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Zofie Cimburova

Capturing the context

Developing GIS methods for modelling the ecosystem services of urban trees

Doctoral thesis

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Thesis for the Degree of
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Summary

Urban trees have the potential to mitigate urban environmental problems caused by climate change and urbanization, and to increase the resilience of cities by delivering a range of ecosystem services. Spatial context, i.e. the location of trees in relation to structures and processes in their surroundings, has been recognized as an important mediator of the ecosystem services that trees provide. Geographical information systems (GIS) are useful for accurate, objective and efficient modelling of the spatial context of urban trees and for bringing this knowledge to urban forestry, urban planning, and other application areas aiming to support the ecosystem services of urban trees.

However, the current use of GIS methods in modelling spatial context is limited. For more complex spatial contextual factors, suitable modelling methods are often lacking because such methods have not been developed, or the developed methods are not transferable beyond the study-specific scopes. The absence of spatial modelling methods might lead to disregarding spatial context and, in turn, inadequate accounting for the ecosystem services of urban trees relevant to a wide range of application purposes, including strategic tree planting, urban ecosystem accounting and public awareness-raising.

This thesis addressed this research gap by developing GIS methods for modelling selected measures of the spatial context of urban trees, here referred to as spatial contextual factors.

First, the thesis reviewed and synthesized the fragmented literature on the specific spatial contextual factors that mediate ecosystem services of urban trees. The review identified 114 specific factors that together mediate 31 ecosystem services of urban trees and clarified the conceptual understanding of spatial context in ecosystem services of urban trees. This, in turn, helped to justify the selection of the specific factors for which new GIS methods were developed and provided a conceptual guidance on approaching the modelling tasks.

Second, the thesis developed five GIS methods for modelling selected spatial contextual factors that currently lack suitable GIS methods. The five developed methods enable modelling (i) visual exposure to tree canopy, (ii) individual tree visibility, (iii) tree crown light exposure and (iv) distance and (v) direction to nearest residential buildings. The method development was driven by the demands of specified application purposes. The first and the second methods were developed as flexible and efficient GRASS GIS tools usable for a broad range of research and practical applications. The remaining three methods were developed as alternatives to manual assessment for analyzing regulating ecosystem services from municipal trees in Oslo, Norway.

The developed methods add to the emerging number of quantitative methods supporting ecosystem service quantification and assessment tailored to urban settings, and highlight the potential of GIS for high-resolution, large-scale ecosystem service assessment. Furthermore, the methods are transferable to modelling spatial context in other application areas to fulfil alternative purposes, including modelling the spatial context of structures other than trees. Finally, the thesis contributes to the literature by emphasizing the importance of spatial context for the delivery of ecosystem services from trees in urban landscapes specifically, and by improving our understanding of spatial context in ecosystem services of ecosystem assets in general.

Acknowledgements

Although this thesis has only one author, it would not have been possible to finish it without a great deal of help and support from many other people.

First of all, I would like to give my deepest thanks to my three supervisors: Yngve Karl Frøyen, Meta Berghauser Pont and David N. Barton. Yngve, thank you for giving me the chance of undertaking the PhD at NTNU. Thank you also for your constant kind feedback and assurance. Meta, thank you for guiding me through the PhD and challenging every step, while being extremely supportive. The thesis would have looked very different without your supervision. David, thank you for convincing me to accept the PhD position in the beginning. Thank you also for always thinking ahead and providing a broader picture and practical relevance to my work.

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Last but not least, big thanks to my family, my partner and my friends far and close. Thank you for showing genuine interest in my work, but perhaps more importantly, thank you for making me leave the work behind in our uncountable adventures. You have been extremely important in these challenging years.

Thank you,
Zofie

List of papers and author contributions

Paper I

Cimburova, Z., & Berghauser Pont, M. (2021). Location matters. A systematic review of spatial contextual factors mediating ecosystem services of urban trees. *Ecosystem Services, 50 (0855)*, 101296. https://doi.org/10.1016/j.ecoser.2021.10129

Author contributions: **ZC** and MBP formulated the overarching research goals and aims. **ZC** developed and designed the methodology. **ZC** performed formal analysis. **ZC** and MBP wrote the initial draft, **ZC** and MBP reviewed and edited the draft, **ZC** prepared the visualizations. MBP supervised the research.

Paper II

Cimburova, Z., & Blumentrath, S. (2022). Viewshed-based modelling of visual exposure to urban greenery – An efficient GIS tool for practical planning applications. *Landscape and Urban Planning, 222*, 104395. https://doi.org/10.1016/j.landurbplan.2022.104395

Author contributions: **ZC** formulated the overarching research goals and aims. **ZC** and SB developed and designed the methodology. **ZC** and SB implemented the software. **ZC** performed the validation. **ZC** performed formal analysis. **ZC** and SB wrote the initial draft. **ZC** and SB reviewed and edited the draft. **ZC** prepared the visualizations.

Paper III

Cimburova, Z., Blumentrath, S. & Barton, D. N. Making trees visible: a GIS method and tool for modelling visibility in valuation of urban trees. *Manuscript in review.*

Author contributions: **ZC** and DNB formulated the overarching research goals and aims. **ZC** developed and designed the methodology. **ZC** and SB implemented the software. **ZC** performed formal analysis. **ZC** and DNB wrote the initial draft. **ZC**, SB and DNB reviewed and edited the draft. **ZC** prepared the visualizations. DNB supervised the research. DNB acquired the financial support.

Paper IV

Cimburova, Z., & Barton, D. N. (2020). 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

Author contributions: **ZC** formulated the overarching research goals and aims. **ZC** and DNB developed and designed the methodology. **ZC** performed formal analysis (GIS and statistical analyses). DNB performed formal analysis (Bayesian Belief Network analysis). **ZC** and DNB wrote the initial draft. **ZC** and DNB reviewed and edited the draft. **ZC** prepared the visualizations. DNB supervised the research. DNB managed and coordinated the research activity. DNB acquired the financial support.

All authors have given their consent to use their work in this thesis.

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Part I: Extended Summary

Introduction 1

The cities of today are challenged by unprecedented population growth and ongoing climate change (Bazaz et al., 2018; United Nations & Department of Economic and Social Affairs, 2018). Urban planning in light of these challenges requires addressing a range of complex tasks and issues – to accommodate the growing numbers of people, safeguard transport systems, ensure equitable access to goods and services including green and open spaces, while at the same time preventing urban sprawl and land consumption, and reducing the environmental impact of cities (Goal 11 of United Nations Sustainable Development Goals[1]).

A specific group of urban planning tasks focuses on employing urban greenery as an effective solution in mitigating urban environmental problems caused by urbanization and climate change, and increasing the resilience of cities (Demuzere et al., 2014). Urban greenery has been recognized, for instance, for its cooling effects (Bowler et al., 2010), capacity to mitigate air and noise pollution (Abhijith et al., 2017; Ferrini et al., 2020), provisioning of habitats for various organisms (Roeland et al., 2019) and promoting mental and physical health (de Vries et al., 2003; Maas, 2006; T. S. Nielsen & Hansen, 2007). These various benefits that nature can provide to humans have been collectively referred to as *ecosystem services* (Millennium Ecosystem Assessment, 2003; TEEB, 2010).

