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Comparing ground and remotely sensed measurements of urban tree canopy in private residential property

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ABSTRACT

Private residential areas represent a large portion of urban tree canopy and provide a significant amount of ecosystem services for mitigation of negative environmental impacts. With densification, construction of impermeable surfaces, loss of plantable space and urban tree canopy loss, communities are facing a potential degradation of urban environment and loss of living quality. Monitoring urban tree canopy change with repeated assessments over time is key for supplying information for management decisions.

We examined how remote sensing has been used in the past assessments of urban tree canopy area, the public availability and quality of geodata sources and grey literature examples. Field measurements of tree canopy area were collected in private residential properties in Malmö, Sweden and compared to estimates of canopy area using remote sensing data collected by the public mapping agency 'Lantmäteriet'. The remote sensing model was derived using normalized difference in vegetation (NDVI) and LiDAR.

Most Swedish municipalities conduct urban tree monitoring schemes only on street and park trees. Our results show a correlation in remotely sensed tree canopy area and field measurements, suggesting that monitoring of private residential areas can be conducted frequently and non-invasively where remote sensing information of similar quality is available.

Introduction

Urban forests have been defined as consisting of individual trees, stands of trees, and urban woodlands near or within urban areas (Konijnendijk et al., 2006). The value of urban forests for human life and well-being has been widely documented and described (WHO, 2016). They provide a wide array of ecosystem services (UN, 2014), including mitigation of negative impacts associated with climate change by removal of pollutants, carbon sequestration, and water uptake (Gill et al., 2007; Nowak et al., 2006).

The spatial configuration of urban areas, with numerous different land uses, can involve half the land area being dedicated to housing, also referred to as residential land use (UN, 2014). Trends in European cities in past decades have resulted in an increase in residential areas, making them the most common setting for daily human-nature interactions (Kabisch and Haase, 2013). Residential areas are made up of different forms of housing, but most of the area belongs to private individuals or housing associations. Therefore private residential property not only provides housing amenities, but is also a large component of green infrastructure (GI), a term used to describe a wide range of natural features located at different scales and all forming an interconnected ecological network. For example, a single tree in a residential area is part of the overall GI, contributing key local environmental values (EC, 2013).

Urban forests on public land is most often planned and managed by local governments (de Magalhães and Carmona, 2009; Jansson and Randrup, 2020). However, very few local governments include assessments of privately-owned trees and vegetation in their urban forest inventories (Östberg et al., 2018). Trees growing in private residential areas are vulnerable to removal, e.g., a study of single-family residential neighborhoods in Los Angeles County found a 1.2% annual decrease in tree/shrub cover (Lee et al., 2017) where other authors also found that fine-scale changes in canopy cover affect vulnerable social groups disproportionately (Locke et al., al.). When a substantial part of the urban forest is not included in assessment, there is a risk of significant contributions of ecosystem services from the total urban forest being overlooked. Additionally, future planning and management is at risk of omitting valuable inputs in terms of location and specific ecosystem services provided by trees on private residential plots. This may lead to inadequate operational management and policymaking. To evaluate the

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complete volume of ecosystem services provided by urban trees across the urban landscape, privately owned vegetation needs to be included in assessments of urban forest (Cook et al., 2011).

Recording work on urban trees by local governments broadly falls into two categories: on-site approaches using field work and on-ground measurements, or top-down approaches using remote sensing imagery (satellite or aircraft-mounted cameras) (Morgenroth and Östberg, 2017) to detect the extent of vegetation in an area (Miller et al., 2015; Shojanoori and Shafri, 2016). A central argument for not applying bottom-up approaches to include residential trees in public tree databases is the private rights to the property and the related restriction on physical access by local government staff for monitoring and data collection. Top-down approaches, on the other hand, can be used to detect the total urban forest composition via canopy cover assessment. Its limitations in urban areas lie in determining tree species, vitality, and site conditions for individual trees (Huang et al., 2019; Johnson et al., 2015). Due to regular image-generating observations and relatively simple access, the cost of obtaining high-resolution imagery has considerably decreased in recent years, simplifying the data-gathering process and driving transition of tree management to a digital future (Galle et al., 2019). For the same reason, remote sensing is recognized as an important tool for assessing sudden changes in tree cover caused by development, diseases, or similar underlying reasons (Kangas and Maltamo, 2006).

This study compared data on trees in private residential property obtained in manual field surveys with data obtained using Normalized Difference Vegetation Index (NDVI) and Light Detection and Ranging (LiDAR) classified remote sensing imagery. The aim was to compare *remote sensing to plot based field surveys in producing tree canopy information in private residential areas.* The specific objective was to evaluate whether statistical extrapolations from field data align with those from remote sensing. .

The terms ‘assessment’, ‘monitoring’, and ‘inventory’ are often used inconsistently in the literature. For clarity, we delimited the analysis to ‘assessment’, as in ‘assessing the extent or amount of’, since both inventory and measurement might imply a degree of completeness inappropriate to a sampled approach. Monitoring implies some sustainable longer-term consistency in data collection, which must be left to future work once the more limited aim of potential for assessment is investigated. However, due to the ambiguity and overlap in terms, we employ other authors’ choice of term when citing other work.

