels)*

Tree height	stats	Crown area	Carbon storage	Carbon sequestr.	Run-off reduction	NO2 reduction	PM2.5 reduction	SO2 reduction
m		daa	kg	kg/yr	m3/yr	g/yr.	g/yr.	g/yr.
<3	sum	3039	2553096	163372	24774	2567891	229298	185056
	N	121576	121576	121576	121576	121576	121576	121576
3-5	sum	2452	2059260	206717	19982	2089232	187074	150667
	N	98060	98060	98060	98060	98060	98060	98060
5-10	sum	5501	9147568	790164	44841	4704066	421670	339277
	N	220058	220058	220058	220058	220058	220058	220058
10-15	sum	2743	17145921	590376	22356	2334886	209012	168318
	N	109710	109710	109710	109710	109710	109710	109710
15-20	sum	960	16871016	301985	7828	812554	72593	58553
	N	38414	38414	38414	38414	38414	38414	38414
20-25	sum	126	2984350	46549	1028	103503	9155	7444
	N	5043	5043	5043	5043	5043	5043	5043
25-30	sum	13	455398	4973	103	10195	896	732
	N	507	507	507	507	507	507	507
30-35	sum	1	32782	474	4	377	32	27
	N	21	21	21	21	21	21	21
>=35	sum	0	563	12	0	75	8	6
	N	2	2	2	2	2	2	2
Total	sum	14835	51249954	2104623	120915	12622779	1129737	910079
	N	593391	593391	593391	593391	593391	593391	593391

Table A2.4 *Ecosystem services based on TerraSAR-X (tree height data, 25m² pixels)*

Tree height	stats	Crown area	Carbon storage	Carbon sequestr.	Run-off reduction	NO2 reduction	PM2.5 reduction	SO2 reduction
m		daa	kg	kg/yr	m3/yr	g/yr.	g/yr.	g/yr.
5-10	sum	6180	10283018	888378	50369	5240763	468557	377729
	N	247184	247184	247184	247184	247184	247184	247184
10-15	sum	2910	18185433	626535	23717	2468980	220777	177970
	N	116390	116390	116390	116390	116390	116390	116390
15-20	sum	1823	32022875	572618	14855	1530914	136448	110266
	N	72903	72903	72903	72903	72903	72903	72903
20-25	sum	1225	29167480	454033	9988	1032165	92080	74356
	N	49015	49015	49015	49015	49015	49015	49015
25-30	sum	461	16491476	179981	3754	380919	33778	27407
	N	18422	18422	18422	18422	18422	18422	18422
30-35	sum	185	10291322	150831	1507	152878	13553	11000
	N	7398	7398	7398	7398	7398	7398	7398
>=35	sum	87	978213	21197	708	71588	6340	5150
	N	3475	3475	3475	3475	3475	3475	3475
Total	sum	12870	117419817	2893573	104898	10878207	971533	783879
	N	514787	514787	514787	514787	514787	514787	514787

Appendix 3 – Selecting accounting prices for i-Tree Eco physical ecosystem service outputs

Introduction

In this appendix, we provide justification for accounting prices of ecosystem services from trees used to value outputs from i-Tree Eco v6, for the URBANECO Project's demonstration of ecosystem accounting based on remote sensing data alternatives. The section represents an updating of supplementary material to Cimburova and Barton (2020). The economic valuation of ES benefits in i-Tree Eco is documented in "Understanding i-Tree: Summary of Programs and Methods (Nowak, 2020b). They were not valued by Cimburova and Barton (2020), nor do we value them in this URBANECO project demonstration for accounting:

- Oxygen production
- Ultraviolet radiation protection
- Wildlife habitat
- Volatile Organic Compound (VOC) Emissions

General price indexing

All values are adjusted to 2021 prices using Norwegian CPI[1]. Note that physical tree canopy estimates for satellite data sources is for 2021, while the LiDAR canopy is detected in 2017. The most recent year for LiDAR data from Oslo, but this data was not available to the URBANECO project. We use OECD PPP[2] adjusted exchange rates to convert from US$ to NOK.