Particular focus has been directed at urban trees as a type of urban greenery that demands relatively little space and can be easily integrated in cities where space is often limited (Haaland & van den Bosch, 2015; Vogt et al., 2017). Urban trees thus represent an effective way of safeguarding ecosystem services in cities where endeavors for more sustainable urban growth such as densification and compact city development might conflict with establishing larger green spaces (Gren et al., 2019; Haaland & van den Bosch, 2015). For this reason, individual urban trees, i.e. trees in public (e.g., streets, parks, peri-urban forests) and private (e.g., yards, gardens) areas, are the study objects of this thesis.

The ecosystem services of urban trees are largely affected by the trees' *spatial context*, i.e. by the location of the trees in relation to various structures and processes in their surroundings. Spatial context affects the ecosystem services of trees at different scales and by different means. For example, while at the scale of the street, the light and soil conditions affect the trees' health and thereby their potential to provide the various services (Keeler et al., 2019; Nowak, 2020; Vogt et al., 2017), the location of the trees within the street determines who sees them and thereby who can benefit, for example, from the aesthetics and positive mental health effects (Davies et al., 2017; Keeler et al., 2019; Nesbitt et al., 2017). Furthermore, the cultural and socio-economical background of the inhabitants at the neighborhood or city scale influences how much the various services are appreciated (Jim and Chen, 2009;

[1] https://sdgs.un.org/goals/goal11

Keeler et al., 2019; Wilkerson et al., 2018;). Many more notions of such specific tree location characteristics that influence ecosystem services of urban trees can be found in the literature (e.g., Roeland et al., 2019; Roy et al., 2012; Salmond et al., 2016). In consequence, considering the spatial context of urban trees should be essential in tree planning and management that aims to support the ecosystem services of urban trees.

Geographical information systems (GIS) are increasingly used in urban planning due to their capability to provide insight into spatial patterns, interactions and relationships between objects through spatial analysis and thereby provide objective, robust, relevant and actionable information for a range of urban planning tasks (van Maarseveen et al., 2018; Yeh, 1999). GIS can thus be equally useful in studying the spatial context that influences ecosystem services of urban trees and bringing this knowledge to urban forestry, tree management, urban planning and other application areas aiming at supporting the services of urban trees. For example, spatial modelling in GIS can guide decisions in strategic tree planting by identifying locations where spatial context best supports the ecosystem services of trees (e.g., Almeter et al., 2018; Morani et al., 2011; Sass et al., 2019) or analyzing how spatial context affects the distribution of the services to the potential beneficiaries (e.g., Baró et al., 2019; Łaszkiewicz and Sikorska, 2020). Furthermore, spatial modelling in GIS can support studying the relationship between spatial context and various tree ecosystem services in research (Escobedo et al., 2018). Importantly, compared to, for instance, manual assessment of trees' spatial context, GIS has the advantage of cost-effectiveness and consistency of assessment (A. Nielsen et al., 2014; Scholz et al., 2018).

In current practice, GIS is often used to detect and map urban trees and their geometry (e.g., Fekete and Cserep, 2021; Hanssen et al., 2021; Hartling, Sagan, and Maimaitijiang, 2021). Furthermore, GIS has facilitated simple insights into the various characteristics in trees' spatial context. However, GIS also has the capacity for more than simple spatial analysis of the characteristics of spatial context of trees. For instance, in the example of spatial context effects mentioned above, GIS can be used not only to map the spatial distribution of soils and cultural and socioeconomic characteristics at the trees' location. GIS also enables modelling from which places the trees can be seen or how the surrounding structures affect the sunlight the tree receives. Broadly speaking, GIS has the capacity to model and analyze the often complex spatial relationships and configurations between trees and their surroundings. However, using the capabilities of GIS for such complex modelling tasks is much less frequent, and suitable modelling methods are often lacking because such methods have not yet been developed, or the developed methods are not transferable beyond the study-specific scope (e.g., Cox et al., 2019; Escobedo et al., 2018; Labib et al., 2021).

To ensure that the effect of spatial context on the ecosystem services of urban trees is adequately accounted for in research and practical applications, it is important to direct our focus towards developing GIS methods for modelling the more complex spatial relationships between trees and their surroundings. Therefore, this thesis has the following main objective:

Main objective
Develop GIS methods for modelling the spatial context of urban trees for the purpose of informing research and practical applications that aim at supporting the ecosystem services of urban trees.

Before addressing the main objective of the thesis, it is important to ensure that the developed methods build on a solid understanding of spatial context and its role in the ecosystem services of urban trees. Such understanding is important for justifying the selection of the specific tree location characteristics that can be modelled and providing conceptual guidance on approaching the modelling tasks. Furthermore, it is necessary to explore and assess the current use of GIS in modelling the spatial context of urban trees so as to identify the specific tree location characteristics for which modelling methods are lacking. Therefore, the thesis has the following supporting objectives, which will be addressed before focusing on the thesis' main objective:

Supporting objectives
S1: Review and synthesize existing knowledge on spatial context in ecosystem services of urban trees.
S2: Review and assess the current use of GIS in modelling the spatial context of urban trees.

1.1 Scope

The scope of the thesis can be located on the intersection between four bodies of knowledge (Figure 1.1):

- **Geographical information science (GISc)**, i.e. the discipline studying geographic information, its representation, capturing, organization and analysis (Goodchild, 2010). GISc is brought into action through GIS, which is the actual computer system to carry out the tasks. In the thesis, GISc provides the conceptual background for developing the methods and the technological solution to do so.
- **Urban planning**, i.e. the "*design and regulation of the uses of space that focus on the physical form, economic functions, and social impacts of the urban environment and on the location of different activities within it*" (Fainstein, 2021). In the thesis, urban planning provides the application background for the developed methods.
- **Urban forestry**, i.e. the art, science and technology of planning and management of trees and forests in and around built environments for their contribution to the physiological, sociological, economic and aesthetic benefits to society (Konijnendijk et al., 2006; Miller et al., 2015). In the thesis, urban forestry provides the application background for the developed methods.
- **Ecosystem service assessment**, i.e. assessment of the benefits and contributions of natural environment and ecosystems to humans (Millennium Ecosystem Assessment, 2003; TEEB, 2010). In the thesis, the ecosystem service framework is used to recognize the various benefits of urban trees and ecosystem service assessment provides the application background for the developed methods.

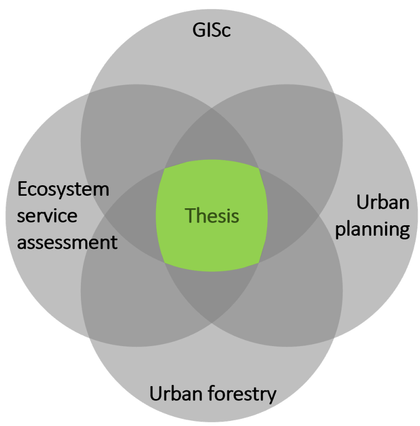

Figure 1.1: The scope of the thesis on the intersection between four bodies of knowledge: Geographical information science (GISc), urban planning, urban forestry and ecosystem service assessment

1.2 Thesis structure

The thesis is article-based and consists of *four papers* published or submitted to scientific journals and an *extended summary*. The extended summary provides a broader background to the thesis, introduces the knowledge gaps and research questions, and presents and discusses the findings of the respective papers within the thesis context. The extended summary comprises six chapters (Figure 1.2):

Chapter 1 introduces the thesis. It formulates the thesis objectives, delimits its scope and presents its structure.