Similarly, the term “validation” is often used to mean validation of the classified products from remote sensing (e.g., by pixel-level confusion matrix). The aim of this study required a different test; not the proportion of pixels validly classified, but whether canopy area estimated from remote sensing is comparable to area measured in field assessments, at plot level, in private residential gardens. We did not consider either the field or image dataset to be the “absolute truth”, but were simply interested in whether the two methods produce similar estimates.

Remote sensing in assessment of tree canopy cover

In managing trees, there is a long history of using remote sensing as a means to monitor and assess tree canopy coverage, starting with manual assessment of aerial photographs in the forestry industry and for land-cover mapping (Heller, 1964). The introduction of multi-spectral imaging greatly improved the accuracy of automated assessments, in particular NDVI (Pettorelli, 2015), which uses infra-red absorption to distinguish plant life (specifically chlorophyll) from other green land cover (see Pettorelli *ibid.* for development of the principle). NVDI was first proposed in the early 1970s (Rouse et al., 1974), and has proven useful in a wide array of application areas where vegetation plays a role (e.g., mapping urban heat islands, landslides (Hidalgo et al. 2021), soil erosion (Jianlin et al. 2016), epidemiology (Zaldo-Aubanell et al., 2021, psychology (Reyes-Riveros et al., 2021), and hedonic property pricing (Zambrano-Monserrate et al., 2021), at a wide range of scales from individual residential areas (Retes-Paecke et al. 2019) to global maps (Juliean and Sobrino, 2020). This section represents a selected overview of key themes within context of urban forestry, based on a structured literature search which found over 4000 journal papers referencing the technique in an urban context (See Appendix 1 for search terms and hits). Space does not allow for a complete literature review, but only to present a brief overview.

In urban areas, until relatively recently satellite resolution for freely available multi-spectral imagery was limited at around 20–30 m (e.g., Landsat TM, SPOT) in terms of satellites with affordable global coverage. Consequently application to urban areas remained complex, with various attempts to extract greater thematic detail such as pixel unmixing (Liu and Yang, 2013) and panchromatic texture analysis (Ozkan et al., 2016) to improve estimated total area of different types of vegetation per pixel. These lacked sufficient geometric precision to reveal the contribution of scattered trees in complex environments, limiting utility for canopy area estimation in places where this was the predominant pattern, such as private residential areas. Distinguishing between the urban forest and other elements of the urban GI was further hampered by lack of sufficient Digital Surface Models (DSM) in nationally collected datasets. Until c2000, a typical DSM had 20–30 m resolution, with building data possibly added in the form of 3D models but often without vegetation height data. The advent of LiDAR provided the possibility to automatically identify 3D structures such as canopy edges and individual tree crowns for the first time (Meng et al., 2018) (for a review in urban forestry see Wang et al., 2019).

In theory, LiDAR can work to almost arbitrarily detailed resolution. However, collection over large areas presents data volume issues and national data are usually limited to around 2 m resolution for urban areas. Thus while many studies have used very high resolution (VHR) LiDAR to identify and classify individual trees, resolution of 10 cm or 25 cm cannot be assumed to be generally available. Earth observation satellite missions Sentinel 2A and 2B, launched in 2015 and 2017 respectively, increased the available resolution of freely available multi-spectral data to 10 m and in doing so crossed a threshold for utility in urban areas in general (Baines et al., 2020; Moreno et al., 2020). This, plus the dramatic expansion of GIS and data science use in the public sector (Statistics Sweden, 2020), has led to growing use of remote sensing to assess residential green space and its importance for various aspects of human wellbeing (Singh et al., 2018).

Resolution is not the only reason why it is challenging to use NDVI to assess urban areas particularly when also needing indicators such as soil type and vegetation density (Sadeh et al., 2021). This has led to some concern that NDVI might locally underestimate urban GI in general (Gascon et al., 2016), and in the development of indices to address this (e.g. EVI, SAVI)(Pettorelli, 2015). The urban tree canopy is arguably less vulnerable to such underestimation than other constituents of the urban GI, since canopies are relatively dense and elevated above the background surface. LiDAR data on elevation can be used to distinguish larger trees from other land covers, although a resolution of 10 m would still make extraction of smaller tree crowns difficult. Although not freely available, VHR imagery can remove this size barrier, but there are problems associated with VHR due to spectral diversity across the tree crown (Ardila et al., 2012). This has been described as a ‘salt and pepper effect’ and solutions might necessitate more complex object-based methods (e.g. Ardila et al., 2012, O’Neil-Dunne et al., 2013) and artificial intelligence (AI) approaches (Chouhan et al., 2019; Timilsina et al., 2020) to tree crown identification. This includes attempting to identify likely species from hyperspectral imagery or multi-spectral LiDAR (Dai et al., 2018).