Summary for adjustment in i-Tree

Table A3-1 *Prices used in i-Tree Eco Oslo*

		Default prices [NOK] i-Tree Eco v6	Prices 2017 [NOK] Cimburova and Barton (2021)	Prices 2021 [NOK] URBANECO monetary accounts
Carbon storage	**Tonne C02**	543,00	2600	1500
Carbon sequestration	**Tonne CO2**	543,00	2600	2266
Energy	**kWh**	1,590	0,639	1,08 (2021) 4,75 (2022)
	MBTU	236,81	43	n.r.
Runoff	**m3**	27,19	7,80	7,80 (avoided sewage expenditures
CO	**kg**	6,76	0,00	0,00
O3	**kg**	597,79	0,00	0,00
NOX	**kg**	597,79	324,00	374,00 (damage cost) 22,00 (compliance cost)
SO2	**kg**	575,37	160,00	22,00 (compliance cost)
PM2.5	**kg**	15 179,44	6 267,00	5223,00 (damage cost) 22,00 (compliance cost)

All accounting prices applied in the Oslo accounting case are lower than the default US marginal benefit estimates used in i-Tree Eco.

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[1] https://www.ssb.no/kpi
[2] https://data.oecd.org/conversion/purchasing-power-parities-ppp.htm

Air Pollution Removal

The i-Tree Eco v6 model estimates the number of incidents and the total dollar value of several health factors related to four major pollutants; NO2, SO2, O3, and PM2.5. The I Tree Eco default dollar value estimates are based on healthcare expenses (i.e., cost of illness and willingness to pay to avoid illness), productivity losses associated with specific adverse health events, and the value of a statistical life in the case of mortality as derived from the U.S. EPA BenMAP model (Nowak et al. 2014, Abt Associates 2010). The value of statistical life (VOSL) does not conform with SEEA EA. Below we argue further why we did not use these default values.

For international estimates the i-Tree Eco manual recommends using regression equations adjusting for population density to estimate a dollar value per ton of pollution removal (Nowak, 2020b). Regression equations have been estimated covering populations in Alaska, Hawaii, Puerto Rico/Australia/Canada/The UK. The IIASA GAINS model (https://gains.iiasa.ac.at/models/) has several studies specifying the value per ton of PM2.5 removed for European countries. For our study, we use accounting prices recommended for Norway.

For ecosystem accounting prices, we do not use the i-Tree Eco monetary benefit estimates for air pollution removal because we are unable to examine in detail the assumptions of the externality values (in the case of CO), or a combination of cost-of-illness, productivity losses and values of a statistical life in the case of mortality (NO2, SO2, O3, and PM2.5) that were sourced from US studies (Nowak, 2020b). Rather than try to disentangle the default values in i-Tree Eco we source accounting prices specific for Oslo/Norway (Statens Vegvesen, 2021).

Norwegian calculations of health costs have modelled PM2.5 and PM10 fractions combined. Only the tabulated values for PM10 are used in impact assessment to avoid double counting – they implicitly capture variations in PM2.5 according to the guidance in Statens Vegvesen (2021).

Table A-1

Pollutant	Unit	Assumptions	Source
NOX	21 NOK-2020 / kg	Environmental tax on NOX approximately equal to the marginal cost of measures	Statens Vegvesen (2021)
	84 NOK-2020/kg	Damage cost in cities with a population >15-100 000 inhabitants.	
	374 NOK-2020/kg	Damage cost in cities with a population > 100 000 inhabitants.	
PM10 and PM2.5	5223 NOK-2020/kg PM10	Damage cost estimates for cities with population densities >100 000 inhabitants where exposure does not exceed 50 ug/m3 for 7 days.	Statens Vegvesen (2021)
	579 NOK-2020/kg PM10.	Cities 15-100 000 inhabitants the damage cost	
	21 NOK-2020/kg PM10	PM2.5 entered the Gothenburg protocol in 2012 with a target of a 30% reduction by 2020 relative 2005. Nevertheless, no separate cost-of-measure estimates are available for Norway for PM10. The marginal cost-of-measure recommended is set equal to NOX .	Statens Vegvesen (2021)

		Note that estimates of marginal externality costs in other European countries are much lower as they are cross sectoral (Denmark 211 2014-DK/kg PM2.5; Sweden: 110-330 2014-NOK-2014/kg PM2.5; Germany 1350 NOK-2014/kg PM2.5).	(Ibenholt et al., 2015)
SO2	22 NOK-2019/kg 11 NOK-2019/kg	Cost estimates for cities with population densities >100 000 inhabitants Cost estimates for cities with population densities of 15-100 000 inhabitants Material damage costs due to corrosion of materials and costs due to acidification. No health costs. These costs vary geographically and have fallen over time (SFT, 2005).	(Rødseth et al., 2019)
O3	0 NOK/kg	Local ground formation of ozone due to NOx and NMVOC, is not considered to be a problem in Norway. Long distance transport has not been considered in recent studies.	Vista (2015), TØI (2014)
CO	0 NOK/kg	Carbon monoxide (and lead) emissions from traffic are no longer considered to have significant health effects in Norway	St.meld. nr. 46 43 Nasjonal transportplan 2002-2011