Chapter 2 is dedicated to the first supporting objective (S1). First, the ecosystem services framework is presented as a means for conceptualizing the benefits of urban trees. Next, the chapter identifies a knowledge gap in terms of the lacking overview of the specific tree location characteristics that influence ecosystem services of urban trees. Based on the knowledge gap and the supporting objective, a research question (RQ1) is formulated. Finally, the chapter addresses the research question through the findings of Paper I and reflects on the consequences for the main objective of the thesis.

Chapter 3 is dedicated to the second supporting objective (S2). It presents the reasons and current methods for measuring the spatial context of urban trees. Further, the current use of GIS in modelling the spatial context of urban trees is assessed, resulting in a knowledge gap in terms of lacking GIS methods for modelling tree location characteristics.

Chapter 4 is dedicated to the main objective of the thesis. Building on the knowledge presented in chapters 2 and 3, a research question (RQ2) is formulated. The chapter then addresses the research question by presenting the GIS methods for modelling selected tree location characteristics developed in Papers II, III and IV.

Chapter 5 concludes the thesis. The wider contributions of the thesis beyond the thesis scope are discussed together with limitations and suggestions for further research directions.

Chapter 6 provides a summary of the individual papers.

The respective papers are appended in the second part of the thesis. Paper I is dedicated to reviewing and synthesizing the current knowledge on spatial context in ecosystem services of urban trees and thereby addresses the first supporting objective of the thesis (S1). Papers II, III and IV are dedicated to developing GIS methods for modelling spatial context of urban trees and thereby address the main objective of the thesis (Table 1.1).

Note on the use of pronouns

The pronouns in the extended summary are used with the following rules. The pronoun “we” is used when referring to collaborative work conducted in the respective papers. The pronoun “I” is used when referring to personal decisions and work conducted individually.

Table 1.1: The four papers constituting the thesis

Paper	Title	Authors	Paper objective
Paper I	Location matters. A systematic review of spatial contextual factors mediating ecosystem services of urban trees	Cimburova, Z. Berghauser Pont, M.	Develop a comprehensive overview of tree location characteristics recognized by research as relevant for the delivery of ecosystem services of urban trees.
Paper II	Viewshed-based modelling of visual exposure to urban greenery – An efficient GIS tool for practical planning applications	Cimburova, Z. Blumentrath, S.	Develop a viewshed analysis-based method for modelling visual exposure to urban greenery with a special focus on the method's applicability in research and practice.
Paper III	Making trees visible: a GIS method and tool for modelling visibility in valuation of urban trees	Cimburova, Z. Blumentrath, S. Barton, D.N.	Develop a flexible, efficient and easy-to-use GIS method for modelling individual tree visibility to support tree valuation methods and tree management and planning.
Paper IV	The potential of geospatial analysis and Bayesian networks to enable i-Tree Eco analysis of existing tree inventories	Cimburova, Z. Barton, D.N.	Demonstrate the potential of GIS and machine learning methods to supplement missing and incomplete i-Tree Eco attributes in existing municipal tree inventories to enable running i-Tree Eco analysis.

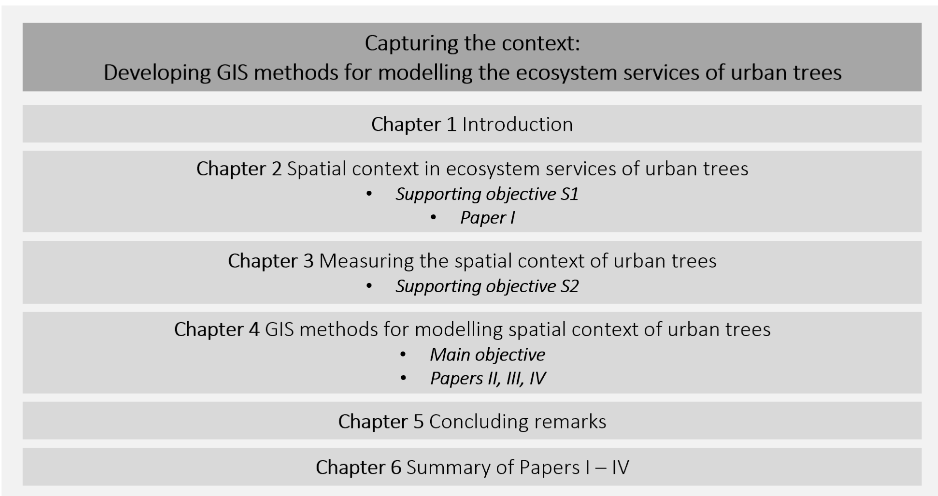

Figure 1.2: Structure of the extended summary and its relation towards the thesis objectives and the papers

Spatial context in ecosystem services of urban trees

2

In this chapter, I first present the ecosystem service framework as a means for conceptualizing the benefits of urban trees. Next, I briefly review the current knowledge on spatial context in ecosystem services of urban trees and identify a knowledge gap in terms of the lacking overview of the specific tree location characteristics that influence ecosystem services of urban trees. Then, based on the knowledge gap and the first supporting objective of the thesis (S1), I formulate a research question (RQ1). Finally, I answer the research question by presenting the findings of Paper I and reflect on the consequences for the main objective of the thesis.

2.1 The ecosystem service framework

Given the first supporting objective of the thesis, i.e. to review and synthesize existing knowledge on spatial context in ecosystem services of urban trees, the following question had to be answered first:

What are the specific ecosystem services of urban trees?

Acknowledging that there are different means for organizing the currently recognized benefits of urban trees (e.g., Nature's Contributions to People: Kadykalo et al. (2019)), I chose to use the *ecosystem service framework* (Daily, 1997; de Groot et al., 2002; Millennium Ecosystem Assessment, 2003; TEEB, 2010) because it is highly comprehensive and widely used in research and for decision support in practice. The framework thereby provides a foundation for addressing the thesis' first supporting objective.

The ecosystem service framework is a conceptualization of the different ways in which ecosystems in general (i.e., not only urban trees) contribute to human wellbeing. In the framework, the individual contributions of ecosystems to humans are referred to as ecosystem services, defined as "*the direct and indirect contributions of ecosystems to human well-being. They support directly or indirectly our survival and quality of life*" (TEEB, 2010). Examples of ecosystem services are air and water purification, generation and renewal of soils, protection from the sun's ultraviolet radiation and provision of aesthetic beauty (Daily, 1997).