Swedish local authorities now have access to VHR imagery at sub-30 cm resolution updated bi-annually and LiDAR at resolution of 1–2 points per square meter in urban areas (Lantmäteriet, 2020). However, increasing use of unmanned aerial vehicles (UAV) in the forestry sector (Baek and Hong, 2017) for object, texture, and AI approaches to identify individual tree crowns are at the forefront of current knowledge. This methodology appears to be most useful when attempting to identify the characteristics of individual trees within a multi-tree stand, i.e., when canopy height does not suffice to distinguish the cover of interest. When the task is simply one of measuring canopy extent, there are practical reasons for attempting to do so using as simple and standardized approaches as possible, e.g. relying only on GIS software and skills sets typically available to local planning departments (Sang, 2020).

The standard NDVI/LiDAR combination approach to assess tree canopy in private gardens is limited by lack of ground data, since: *"Although inventory measurements are locally comprehensive, they can be sparse in a heterogeneous urban landscape, laborious and time-consuming to measure"* (Baines et al., 2020, page 2). On the one hand, wide experience of use of the NDVI-LiDAR method for urban canopy assessment in general (Parmehr et al., 2016) and successful application in studies within residential areas as a whole (Gernes et al., 2019; Peng et al., 2020; Sadeh et al., 2021) give reason for confidence. On the other hand, specific characteristics of private residential areas might give reason to expect confounding issues. For example:

- Compared with parks and streets, trees in private gardens are often close to buildings, meaning that off nadir shadow formation (i.e. areas where the LiDAR signal is occluded) and resolution might interfere with the signal.
- Private gardens are likely to have a diverse, unusual mix of tree species, particularly with more fruit trees and non-native tree species, which might have different spectral responses (Avolio et al., 2015).
- In private gardens, there are fewer large stands of trees and a higher proportion of younger, smaller trees compared to parks and streets (Grove et al., 2006; Guo et al., 2019; Nitoslawski and Duinker, 2016).
- In private gardens there are suboptimal management practices (e.g., cutting branches off at a property boundary), which may compromise crown projection and leaf area index estimations (Miller et al., 2015).

Ardila et al. (2012), showed that when attempting to map tree crowns from VHR images there were "false negative errors concentrated on small trees and false positive errors in private gardens". Thus, both forms of error may be a particular issue in private gardens, since smaller trees can also be expected in smaller plots.

Whether these particular issues might accrue from the pixel level in sufficient quantity to confound comparability with plot-level, field-based canopy assessment is thus an unresolved question of interest for two key reasons. Firstly, while remote sensing is well established for monitoring urban canopy as a whole (Alonzo et al., 2016) urban residential areas are a significant component (Ossola et al., 2019b) to which different policy tools apply for their governance and management (Conway and Lue, 2018; Cook et al., 2011; Ossola et al., 2019a) so it is important to put this sub context on equally firm ground. Secondly, research seeking to understand effective management and governance of trees in private gardens will typically rely on a sample approach to select tree properties, supplemented with questionnaires to the owners, while requesting site access to the site. Ground survey will thus be plot based, e.g. that of the property boundary or via a standard protocol. However, requesting site access is problematic in regards to respect of private property rights and thus for obtaining a sufficient response rate (Dyson et al., 2019). So it is important to know whether, at this more detailed level of assessment, remote sensing provides a reasonable alternative and how comparable the results from field-based measurements and remote sensing are. This could both help to maximize utility of survey responses refusing access and for comparability across studies with differing assessment methods.

Urban tree canopy assessments by local governments

Urban tree canopy assessments provide a systematic overview of the urban tree resource, to better assess that resource. The history of local government monitoring of urban trees stretches back over a century (Morgenroth and Östberg, 2017), and predates formalization of urban forestry as a discipline. In a review of contemporary urban tree inventory methods used to monitor data at single-tree level, Nielsen et al. (2014) found six studies using remote sensing out of 57 (11%). More recently, (Klobucar et al., 2020) found that only 31% of papers they reviewed reported use of remote sensing in urban tree inventories, suggesting that the current level of documented information and qualities of using remote sensing (as cited above) are not yet widely adopted in practice. Tree assessment methods are subject to traditions from adjacent disciplines, e.g., monitoring of "trees outside forest" often includes urban areas in national forest inventories, applying identical methodologies with sparse networks of plots (Schnell et al., 2015), meaning that more detailed urban tree canopy assessments are conducted at the local government level.

There are several examples in which remote sensing methodologies have been applied to monitor urban trees in practice. The United States Forest Service (USFS) provides important methodological descriptions for practice (USDA, 2019b). Its guidelines touch upon using LiDAR mapping, high-resolution imagery, and spectral imagery for assessments of urban tree canopy. LiDAR is described as necessary to improve the accuracy based solely on imagery, especially in distinguishing vegetation from other features. In its report, the USFS also suggests that practitioners take advantage of the potential to monitor tree canopy changes using remote sensing tools and not merely offer single "point-in-time" assessments for local planning bodies (USDA, 2019b). The (brief) report does not mention any potential issues related specifically to residential areas. It also directs practitioners towards use of i-Tree Canopy (a Google Earth-based tool for sampling assessment of tree canopy) and i-Tree Landscape (a web-based geographic database of Landsat imagery and demographic information, USDA, 2019b) both of which are sample based methods.