Sources: Ibenholt, K. et al. (2015) Marginale eksterne kostnader ved enkelte miljøpåvirkninger Vista Analyse Rapport nummer 2015/19
SFT (2005): Marginale miljøkostnader ved luftforurensning. Skadekostnader og tiltakskostnader. En oppsummeringsrapport av resultater fra SFTs LEVE-prosjekt (Luftforurensninger - Effekter og Verdier) og SFTs tiltaksanalyser for klimagasser, NOx, SO2, nmVOC og NH3. Rapport TA -2100/2005, Miljødirektoratet.
TØI (2014): Marginale eksterne kostnader ved vegtrafikk. TØI-rapport 1307/2014. Utarbeidet av H. Thune-Larsen, K. Veisten, K. L. Rødseth og R. Klæboe. Transportøkonomisk institutt.
St.meld. nr. 46 43 Nasjonal transportplan 2002-2011 https://www.ntp.dep.no/Nasjonale+transportplaner/2002-2011/_attachment/504878/binary/817320?_ts=1402fd56568

Air Pollution Removal accounting prices used in the URBANECO study

PM10 and PM2.5	22 2021-NOK/kg	
NO2	22 2021-NOK/kg	
SO2	22 2021-NOK/kg	
CO	0	NOK/kg
O3	0	NOK/kg

Building Energy Use and Emissions

In this section, we provide a summary of economic valuation assumptions in i-Tree Eco v6 (Nowak, 2020b). The total shading, windbreak, and climate energy effects due to trees on a plot are calculated by summing the individual tree's energy effects for the particular energy use and housing vintage. Any tree that is less than 6 m in height or farther than 18 m from a building is considered to not affect building energy use. This ecosystem service makes a relatively small contribution to calculations in Oslo.

The following caveats are specified in the i-Tree Eco :
"Because this model component is designed specifically for the U.S., its utility is limited in international applications. International users will receive energy results that are based on the characteristics of the user-defined U.S. climate region, including emission factors, typical construction practices and building characteristics, and energy composition (i.e., type of and amount used). Therefore, results should be used with caution as they assume that the building types, energy use, and emission factors of the U.S. are the same as those internationally (i-Tree 2019b).
The only local values used in the estimates outside the United States are electricity and fuel costs. The remainder of the estimation is based on U.S. conditions from the assigned climate zone. "

In their i-Tree application for Oslo Cimburova and Barton (2020) make some adjustments to the implementation. The production energy mix in Norway is almost exclusively hydropower production. Nevertheless, a certain percentage of electricity is imported, with social costs of emissions occurring outside Oslo/Norway. Since European median values for air pollution are used in i-Tree, the % of imported electricity based on fossil fuels could be used to adjust i-Tree Eco default values for air pollution.

Share of fossil fuels in Norwegian electricity consumption in 2017: 46%[3]. The energy use and emissions adjustment factor was 0.46 in the calculation of avoided CO2 emissions benefits. Norwegian cost of electricity assumed in Cimburova and Barton (2020) was average electricity cost in 2017 was 0.36 NOK/kWh; transmission network rental 0.279 NOK/kWh; total electricity cost not including VAT: 0.639 NOK/kWh[4].
Average electricity prices for 2021 were 0,634 NOK/kWh[5] and 0.448 kr/kWh for transmission charges, for a total of 1.08 kr/kWh. Electricity prices are now highly volatile because of coincidences of weather and war in European energy markets to which Southern Norway is connected. At the time of writing (August) electricity prices in Region 1 south Eastern Norway are 4.301 kr/kWh[6], including transmission costs for a total of 4.75 kr/kWh, or more than 7 times higher than in 2017.

Energy prices were not used in the URBANECO study. We did not used iTree Eco "energy savings" benefits as they were the lowest of all ecosystem services in Oslo and model simplification speeded up model run times.