The individual ecosystem services in the framework are often categorized into thematic groups. The Millennium Ecosystem Assessment (Millennium Ecosystem Assessment, 2003) and The Economics of Ecosystem Services and Biodiversity (TEEB, 2010) recognize four groups of ecosystem services:

- **provisioning services**, i.e. the material and energy products obtained from ecosystems (e.g., food, fuelwood),

- **regulating services**, i.e. the benefits obtained from the regulation of ecosystem processes (e.g., climate regulation, water purification),
- **cultural services**, i.e. the non-material benefits obtained from ecosystems (e.g., aesthetic experience, education),
- **supporting services**, i.e. the ecosystem services necessary to produce all other ecosystem services (e.g., soil formation, primary production).

The literature also distinguishes an additional but equally important group of so-called *ecosystem disservices*, which are the negative consequences of ecosystem functioning that are harmful to human wellbeing and lead to nuisances, damages and costs. Examples of ecosystem disservices are, for instance, diseases, pests or animal attacks (Lyytimäki et al., 2008; von Döhren & Haase, 2015).

Urban trees, along with other types of urban greenery, are an important source of ecosystem services in urban areas. Urban trees deliver numerous provisioning, regulating, cultural and supporting services (Escobedo et al., 2011; Roy et al., 2012; Salmond et al., 2016; Säumel et al., 2016) as well as disservices (Lyytimäki, 2017; von Döhren & Haase, 2015), leading to a variety of economic, social, health and aesthetic benefits (Roy et al., 2012) as well as detriments and costs (Lyytimäki, 2017; Roy et al., 2012; von Döhren & Haase, 2015). Table 2.1 provides an overview of the ecosystem services and disservices of urban trees commonly mentioned in the literature.

For instance, urban trees improve air quality by depositing air pollutants, ameliorate microclimate by shading and reducing wind speed, mitigate climate change by sequestering and storing carbon and absorb rainwater, thereby helping to avoid surface runoff and reducing flooding (regulating services). Urban trees also deliver cultural services such as recreation opportunities, aesthetics and educational benefits. Further, urban trees can serve as a source of fruits or fuel material (provisioning services) and provide habitat for various species (supporting services). Importantly, urban trees also provide disservices, such as allergies caused by pollen from certain tree species, blocked views by tree crowns and infrastructure damage by tree roots or fallen branches.

Table 2.1: Ecosystem services and disservices of urban trees commonly mentioned in the literature. Based on Escobedo et al. (2011), Roy et al. (2012), Salmond et al. (2016), Säumel et al. (2016).

Group of ecosystem services	Ecosystem service
Provisioning services	Food provisioning Fuelwood provisioning
Regulating services	Air pollution removal Carbon storage and sequestration Coastal protection Indoor temperature regulation Noise attenuation Outdoor temperature regulation Soil formation and protection Stormwater regulation UV radiation regulation Water supply Wind regulation
Cultural services	Aesthetics Cultural heritage Education Recreation and health Social cohesion
Supporting services	Habitat provisioning
Disservices	Accidents Allergy Animal excrements Damages to infrastructure Decrease in air quality (ozone and PM formation) Fear and stress Fruit and leaf fall Invasive species Maintenance emissions Spread of disease and pests View blockage
Other	Provisioning of grey infrastructure resilience

A useful framework when exploring the different effects of spatial context on ecosystem services of urban trees is the *ecosystem service cascade*, introduced first by Haines-Young and Potschin (2010) (Figure 2.1). The cascade conceptualizes the process of ecosystem service delivery as a linked set of five components spanning both the supply and demand side of the process. The components of the ecosystem service cascade are (based on Potschin and Haines-Young (2016a, 2016b)):

- **biophysical structure**, i.e. the representation of the studied ecosystem (an urban tree in the thesis),
- **function**, i.e. the subset of all properties and characteristics of the ecosystem that determine its capacity to deliver ecosystem services (e.g., dry deposition of gasses which determines the potential of a tree to remove air pollutants),
- **ecosystem service**, i.e. the outcome from the ecosystem that directly contributes to human wellbeing (e.g., removed air pollutants),
- **benefit**, i.e. the satisfaction of peoples' demand for the consumption, use or experience of the ecosystem service, which can change people's wellbeing (e.g., breathing cleaner air),
- **value**, i.e. the monetary, moral, aesthetic or spiritual expression of the relative importance of the benefit to people (e.g., the value of cleaner air).

Furthermore, when exploring the effects of spatial context on ecosystem service delivery along this cascade, it is useful to distinguish between the different ways in which the spatial context influences the services. A helpful conceptualization in this regard has been introduced by Fedele et al. (2017), who extended the cascade by making explicit the four different *mediating mechanisms* that lead from one component of the cascade to the next (Figure 2.1). Therefore, in the thesis and Paper I, I use the term *mediate* to express that spatial context affects or influences ecosystem services. The individual mediating mechanisms are (based on Fedele et al. (2017) and findings from Paper I):

- **management**, i.e. a mechanism mediating the potential of a biophysical structure to provide an ecosystem service,
- **mobilization**, i.e. a mechanism mediating how much of the potential is translated into an ecosystem service,
- **allocation-appropriation**, i.e. a mechanism mediating the allocation of the ecosystem service to potential beneficiaries,
- **appreciation**, i.e. a mechanism mediating the demand for the benefits, thereby determining their value.

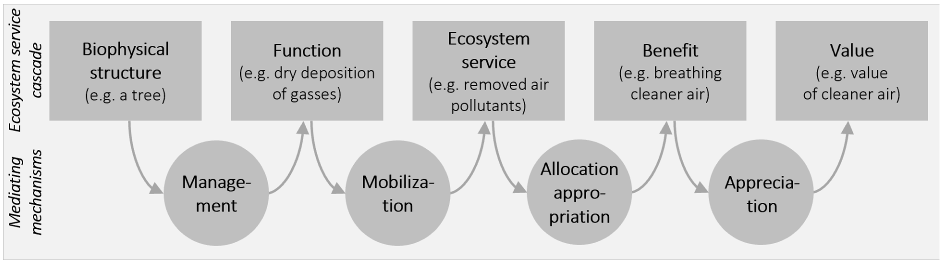

Figure 2.1: The ecosystem service cascade with exemplified mediating mechanisms. Adapted from Haines-Young and Potschin (2010) and Fedele et al. (2017).

2.2 The effects of spatial context on ecosystem services of urban trees

Spatial context is recognized as an important determinant of the ecosystem services that trees deliver along the entire ecosystem service cascade[2]. In the literature, the importance of accounting for tree location in ecosystem services has been widely discussed on both theoretical and practical levels (e.g., Andersson et al., 2015; Bruckmeier, 2016; Luederitz et al., 2015; Wilkerson et al., 2018).