In order to get an overview of how urban communities across the globe utilize remote sensing for canopy cover assessments, a further grey literature search was conducted focusing on reports of various local agencies conducting canopy assessments. Google was used as the search engine and search terms were comprised out of three components joined with a Boolean operator:

- Keywords related to urban tree canopy (urban; canopy; cover; tree; assessment; map; report; summary)
- Location (names of larger global cities)
- Type of file (we used filtering by pdf as it is the primary format for online reports)

In some instances we sub-searched municipal websites to find reports on canopy cover. The search included largest cites from North America, South America, Asia and Europe. Despite this search method, for some cities a report on canopy cover assessment in English language simply had no hits, particularly, no reports from the cities in South America were found to have been published in English. In Appendix 1 we list the instances where a report on urban tree canopy was found and describe the method that was utilized for the collection of its baseline data. Limiting this search to English does, of course, create caveats.

An advanced example of monitoring practice is the Tree Canopy Assessment by the city of Philadelphia, where a combination of aerial photography and LiDAR, acquired through government agencies, was used for obtaining fundamental information about the urban tree canopy (O'Neil-Dunne, 2019). The local government goal of obtaining 30% cover in each neighborhood was repeatedly evaluated for implementation of necessary policies. The findings provided information on land cover change, loss of canopy cover, potential plantable space, and more. The greatest change was recorded in residential areas, but the analysis encountered issues when comparing datasets from different years, due to differences in sensors and time of acquisition (O'Neil-Dunne, 2019).

They do not discuss the specific sources of error for residential areas or the vegetation indices used for mapping change (O'Neil-Dunne, 2019).

In Sweden, 26 municipalities and organizations collaborated in a recent project assessing ecosystem services provided by publicly managed urban trees at local government level using i-Tree Eco v6 (Deak Sjöman and Östberg, 2020). Canopy assessments were made using field measurements and primarily on public property. The University of Gothenburg has used LiDAR to successfully map trees at city level using high-resolution LiDAR point clouds with highly accurate tree models (Lindberg et al., 2013). To the authors' knowledge, no report on urban canopy assessment based on NDVI and LiDAR has been published in Sweden. Instead, local governments rely on collaborations with research institutions and mixtures of methods to assess urban tree canopy.

Overall, a divergent picture emerges on the use of RS in general, and Lidar-NDVI in particular within urban forestry. It is a well-documented method with studies as to method and accuracy for monitoring urban forestry at larger spatial extents, particularly as to canopy and larger individual trees in public spaces. However it is still not standard practice internationally (as demonstrated by the case of Sweden which certainly has the technical and financial capacity) particularly outside major conurbations. The specific context of private gardens has also been studied but less conclusively as to accuracy at the pixel level but perhaps more importantly given the mixed methods currently in use, as to comparability between remote sensing and field assessment at plot level. Indeed there are some reasons why, prima facie, one might expect site and remotely sensed plot data to diverge.

Method

This study applied a case study approach, using one city (Malmö, Sweden) as a detailed examination of a single case (Flyvbjerg, 2016). The city of Malmö (55°36′21″N 13°02′09″E) is the third most populous city in Sweden, with 338 230 inhabitants (2020). It is located in the temperate vegetation zone, on the southern Swedish agricultural plains, a region with overall fertile soils and mean precipitation of 600 mm/year (SMHI, 2021). The urban area extends to 8105 ha, with 1877 ha of this (23%) classified as private residential area. The city government has been proactive in using urban trees as part of overall strategies for mitigation of climate change, and has a full inventory of street and park trees (Sjöman et al., 2012). As a result, a "tree plan" strategy for long-term development of urban vegetation has been repeatedly updated and developed (Malmö Stad, 2017).

Plot definition and canopy extent

In order to compare remote sensing to plot based field surveys in producing tree canopy information in private residential areas, we focused on the evaluation of whether statistical extrapolations from field data would correlate with those from remote sensing.

Sampling of circular plots is common practice for estimating urban forest parameters, to obtain estimates of the total sampling area, to obtain precise estimates for sub-regions and to attain an acceptable compromise between cost and precision (Miller et al., 2015). Even though residential landscapes are comprised of a mosaic of individual properties that can be seen as management units within their legal boundary (Cook et al., 2011), the sampling plot approach is more common as opposed to full inventories of individual properties. The added benefit in inventorying entire property lots would be to identify direct measures of urban form and governance through dispersion of values and its effect on canopy cover as described in (Klobucar et al., 2021).

Whether the circular plot is used or the whole garden, both face a definitional problem for comparison with areal imagery; the canopy above a plot does not necessarily grow from a stem located within that plot. In the case of i-Tree, the aim is to measure that which grows from the plot (regardless of whether it then hangs beyond the plot). In the case of the imagery, the aim is to measure what covers that plot, regardless of where the measured trees grows from. Not only do these (literally) ground up and top down approaches mismatch conceptually, they might also be expected to operate with anti-thetical effect as regards estimation of canopy cover within that space. The ground up may systematically over estimate canopy within the plot (since it includes that which hangs outward) the top down systematically over estimate that which grows in the plot (since it includes that which hangs inward).