Carbon Storage and Sequestration

In i-Tree Eco (Nowak, 2020b) carbon valuation is based on the social cost of carbon as reported by the Interagency Working Group on Social Cost of Carbon (2015). The social cost associated with a pollutant (e.g.CO2) refers to an estimate of total (global) economic damage attributable to an incremental increase in the level of that particular pollutant in a given year. The current value (in 2015) is $51,23 per metric ton of CO2 based on a three percent discount rate (Interagency Working Group 2015). Users can adjust this value to other values, if they so desire, by taking a ratio of the desired value (DR) per tonne CO2 to the $51,23/tonne CO2 (updated value = i-Tree

[3] https://www.tu.no/artikler/i-norge-produserer-vi-98-prosent-fornybar-kraft-men-vi-bruker-hele-57-prosent-fossil-varmekraft-fra-europa/441422
https://www.nve.no/reguleringsmyndigheten-for-energi-rme-marked-og-monopol/varedeklarasjon/nasjonal-varedeklarasjon-2017/
[4] https://www.ssb.no/energi-og-industri/artikler-og-publikasjoner/hoyere-strompriser-for-husholdningene--341557
[5] https://www.energinorge.no/fagomrader/strommarked/derfor-er-stromprisen-hoyere-i-ar-enn-i-fjor/#:~:text=I%202021%20var%20prisen%20i,nettleie%2C%20moms%20og%20andre%20avgifter.
[6] https://norgesenergi.no/hjelp/strompriser/historiske-strompriser/

reported value x DR/51,23) (Nowak, 2020b). This is equivalent to 534 NOK-2021/tonne CO2 using PPP-adjusted exchange rates.

Nordhaus (2017) estimate for 2020 emissions and 3% discount rate is 87 U$S-2010 /tonne (876 NOK-2021/tonne). By comparison, the EPAs Fact Sheet on the Social Cost of Carbon[7] refers to an average of $42/ton of CO2 or a 95th percentile price of $123/ton (2007 dollars, 3% discount rate) for 2020 emissions (1630 NOK-2021/tonne). The cost of achieving the Norwegian emissions reduction target by 2030 depends on flexibility in the rules in the ETS quota system: 450-4800 NOK/tonne (SSB 2016)[8]. Oslo municipality uses the following prices for benefits from increased electric cars: 600-1100kr/tonne CO2. https://www.nrk.no/norge/analyse_-elbilen-stadig-billigere-klimatiltak-1.13182628.

The calculation price for CO2 emissions in the new Norwegian EIA Guidance is 1500 NOK-2020/tonne eCO2 (Statens Vegvesen, 2021), and is assumed to grow by 4% per year. Statistics Norway calculated effective marginal prices for CO2 emissions (including quota prices and energy taxes) faced by different sectors of between 0-2200 NOK-2020/tonne, where households faced the highest rate of 2200 NOK/tonne (SSB, 2021). i-Tree Eco calculates carbon (Ckg) storage and sequestrations which must be multiplied by 3.67 to find the equivalent weight of atmospheric CO2 mitigated.

Guidance on monetary accounts (NCAVES and MAIA, 2022) recommends using the social cost of carbon for carbon storage service as it aligns with the avoided damages framing. For carbon sequestration, it is recommended to use the "best available" compliance market price.

Carbon Storage and Sequestration prices used for URBANECO
Carbon default value in iTree Eco v6: 543 NOK-2021 /tonne CO2
Carbon storage price – social cost of carbon Norway (Statens Vegvesen, 2021): 1500 NOK-2021/tonne CO2
Carbon sequestration compliance market price for households Norway (SSB, 2021): 2266 NOK-2021/tonne CO2

Avoided run-off and flood control service

i-Tree Eco (Nowak, 2020b) simplifies surface and subsurface hydrology to focus on the effects of trees. Estimates are generated based on current tree conditions and then without trees to estimate the impact of trees on surface runoff. i-Tree Eco's subsurface routines are simplified and do not consider varying amounts of impervious cover. i-Tree Eco also uses default soil and hydrologic parameters (e.g., soil texture class) for the nation. Impervious cover beneath trees is assumed to be 25.5 percent which is the national average impervious cover for the US. i-Tree Eco does not account for the effects of different spatial arrangements of trees or other land covers. The model is statistically rather than spatially distributed rainfall-runoff models, accounting for tree cover relative to other land cover types.