Concrete examples of tree location characteristics that influence ecosystem services of urban trees are the proximity of a tree to surrounding buildings, its connectivity to other greenspaces, the concentration of air pollution at the tree location, the socio-demographic profile of the inhabitants in the tree's surroundings or growing conditions such as light and soil characteristics. For instance, the proximity of a tree to surrounding buildings determines how much the tree reduces energy usage in the building (an ecosystem service) because trees standing close to buildings may decrease the need for indoor cooling and heating by shading the buildings in summer and protecting them from wind in winter (Nowak et al., 2017). Also, trees standing close to buildings and visible from the buildings' windows are likely to contribute to the mental wellbeing of the inhabitants and provide aesthetic benefits more than trees far from people's sight (Gómez-Baggethun et al., 2013; Kaplan, 2001; Lottrup et al., 2015). The connectivity of a tree to other greenspaces influences the tree's potential to provide habitat for a range of animal species (Roeland et al., 2019; Säumel et al., 2016) and air pollution concentrations at tree location determines the amount of air pollutants a tree captures (Escobedo et al., 2011). Tree growing conditions determine, for instance, the tree's growth rate, which is directly related to the amount of sequestrated atmospheric carbon (Nowak, 2020). The socio-demographic profile of the inhabitants in the tree's surroundings influences how much the individual ecosystem services are appreciated and valued (Bratman et al., 2019; Keeler et al., 2019; Wilkerson et al., 2018).

Apart from the provided examples, many more notions of such specific tree location characteristics that influence ecosystem services of urban trees can be found in the literature (e.g., Roeland et al., 2019; Roy et al., 2012; Salmond et al., 2016). We can also find more general notions of the impacts of, for example, surrounding natural conditions, socioeconomic contexts and character of the built environment on ecosystem services of urban trees (e.g., Andersson et al., 2015; Davies et al., 2017; Roy et al., 2012; Salmond et al., 2016).

[2] The ecosystem services delivered by urban trees are also influenced by the tree's "internal" characteristics, i.e. characteristics that do not change with the tree's location. These are for instance tree dimensions (e.g., stem diameter, leaf area, canopy height), tree species (and, consequently, for example leaf physical traits such as shape, roughness and albedo) and tree condition (e.g., cavities, dead branches). For instance, the ecosystem service of carbon sequestration is proportional to stem diameter, which influences the increase in tree biomass (Nowak & Crane, 2002; Nowak et al., 2002). Similarly, the characteristics of tree leaves determine the tree's ability of a tree to deposit air pollutants, and thereby influence the ecosystem service of improving air quality (Grote et al., 2016).

2.3 Research question

Despite the importance of spatial context in ecosystem services of urban trees, little research has been done to synthesize the current knowledge and create a comprehensive overview of the specific tree location characteristics to provide a holistic understanding of how spatial context mediates the ecosystem services of urban trees (Wilkerson et al., 2018). Studies that review the different tree location characteristics often focus on a single ecosystem service (e.g., air quality, microclimate regulation (Abhijith et al., 2017; Salmond et al., 2016)) or a single group of characteristics (e.g., institutional barriers (Biernacka & Kronenberg, 2018)). Moreover, they do not link the tree location characteristics to the specific services (Vogt et al., 2017) or do not explicitly study the impact of spatial context on trees' ecosystem services (Keeler et al., 2019).

This knowledge gap hinders selecting the specific tree location characteristics that could be modelled to reach the main objective of the thesis. Therefore, the following research question (RQ1) was formulated in response to the knowledge gap:

RQ1

Within the ecosystem service framework, what specific tree location characteristics mediate ecosystem services of urban trees?

To ensure that the answer to the research question helps to reach the main objective, it should not only provide an overview of the different tree location characteristics. The answer should also relate the individual tree location characteristics to the mediated ecosystem services to suggest the importance of the individual characteristics. Moreover, the answer should help find suitable ways of modelling the tree location characteristics in GIS (for example, selecting an appropriate spatial modelling approach, finding suitable spatial data representation etc.). Therefore, I specified the research question with the following sub-questions:

- ***What ecosystem services are mediated by the individual tree location characteristics and by what mechanisms?***
- ***How can tree location characteristics be represented as a conceptual model?***
- ***What are the implications of such conceptual representation of tree location characteristics for spatial modelling?***

2.4 Spatial contextual factors as a conceptualization of tree location in ecosystem services of urban trees

In response to the research question, we developed a comprehensive overview of the different tree location characteristics that influence the ecosystem services of urban trees. Developing the overview was the main objective of Paper I. The methodological steps taken to create the overview (two systematic literature reviews) and a synthesis of the overview are thoroughly documented in the paper. In this section, I first introduce the term *spatial contextual factors*. Then, I present and elaborate the findings of Paper I relevant to the research question and its sub-questions and reflect on the consequences for reaching the main objective of the thesis.

In the thesis and Paper I, I refer to the specific tree location characteristics that influence tree ecosystem services as *spatial contextual factors*. This term is based on the name *contextual factor* used by, for example, Andersson et al. (2015) and Reyers et al. (2013); the prefix *spatial* was added to emphasize the important role of space and tree location.

Through a systematic literature review conducted in Paper I, we identified 114 specific spatial contextual factors. The identified factors mediate, through four mediating mechanisms, all 31 ecosystem services of urban trees commonly mentioned in the literature (Table 2.1). We further found that one factor can mediate several ecosystem services. These multifunctional factors could be interpreted as more important to measure and model because they mediate many ecosystem services and thus are more important to include in tree planting strategies. Table 2.2 (columns "Spatial contextual factors" and "Mediated ecosystem services") shows examples of 10 spatial contextual factors identified in Paper I as mediating the largest number of ecosystem services.

Paper I showed that conceptually, spatial contextual factors can be understood as capturing a *spatial relationship* between an *urban tree* and various *structures and processes* in the tree's surroundings (Figure 2.2). Both the tree and the structure/process can be associated with a specific geographical location, although the spatiality of some factors might not be immediately evident, as in the case of "management practices" or "personal characteristics". This conceptualization of spatial contextual factors as a tree, spatial relationship and structure/process is important when translating the individual factors into a spatial model in GIS. While tree and structure/process represent the necessary input spatial data, the spatial relationship reflects the type of spatial analysis conducted. Table 2.2 (column "Structure/process") shows the structure/process that constitutes each factor.

The structures and processes that constitute spatial contextual factors can be classified into five broad domains: *aggregation of trees* (e.g., other trees or tree aggregations), *natural structures and processes* (e.g., temperature, soils, terrain), *built structures and processes* (e.g., buildings, streets), *individuals and society* and *maintenance and governance* (Table 2.2 column "Domain").

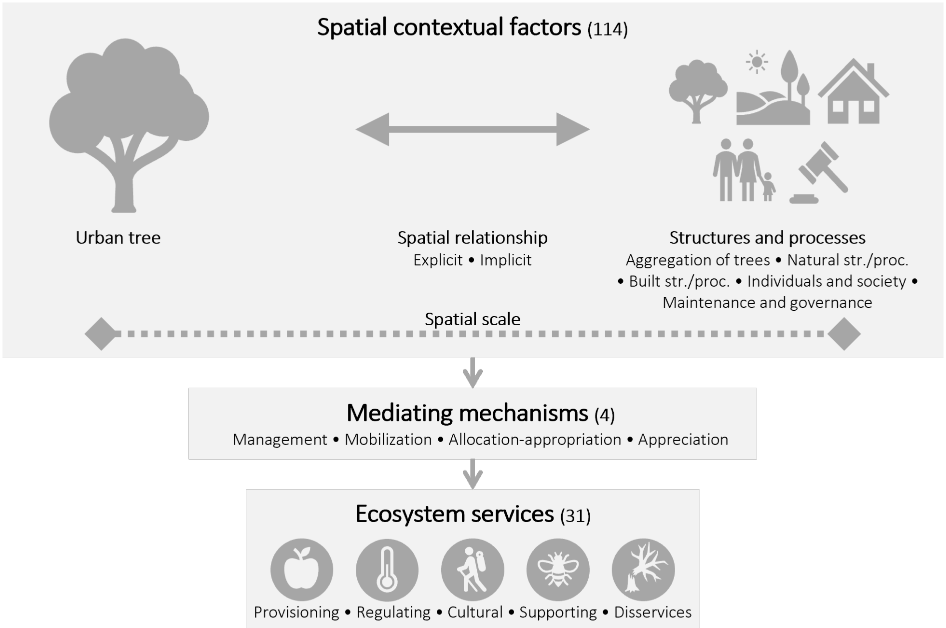

Figure 2.2: Conceptual understanding of spatial contextual factors in ecosystem services of urban trees