The only way these two methods will record the same total canopy for a plot is if no overhang occurs or if in the ground based approach that which is "gained" on one stem is "lost" at another, while for the top down approach that "gained" from outside is "lost" from stems inside with crowns which hang beyond the boundary. Whether that happens on average depends on spatial pattern at a higher scale. Comparability between ground based (plot based) and area based (image based) canopy extent assessment is therefore not a simple question of whether pixel classification is sufficiently accurate to map urban canopy, or even whether it is sufficient to map this in private gardens. Rather it is a question of whether the two methods converge statistically and if so under what conditions of plot size, scale, urban morphology, extent and so on. First and foremost this method aims to answer only whether the methods converge, but since the i-Tree plot samples stem position not canopy, some slight alternative plot diameters are also tested.

Another potential confounding factor is that canopy may overlap, which the ground level assessment would include but the aerial view does not (at least in simple 2D extent). Again, the significance or otherwise of this for comparability of the two methods *in private gardens* depends on how often it happens *in private gardens.* While of course overlap does occur, there are structural reasons to expect it *may* be not particularly significant e.g. plot size, tree age and the fact that most trees are planted with some forethought as to how much space their canopy will need (or are managed/removed subsequently). So while, in terms of RS classification, gardens may present some additional challenges at the pixel level, other characteristics could prove advantageous for *statistical* comparability with ground survey assessment at the plot level.

Field data

Field work was conducted in autumn 2018. In urban tree assessments, a sampling design with 200 sampling plots gives ~12% relative standard error in estimating tree populations (Nowak et al., 2015). Within the 1877 ha of private residential areas in the city of Malmö, we therefore selected 225 spatially-balanced sampling points to compensate for potential refusal rate. In Sweden, the term "small housing unit" is being used for detached and semi-detached residential single family property. Depending on construction year, several different configurations exist in regards to front and backyard space, following major housing reforms that shaped the residential landscape. Mean size of such properties was 654 m^2 with a mean potential plantable space of 579 m^2 (Klobucar et al., 2021).

Residents were notified by mail, and visits were individually scheduled after agreement to participate. At each sampling point, a 100 m^2 circular plot was outlined and surveyed for trees.

For tree stems with diameter at breast height (DBH) above 5 cm present within the plot, the following measurements were taken:

- Azimuth and distance of tree stem from plot center
- Tree species
- Stem DBH
- Crown width in two perpendicular directions
- Tree height

Tree canopy measurements were made ignoring residential plot boundaries.

Regulating ecosystem services supplied by trees are generated through photosynthesis, where the capacity to produce CO_2 is closely related to leaf biomass. These can be calculated using allometric equations (Nowak et al., 2013). The data were entered into the i-Tree Eco model (USDA, 2019a) for each plot individually and, as a result, canopy area and total leaf biomass were available for each plot. Individual plots were also classified by type of vegetation, divided into three categories: deciduous, coniferous or mixed, based on the tree species. In total, 200 plots were surveyed, since not all plots were accessible due to residents not consenting to participate in the study.

Orthophoto imagery and NDVI classification

The plot unit was used to compare field measurements to remote sensing imagery. Cadaster maps of real estate records, which include shape and size of private property with building footprint, were acquired through public freedom of information. Coordinates of sampling points from the field measurements were buffered to create digital representations of the sampling plots.

LiDAR and orthophoto geodata products were acquired through *Lantmäteriet*, the Swedish mapping, cadastral, and land registration authority (Lantmäteriet, 2020). Geodata on property borders was requested from the City of Malmö through right of access to public information (Table 1). The multispectral imagery product used for the analysis was infrared aerial photography ("IRF-flygbild") at 0.25 m resolution. The imagery from 2016 was most suitable, since the images for 2018 (year of field measurements) were taken in the early spring, when most of the local deciduous vegetation was not in full leaf, and were therefore less suitable for NDVI calculations. Raster mosaic tiles were combined to a single raster layer and values were normalized by the built-in mosaic function. NDVI was derived by ArcGIS Pro 2.6.3. software (ESRI, 2020) using infra-red (IR) and near infra-red (Sadeh et al.) spectral bands included in the product, with manual calibration of thresholds for optimum contrast, calculated as:

$$NDVI = \frac{NIR - R}{NIR + R}$$

The output of this operation was a raster map of NDVI values across the city, which was subsequently extracted to the field plot areas. In order to consider the potential effect of instances where tree canopy extended across the circular plot boundary, two additional sets of areas were extracted for larger radii at one and two standard deviations (SD) of the mean individual tree canopy radius, as recorded in the field. Thus we created three concentric circles for the purpose of assessment of the remote sensing values, with radius 5.64 m, 6.72 m, and 7.8 m (Plot1; Plot + 1 SD; Plot + 2SD, respectively), as shown in Fig. 1. Negative NDVI values were reclassified to zero.

LiDAR vegetation surface model

Low vegetation (lawns and small shrubs) is difficult to distinguish from trees using only NDVI values. Therefore the LiDAR dataset obtained from Lantmäteriet was used to create a raster Digital Surface Model (DSM) from first return point cloud and a Digital Terrain Model (DTM) from ground points. The resolution of the two raster layers was based on the density of available points (0.5–1 point per m^2) and set at 1.5 m. The height difference between surface and elevation models represented all aboveground objects. Our field measurements for canopy height ranged from 16.5 m to 1.3 m, providing a vertical "vegetation window". The re-sampled NDVI classified imagery from the previous steps was then overlain to segment the surface into canopy and non-canopy.