i-Tree Eco uses an estimated average stormwater control cost, which is a very rough approximation of value. The default value in the software is the US national average dollar value of $0.008936/gallon is applied based on 16 studies of costs of storm water control from the US (Nowak, 2020b). Users can also use local values if known, by using a ratio of the local value to

[7] https://www.epa.gov/sites/default/files/2016-12/documents/social_cost_of_carbon_fact_sheet.pdf

[8] https://www.cree.uio.no/publications/pdf_popular_scientific_articles/ssb_rapporter/ssb_rapp2016_25_makrookonomisk_analyse_aune_fehn.pdf

the model default value ($0.008936/gallon runoff). The default i-Tree value ($0.008936/gallon, 2015) is equivalent to 27.2 NOK-2021/m^3.

For valuing flood control services Guidance for monetary accounts (NCAVES and MAIA, 2022) recommends avoided damages as a preferred (Tier 3) method, or replacement costs as a second best (Tiers 1-2). The i-Tree Eco valuation method is an avoided cost approach, focusing on the costs of additional sewage treatment avoided from runoff to the combined sewage network, rather than the costs of flood damages. The approach does not consider any other costs avoided, such as network upgrade needs, or costs of residual sewage overflow.

Cimburova and Barton (2020) used a similar approach to estimate Oslo's average price/m3 values derived from wastewater treatment company accounts (VEAS, 2017). The basis for calculating sewage and stormwater treatment fees in 2017 was 1 470 177 000 NOK, for treatment of 68.2 million m3. Considering that 36% of treated volume to VEAS comes from stormwater, the average volumetric cost attributable to stormwater treatment was estimated at 7.8 NOK-2017/m3. Barton et al. (2021) later extended calculations to full costs of additional sewage treatment and sewage transport network upgrade costs needed to meet climate challenges to 2040. They also estimated additional external costs of residual water release to the recipient based on P-emissions charges. Marginal costs vary in Oslo depending on the sewage transport distance of the property from the sewage treatment plant.

Neither i-Tree Eco nor Cimburova and Barton (2020) consider on-site replacement costs avoiding surface run-off, rather than run-off to the drainage network. Paus et al. (2022) address this. They cite a large range of on-site replacement costs for natural runoff regulation installations depending on the type of infrastructure used, varying between 2000 – 33 000 NOK/m3 installed capacity. This reflects a general problem in using replacement cost approaches where guidance recommends that cost-effective technical solutions should be used as a basis for accounting prices. Paus et al. (2022) address this issue using a benefit-cost optimization approach. Using a small catchment in neighbouring Bærum municipality they simulate the median unit price of run-off mitigation beyond which replacement costs exceed avoided flood damages. The authors find that the median simulated price below which replacement costs are economically viable lies between 1888-2070 NOK-2022/m3 of installed capacity (the probability distribution of the simulation is skewed with a mean of 5300 NOK/m3). Authors recommend 2000 NOK/m3 as a median "benchmark" unit price above which flood mitigation by upstream measures is no longer economically optimal. (The unit price represents the present value of an investment and operating costs.) The authors recommend that catchment and event-specific estimates are necessary to identify the feasible costs of run-off mitigation measures. The median simulated price is specific to a 2-year return period rainfall episode with a run-off regulation range of 130-170 m3/ha. The authors are currently assessing the transferability of their assessment to other catchments.

As an optimization of a supply cost curve (on-site runoff control measures) and a demand curve (downstream avoided flooding costs) the approach is similar to a simulated exchange value. However, the optimum marginal price of run-off mitigation measures from a public economic perspective is not necessarily what could be achieved in simulating a market for run-off avoidance measures.

For the URBANECO calculations, we could use Paus et al. 2022 estimates as an upper bound, and Cimburova and Barton (2021) as a lower bound. It should be noted how large the range is for accounting prices depending on the choice of valuation method and data available. While representing the low range of costs of runoff regulation measures, the simulated accounting price is two orders of magnitude higher than the i-Tree default value for avoided sewage treatment costs.

Avoided run-off / flood control service used in URBANECO
Based on Paus et al. (2022) simulated : 2000 NOK-2022/m^3 (upper bound; avoided costs of measures on property)
Based on Cimburova and Barton (2021): 8 NOK-2022/m^3 (lower bound; avoided costs of additional sewage treatment only; same methodology as iTree Eco adjusted to Oslo data)

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ISSN: 1504-3312
ISBN: 978-82-426-5058-0

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