Paper I also showed that many of the identified spatial contextual factors explicitly describe the *characteristic* of the structure and process. For instance, in the factors "socio-economic status" and "air pollution concentrations", it is the characteristics of the "people" and "air" (socio-economic characteristics and air pollution concentration, respectively) that mediate the ecosystem services, not only their presence. The characteristics of structures and processes vary across space. In spatial modelling of spatial contextual factors, the characteristics of structures and processes can be represented as attributes (in the case of vector representation) or pixel values (in the case of raster representation). Table 2.2 (column "Characteristic") shows the characteristic of the structure/process for each factor, if applicable.

The spatiality of the relationship between the tree and a structure/process in each spatial contextual factor is variable. In some factors, the spatial relationship is *explicit*, i.e. the factor describes the configuration between a tree and a structure/process. In other factors, the spatial relationship is *implicit*, i.e. the factor assumes that the structure/process occurs at the tree location. Examples of the former group are "proximity of tree to people" and "visibility of tree from building" because both "proximity" and "visibility" explicitly describe the spatial configuration. An example of the latter group is "air pollution concentration" because it is the fact that there is air pollution of a certain concentration "at the location" of the tree that mediates the ecosystem services from the tree. The same applies, for example, for the factors "socio-economic status of people" or "urban form". Often it is the latter group of factors that also describes the characteristic of the structure/process, as discussed in the previous paragraph. This point of view on the spatial relationship between trees and structures/processes is important because modelling the factors with an explicit spatial relationship is likely to require a more complex and innovative spatial modelling approach than modelling factors with an implicit spatial relationship, which can be modelled with a simple overlay analysis. Table 2.2 (column "Spatial relationship") identifies for each factor, whether the spatial relationship in that factor is implicit or explicit.

Importantly, there is also variation in the *spatial scale* of the spatial contextual factors. For example, while the factors "climate" and "cultural background" vary on a global scale, the factors "soil moisture" and "distance to building" describe a local spatial context. The spatial scale of the factors is important to consider in spatial modelling because it drives the requirements on the spatial resolution of the analysis. For example, while "distance to building" requires detailed spatial data on the accurate location of individual buildings, the required spatial resolution is much lower to model "climate" at tree location.

Table 2.2: Examples of spatial contextual factors (*str. & proc.: structures and processes*)

Spatial contextual factor	Structure/ process	Domain	Characte-ristic	Spatial relationship	Mediated services
Species diversity	Tree aggregations	Aggregation of trees	Yes (species diversity)	Implicit	11
Socio-economic status of people at tree location	People	Individuals & society	Yes (socio-economics)	Implicit	10
Density of tree aggregation	Tree aggregations	Aggregation of trees	Yes (density)	Implicit	9
Proximity of tree to other trees/ tree aggregations	Other trees, tree aggregations	Aggregation of trees	No	Explicit (proximity)	8
Climate at tree location	Climate	Natural str. & proc.	Yes (climate)	Implicit	8
Proximity of tree to infrastructure	Infrastructure	Built str. & proc.	No	Explicit (proximity)	8
Temperature at tree location	Air	Natural str. & proc.	Yes (temperature)	Implicit	7
Air quality at tree location	Air	Natural str. & proc.	Yes (quality)	Implicit	7
Accessibility of tree to people	People	Individuals & society	No	Explicit (accessibility)	7
Connectivity of tree to other trees/ tree aggregations	Other trees, tree aggregations	Aggregation of trees	No	Explicit (connectivity)	6

3 Measuring the spatial context of urban trees

In this chapter, I will first explain why it is important to measure spatial contextual factors of urban trees. Subsequently, to address the second supporting objective of the thesis (S2), i.e. to review and assess the current use of GIS in modelling the spatial context of urban trees, I will review how spatial contextual factors are currently measured and assess the existing GIS methods used in modelling spatial contextual factors. I will then conclude the chapter by identifying a knowledge gap in terms of lacking methods for modelling spatial contextual factors.

Note on two perspectives in measuring the spatial context of urban trees

Before explaining the reasons and methods for measuring spatial contextual factors of urban trees, I find it helpful to establish two distinct perspectives from which the factors can be measured. If we think of spatial contextual factors as a spatial relationship between a tree and a structure/process (as described in Section 2.4), an important question is from what *perspective* the measurement would be done – whether from the perspective of the *tree* (further referred to as *tree perspective*) or from the perspective of the *structure or process* (further referred to as *structural perspective*).

Measuring spatial contextual factors from a tree perspective means that the assessed tree is associated with a value reflecting the magnitude of the factor for that tree. On the other hand, measuring spatial contextual factors from a structural perspective means associating the magnitude of the factor with the analyzed structure. For example, we can think of the factor "visibility of trees from buildings", an important mediator of the aesthetic and recreational services of urban trees (Gómez-Baggethun et al., 2013; Nesbitt et al., 2017; Y. Wang et al., 2014). Measuring the factor from a tree perspective would mean, for instance, counting how many buildings are visible from each assessed tree. On the other hand, measuring the factor from a structural perspective (here, the buildings) would mean, for instance, measuring the area of tree canopy visible from each assessed building. More examples of this dual perspective are shown in Table 3.1.

Distinguishing between the tree perspective and the structural perspective is important because the reasons to measure spatial contextual factors depend on the perspective taken. Moreover, the methods to measure the factors differ with the perspective as well. Therefore, the following Section 3.1 and Section 3.2 are divided according to the two perspectives.

Table 3.1: Examples of two perspectives in measuring spatial contextual factors of urban trees. The factors used for illustration were selected from the overview of 114 spatial contextual factors created in Paper I.