Regression analysis

The LiDAR surface model, overlaid with NDVI-classified images, was used to count the total number of pixels within each of the three concentric plots for each plot site. To determine total canopy area, the total count of pixels was multiplied by pixel area size. The result was then compared to canopy area estimated from field measurements, where the two perpendicular radius measurements were used to calculate canopy area of trees present within the plot. The resulting dataset thus consisted of 48 observations of both field-based estimates and remotely sensed estimates of canopy area for three concentric areas since that was the number of the plots where trees were recorded at the time of field visit. Plots with no trees present within them were excluded from this analysis (Table 2).

Results

Table 2 shows the results of the three linear regressions, for each of which the field estimate of canopy was the *dependent* variable (Y) against each of the respective plot sizes (*independent variable* $X_{1,2,3}$) using the following formula:

$$Y_i = f(X_i, \beta) + e_i$$

While all three covariates tested were significant for canopy area, the smallest size plot (100 m^2) showed greatest significance, as visualized in Fig. 3. This suggests that the relationship with field measurements was strongest for the original plot area and that canopy extending beyond the plot was not a critical confounding feature. The obvious outlier was a case where multiple canopies overlapped, which strengthened the significance but not critically so as the correlation remained significant when the outlier was removed. Additionally, using plot categorized by type of vegetation (deciduous, coniferous, and mixed) as a factor in a mixed effect model did not improve significance in the relationship with canopy area, and no subgroup had a significant correlation by itself.

After the linear model result showed statistically significant correlation, albeit with wide dispersion, we performed a geographically weighted regression (GWR) to see if the residuals were randomly distributed over the city (Fig. 4).

Discussion

How do you manage something you do not own? This is a frequent and delicate question often posed by public urban forests or green space managers. Studies have shown that in some cities more than 50% of the trees are privately owned (McPherson, 1998), meaning a large number of decisions related to trees in urban areas (species selection, establishment, pruning, and felling) are made by private land owners. In this environment, planting or removal decisions are driven by spontaneous decisions and concerns, casting doubts towards public strategic management goals being reached (Conway, 2016).

Municipal management of green spaces in Scandinavia is based on and related to the publicly owned properties (Randrup and Persson, 2009), and a recent survey of Swedish municipalities, showed that only

Table 1
Geodata sources used in this study with respective metadata.

Geodata	Date	Projection	Collecting agency	Resolution/Density	Raster/Vector
LiDAR dataset	2018–03–01	SWEREF99	Lantmäteriet	0.25–1 points per m^2	Point cloud
Orthophoto	2016–05–09	SWEREF99	Lantmäteriet	0.25 m^2/pixel	Raster
Cadaster data	2019–04–19	SWEREF99	Malmö FGK[1]		Vector

[1] City of Malmö, Fastighets och Gatukontoret, Office for real-estate and streets.

Fig. 1. An infra-red false color image of a typical residential neighborhood in Malmö with property boundaries. It is estimated that residential areas in Malmö have 26–28% canopy cover compared to 19–22&% for the total urban area of Malmö (Deak Sjöman and Östberg, 2020).

Table 2
Canopy area estimated by field measurements compared with remote sensing. A statistically significant correlation was found for all three variables, with the smallest plot showing the strongest relationship. The column "Estimates" contains coefficients of predicted linear model, the column "p" contains the p-value of probability that the observed difference could occur by random chance, meaning that the model using NDVI and LiDAR performs well in predicting canopy area measured on the ground.

	i-Tree Eco canopy area values								
Predictors	Estimates	Conf. Interval	*p*-value	Estimates	Conf. Interval	*p*-value	Estimates	Conf. Interval	*p*-value
(Intercept)	7.75	-10.54 –26.03	0.398	7.35	-12.90 –27.60	0.469	9.20	-11.91 –30.31	0.385
100 m^2 plot	0.65	0.20 –1.11	0.006**						
100 m^2 plot + 1SD			0.46	0.10 –0.82	0.013*				
100 m^2 plot + 2SD						0.32	0.04 –0.60	0.027*	
Observations	48			48			48		
R^2/R^2 adjusted	0.154 / 0.136		0.128 / 0.109		0.101 / 0.082				

2 out of 85 include private trees in their inventories (Wiström et al., 2016). This indicates how resident urban trees are an abundant resource that is under-utilized in against climate change and other contemporary challenges facing urban areas (e.g., urbanization and densification).

Climate change data and reports from the Intergovernmental Panel on Climate Change show a clear need to plan for the effects of predicted future extreme weather events (IPCC, 2014) which can take a toll on urban trees. Still, urban forests are threatened by urbanization. Malmö's yearly population growth of 1.8% rivals developing cities such as Manila and Mumbai. The need to provide more housing in limited space results in densification, which has been the approach of Malmö city to solve the demand for new housing. This means that more people are benefiting from the ecosystem services urban trees provide, but also puts more pressure on the land use, as it becomes harder to justify the need for green surfaces with high demands for new housing. To fight these changes and sustain provision of ecosystem services on a city scale, the response to the number of threats should also come in the form of including residential urban forest in planning and management. For that to happen, we need structural data that will generate an overview of the scale of this resource and how it can be included in future public planning and management.