Spatial contextual factor	Structure/ process	From a tree perspective	From a structural perspective
Visibility of trees from buildings	Buildings	The number of buildings visible from a tree	The number of trees or amount of tree canopy visible from a building
Accessibility of trees to people	People	The number of people within accessibility area of a tree	The number of trees or amount of tree canopy accessible for a person
Light condition of trees' crowns	Light-blocking structures	Percent tree crown shaded by the surrounding light-blocking structures	The number of trees or amount of tree canopy shaded by a light-blocking structure
Air quality at tree location	Air	Air pollution at the tree location	The number of trees or amount of tree canopy in a territory with a certain level of air pollution
Policies at tree location	Policy (e.g., felling permit)	Specific policies applying to individual trees	The number of trees or amount of tree canopy for which specific policy applies

3.1 Why measure the spatial context of urban trees?

As mentioned in Chapter 2, spatial contextual factors of urban trees (together with internal tree characteristics) determine the amount of ecosystem services that trees deliver along the entire ecosystem service cascade. That is, the factors can mediate the potential of a tree to provide a service, the realization of that potential, how the final ecosystem services are allocated to the beneficiaries and the value of the services arising from the demand (Haines-Young & Potschin, 2010). Therefore, in general, measuring spatial contextual factors is necessary to more accurately quantify ecosystem service delivery by urban trees along the ecosystem service cascade.

3.1.1 Reasons for measuring spatial context from a tree perspective

Measuring spatial contextual factors from a *tree perspective* is the foundation for a per-tree quantification of ecosystem services. This, in turn, enables comparing individual trees in terms of the ecosystem services they deliver. To quantify per-tree ecosystem services, spatial contextual factors and internal tree characteristics are often put into a functional relationship. This is especially the case for regulating ecosystem services, where the functional relationships between internal tree characteristics, spatial contextual factors and ecosystem services are well known. For example, per-tree annual net carbon sequestration (an ecosystem service) can be computed by an equation considering the tree species (an internal tree characteristic to identify biomass equation), its stem diameter and height (internal tree characteristics to calculate tree biomass), land use at its location (a spatial contextual factor to assign biomass adjustment factor) and its health and crown light exposure (an internal tree characteristic and a spatial contextual factor to adjust growth rates) (Nowak, 2020).

Spatial contextual factors are also used as indicators or proxies of the ecosystem services they mediate, especially if the functional relationship between internal tree characteristics, spatial contextual factors and the ecosystem services is not established or if measuring all the variables is not possible. Moreover, spatial contextual factors may be used as proxies for ecosystem service demand and value. For instance, the visibility of a private tree may be a proxy for the tree's potential to deliver aesthetic services in assessing recreation and property amenities and mental health benefits (Gómez-Baggethun et al., 2013; Nesbitt et al., 2017; Y. Wang et al., 2014). Furthermore, the value of the service can be estimated, for instance, by assessing the price increase of the property where the tree is standing (Nesbitt et al., 2017).

Dedicated tree valuation tools and methods are often used to quantify per-tree ecosystem services. One of the most widely used tree valuation tools is i-Tree Eco, a software application developed by the United States Department of Agriculture Forest Service. i-Tree Eco quantifies the supply and monetary value of regulating ecosystem services of individual urban trees, including per-tree carbon sequestration, avoided stormwater runoff, air pollution removal and energy savings (USDA Forest Service Research, 2021b). Specifically, i-Tree Eco quantifies per-tree annual ecosystem service indicators by putting internal tree characteristics (e.g., stem diameter, tree condition and species) and spatial contextual factors (e.g., crown light exposure) into peer-reviewed model equations. Furthermore, i-Tree Eco enables estimating monetary value from ecosystem services based on local benefit prices (which is also a spatial contextual factor).

Besides regulating ecosystem services, many methods focus on quantifying and valuing the aesthetic and amenity benefits of urban trees. These are, for example, the British Helliwell system (Helliwell, 1967, 2008a, 2008b) and CAVAT (Capital Asset Value for Amenity Trees) (Doick et al., 2018), the Danish VAT method (Værdisætning af træer) (Randrup, 2005; Randrup et al., 2019; Randrup et al., 2003) or CTLA Guide for Plant Appraisal (Cullen, 2007). Generally, these methods estimate per-tree value based on various indicators of the tree's aesthetic and amenity services, including the tree's spatial context.

Measuring spatial contextual factors from a tree perspective is a helpful empirical input to inform, support and guide decisions in a range of application purposes, including urban forestry, tree management, urban planning and policy setting (Table 3.2). Measuring the spatial context of individual trees provides information for selecting tree species that best profit from local growing conditions (Vogt et al., 2017) and targeting planting locations that can best support the delivery of ecosystem services or where the demand for a given service is high. For example, measuring air pollution at possible tree planting locations (a spatial contextual factor reflecting the demand for air pollution removal) can inform targeted tree planting along highly-trafficked roads (Abhijith et al., 2017).

Furthermore, spatial contextual factors can be used to estimate the supply of ecosystem services by all trees in a neighborhood or a city and create accounting tables of urban forest extent, tree condition and ecosystem service supply as parts of urban ecosystem accounting (United Nations, 2021). This facilitates detecting trends in ecosystem service supply over time and enables communicating the benefits of urban trees to the public. Adding a monetary value to the provided ecosystem services can aid numerous purposes, including justifying budget allocations for tree protection and supporting economic damage and compensation claims.

Measuring per-tree spatial contextual factors is also essential in research to enable empirically studying the relationship between ecosystem services (tree functioning, ecosystem service supply or its appreciation) and the respective factors. For instance, to assess how crown light exposure influences tree growth rate (and thereby carbon sequestration), it is necessary to measure it.

Table 3.2: Examples of application purposes benefiting from measuring spatial contextual factors from a tree perspective. The individual application purposes are classified into four groups of decision support context (awareness-raising, economic accounting, priority setting and litigation) following the established classification of Gómez-Baggethun and Barton (2013).

Application purpose	Explanation & example	Decision support context
Communication to the public	Communicating the importance of ecosystem services of urban trees to the public E.g., aggregate quantification of specific ecosystem services of all city trees E.g., putting a price-tag on a tree to illustrate the value of the tree from ecosystem services	Awareness-raising
Setting and justifying budgets	Gaining public and political support to set and justify budgets for tree maintenance, conservation etc. E.g., aggregate monetary valuation of all city trees	Awareness-raising
Tree protection	Providing rationale for protecting existing trees E.g., quantifying ecosystem services to justify tree protection under construction periods	Awareness-raising
Ecosystem accounting	Creating accounting tables and balance sheets of urban forest extent, tree condition and ecosystem service supply from urban trees to detect trends over time and compare across accounting units (e.g., neighborhoods, cities) E.g., documenting temporal changes in ecosystem service supply following tree planting programs	Accounting
Strategic tree planting and evaluating tree planting scenarios	Estimating how spatial context at different planting locations supports the supply of/demand for specific ecosystem services E.g., which species would best profit from growing conditions at a specific location? E.g., are growing conditions better in location A or B? E.g., is the demand for a specific ecosystem service larger in location A or B?	Priority-setting
Impact assessment	Assessing the consequences of interventions in the tree's surroundings on the ecosystem services of the tree E.g., how would the value of trees in a park change if a hospital is constructed in the vicinity? E.g., how does the value of trees change with climate change and increasing temperature?	Priority-setting, Litigation
Damage and compensation claims	Justifying economic compensation of trees in legal cases and insurance claims E.g., estimating the monetary value of an illegally felled or damaged tree	Litigation
Solving neighbor conflict issues	Illustrating the benefits and detriments a tree has to different types of users (owner, neighbor, public) from an agent-neutral perspective as a basis for a shared objective assessment	Other
Research applications	Empirically studying the relationship between per-tree ecosystem services and spatial contextual factors	Other

3.1.2 Reasons for measuring spatial context from a structural perspective

Measuring spatial contextual factors from a *structural perspective* is the foundation for comparing the different structures and processes in terms of their impact on ecosystem services of urban trees and in terms of the ecosystem services they receive from urban trees. For example, various air pollution sources (structures) can be compared by their impact on the edibility of fruits from trees in the surroundings (an ecosystem service) (Russo et al., 2017). Similarly, different households (structures) can be compared by their access to tree canopy and related recreation, health and aesthetic services (Nesbitt et al., 2017; van den Berg et al., 2015; Wen et al., 2018).