This study compared on-ground field data collection with remote sensing applications, and showed that there is a statistically significant relationship between results from the two methodological approaches. This suggests there is potential for public urban foresters to use remote sensing in future assessments of the entire urban forest, in order to generate a more comprehensive picture of what the urban tree resource really consist of and what it may contribute with in terms of ecosystem services. This can prove valuable information for future planning and management decisions related to future public tree planting schemes (e.g., for choice of planting location and species), but will also potentially generate a means for a new dialogue between the public authorities and the residential land owners. Private property rights are a strong and powerful part of any democracy, and the aim of achieving more information about the residential tree resource should not be to compromise these rights, but to include a substantial part of the entire urban forest, and the associated ecosystem services into better informed decision making by public authorities.

Methodologically, this study was conducted at a single location (Malmö, Sweden). The surrounding area is deforested arable plains and most woody vegetation on private property is planted by human hand, with higher frequency of solitary trees and rare forest stand-like conditions with multi-layered tree canopies. This is perhaps less frequently the case for urban developments encroaching into forested areas, which is potentially problematic from the perspective of generalizing the results found here, given that NDVI analysis does not detect multi-layered canopy (as indicated by the outlier in Fig. 2). In this particular case inclusion of the outlier improved the statistical significance of the relationship between remotely sensed values and field measurements but was not decisive. The outlier is an example of stand-like conditions in Malmö and is quite possibly a frequent occurrence in private residential areas of cities surrounded by forested landscape, where natural regeneration is the leading form of tree regeneration in residential areas (Nowak and Greenfield, 2012). This indicates that surrounding landscape characteristics are an important factor. A further caveat is that Malmö is a comparatively spacious city. Urban form may affect the suitability of plot shape and size used in field work, and the severity of potential issues from occlusions and shadowing by adjacent built structures in remote sensing work. The relationship found and the appropriateness of the spatial sample are likely to be scale- and spatial unit-dependent (Openshaw, 1984), which poses a potential challenge to consistent long-term monitoring as urban form evolves. However, mapping potential disturbances affecting provision of ecosystem services, especially regulating ecosystem services as studied here, long-term monitoring is important in providing representative longitudinal data (Klobucar et al., 2020). The results in this study indicate that remote sensing could also be a valuable resource in designing a monitoring system for urban forest. The geographically weighted regression did not indicate systematic non-stationarity in residuals (Fig. 4), but since the plots were randomly selected and not following urban form sub-groups, further research on how different types of urban development affect the model accuracy would be required to assess the any patterns in dispersion.

We found that annual high-resolution spectral orthophoto imagery in Sweden is not collected consistently during the season when trees are in leaf. Full flushing of leaves also occurs at different times during the spring-early summer for different species, making NDVI-based analysis difficult to compare between years, which is an important limitation. Consistent routines in data collection would greatly assist monitoring of urban vegetation development and should be developed in future research. Such routines should take into consideration the vegetation zone diversity in Sweden. Type of regulating ecosystem services provided and seasonal changes in these are dependent on tree species (Alonzo et al., 2016). Our methodology used a broad generalization for the entire canopy cover, due to sampling design choices for field work. For more detailed information on different types of canopy cover

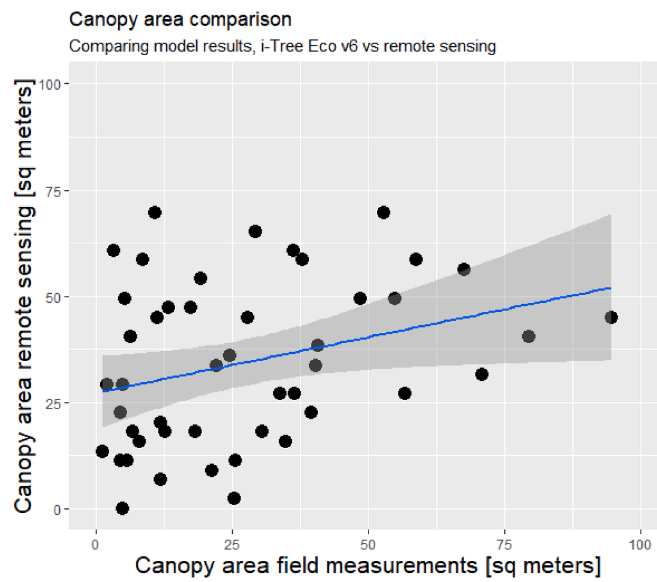

Fig. 3. Validation of ground-measured canopy values to remote sensing values. Each point shown represents a 100 m^2 circular plot on the ground. In this figure, the outlier was removed visually, to fit the 1 to 1 display of values, where the outlier value was still a part of the result.

(deciduous, coniferous, and mixed), a different design would yield important information for improving remote sensing detection of different canopy types, so that seasonal variation and species-dependent provision of ecosystem services could be observed. Currently, the LiDAR point density publicly available for Swedish urban communities ranges from 0.5 to 1 point per m^2 and is unsuitable for species recognition based on crown shape. The accuracy of using LiDAR and spectral aerial photography could be improved using vegetation indices.

Much research has shown increasing interest among private stakeholders in being heard and even engaging in urban forestry applications (see e.g., (Fors et al., 2015; Mattijssen et al., 2017). Remote sensing could be utilized as a methodology to overcome the major obstacle of gaining access to private gardens for monitoring. Klobucar et al. (2020) found that a majority of urban forest inventories performed by local governments did not acknowledge the potential of engaging private residents in collecting urban forest data. The issue of access to private gardens proved relevant in the present study too. Public participation is frequently described as a sampling approach (citizen science) relevant for urban forestry, but may not prove to be efficient or of sufficient accuracy for large sampling areas, e.g., entire city areas (see e.g., (Foster et al., 2017; Roman et al., 2017). If simple field-based indices such as perpendicular axial estimation of canopy area can be reliably cross-referenced with remote sensing sources, as done in this work, then options exist to address both accuracy and coverage issues. In this context, our findings may prove to be valuable for future planning and management of entire urban forests in an efficient manner, without overlooking the important relation to the owners of the trees. A potentially interesting further step would be to use the extensive coverage provided by remote sensing to investigate the wider social relevance of privately managed (and largely ungoverned) urban canopy.

Fig. 2. NDVI-classified high resolution aerial image of sampling point, overlaid with "vegetation window" raster layer, DTM above 1.3 m height at 1.5 m resolution. The intersection of these two layers was used as our measure of canopy area. Green color of NDVI layer represents high reflectance values (vegetation) and orange color representing low reflectance values (non-vegetation). The concentric circles (from smallest to largest) represent: 1) Sampling plot area (100 m^2), 2) sampling plot radius increased by one standard deviation (1.08 m) of average crown radius, and 3) sampling plot radius increased by two standard deviations (2.16 m) of average crown radius.

Conclusions

A relationship was found between remotely-sensed canopy area estimates and canopy area measured on the ground for trees in private gardens. Using the approach described, remote sensing could provide valuable information in evaluating provision of ecosystem services, specifically where high-resolution data are easily accessible. Remote sensing of public trees and private trees in residential areas could be

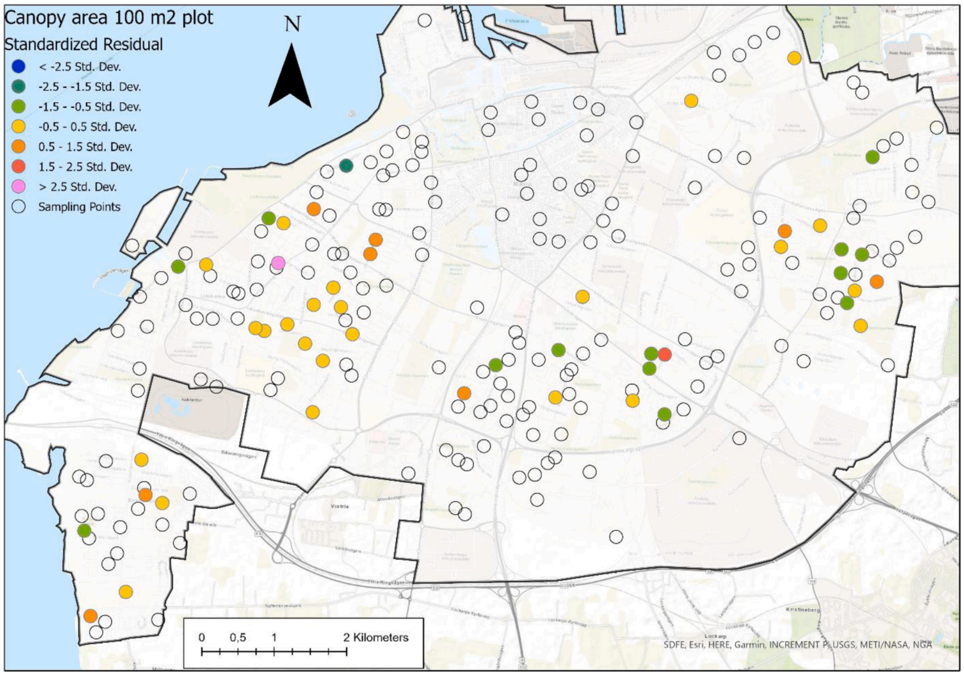

Fig. 4. GWR analysis of the relationship between remotely-sensed canopy area values and i-Tree values. The colored circles contained trees within the plot and correlation to remote sensing values is symbolized with colors to show areas where the model is over/under-estimating the canopy area. The circles are exaggerated in size for readability.

utilized in cases where gaining access for monitoring on private land is challenging. In particular, plot level analysis of remote sensing does correlate with plot level field assessment. As most local governments manage only public trees, use of remote sensing would improve knowledge about the complete urban forest, including information on site condition, vitality, and other data that can influence the survival of trees on residential property.

Declaration of Competing Interest

None

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Supplementary materials

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