Measuring spatial contextual factors from a structural perspective can thereby benefit many application purposes in urban forestry, tree management and urban planning (Table 3.3). For example, measuring spatial contextual factors from a structural perspective can support strategic tree planting by identifying areas with low ecosystem service supply. Complementing such analysis with, for example, spatially explicit data of ecosystem service demand (e.g., locations of vulnerable population) enables the identification of places where tree planting would have the most significant effect on ecosystem service delivery. Strategic tree planting is especially relevant in cities undergoing densification where space for larger green areas may be limited and strategic planting of individual trees can be an effective way of ensuring ecosystem service delivery. Studying the inequitable distribution in access to urban green spaces (including urban trees) and the associated benefits to specific social groups is also a concern addressed by environmental justice studies (Kabisch & Haase, 2014).

Measuring spatial contextual factors from a structural perspective can further inform scenario modelling and impact assessment because it enables planners to empirically compare different tree planting or felling scenarios or various construction projects in terms of their impact on ecosystem service delivery in a given area. For example, comparing different tree planting scenarios in terms of tree canopy visibility from a nearby hospital can help select a tree planting strategy that results in the largest increase in tree visibility for the hospital's patients. Measuring selected spatial contextual factors such as access and visibility to tree canopy from housing is also beneficial in monetary valuation of urban greenery in hedonic pricing studies (e.g., Sander and Polasky, 2009; Saphores and Li, 2012).

Finally, measuring spatial contextual factors from a structural perspective is important to empirically study the relationship between individual factors, ecosystem services and associated benefits (e.g., mental and physical health, aesthetics, socio-economic benefits). For instance, to empirically assess how trees affect energy consumption in surrounding buildings, measuring the position of the trees in relation to the building is needed (Nowak et al., 2017). Similarly, to advance our knowledge on the relationship between visual exposure to tree canopy and mental and physical health (e.g., Kaplan, 2001; Lottrup et al., 2015; Ulrich, 1984), we need to be able to measure and quantify the amount of visible tree canopy.

Table 3.3: Examples of application purposes benefiting from measuring spatial contextual factors from a structural perspective

Application purpose	Explanation & example
Communication to the public	Communicating the importance of ecosystem services of individual urban trees to the public E.g., creating city-wide ecosystem service supply maps
Ecosystem accounting	Creating balance sheets of ecosystem service supply to detect trends over time and compare across accounting units (e.g., neighborhoods, cities) E.g., documenting temporal changes in ecosystem service supply following tree planting programs
Environmental justice studies	Assessing the access to urban greenery and associated benefits for specific social groups E.g., studying the relationship between walking distance from residential housing to tree canopy and socio-economic background of residents
Strategic tree planting	Identifying areas with ecosystem service deficit E.g., identifying areas with low amount of visible tree canopy
Scenario modelling and impact assessment	Assessing the consequences of interventions in the surroundings of the structure/process on the ecosystem service supply E.g., how would the access to urban trees from a school change if trees were planted at a given location? E.g., how would the access to urban trees from a school change if a pedestrian bridge over a railway were built in the vicinity?
Real estate value contributions	Assessing the increase/decrease of property value due to trees on/around the property E.g., how is the access to tree canopy reflected in the residential property value?
Research applications	Empirically studying the relationship between individual spatial contextual factors, ecosystem services and associated benefits E.g., how does visible tree canopy affect mental health? E.g., how does the proximity of trees to a building affect energy consumption in the building?

3.2 How to measure the spatial context of urban trees?

3.2.1 Methods for measuring spatial context from a tree perspective

Different methods for measuring spatial contextual factors from a *tree perspective* exist; manual assessment and spatial modelling in GIS being the most common ones. Manual assessment of spatial contextual factors is a standard approach to measure the factors in the tree valuation tools mentioned previously. For instance, the field guide of i-Tree Eco explicitly specifies the steps to manually assess crown light exposure, distance and direction from tree to buildings and land use at tree location (USDA Forest Service Research, 2021a). Similarly, manual assessment of spatial contextual factors is suggested by the VAT and CAVAT tree valuation methods (Neilan, 2017; Randrup et al., 2019). In these methods, the assessment of spatial context is of a more qualitative character, for example, scoring the appropriateness of the tree in its location, its relation to architecture and its visibility.

In recent years, the accuracy and availability of remote sensing methods such as high-resolution Light Detection and Ranging (LiDAR) (Li et al., 2021) and multi- and hyperspectral imaging (Sun et al., 2021) have increased. These advancements have expanded the possibilities for automatic detection of individual urban trees, including the geometry of their crown and their height (e.g., Chen et al., 2021; Fekete and Cserep, 2021; Hartling, Sagan, and Maimaitijiang, 2021). This, in turn, allowed for increased use of GIS for modelling spatial contextual factors from a tree perspective. However, relatively few studies made use of this option. The factors modelled with GIS include crown light exposure for estimating microclimate regulation (Gangwisch et al., 2021) and carbon sequestration (Scholz et al., 2018), distance to building for estimating the effect of trees on indoor temperature (Bassett, 2015) and building damage potential (Tomao et al., 2015), the number of buildings within sight of trees to estimate the contribution of trees to health benefits (Cox et al., 2019) and the contribution of individual trees to greenspace connectivity to study habitat benefits (Von Thaden et al., 2021).

It is also important to acknowledge that substantial efforts have been dedicated to spatially modelling and mapping the *characteristics* of structures and processes that constitute the spatial contextual factors of urban trees. Such modelling and mapping work is mostly unrelated to urban trees and often has a place in dedicated research fields and disciplines. For example, specific disciplines and research fields are dedicated to natural structure and processes (e.g., meteorology, pedology), built structures and processes (e.g., urban morphology), people and society (e.g., socio-economic geography, demography). The modelling and mapping outcomes from these research fields and disciplines can, however, inform many application purposes related to urban trees, such as strategic tree planting and identifying prioritized tree planting locations. For instance, Morani et al. (2011) overlayed air pollution and population density maps to create a planting priority index to support the MillionTreesNYC initiative[3]. Other studies considered, for example, factors

[3] https://www.milliontreesnyc.org/

capturing available planting locations (e.g., site protection, available space) as well as factors determining the demand for specific ecosystem services (e.g., temperature, population density, distribution of vulnerable population) (e.g., Almeter et al., 2018; 2021; Kraxner et al., 2016; Marando et al., 2016; Norton et al., 2015; Sass et al., 2019).

3.2.2 Methods for measuring spatial context from a structural perspective

Manual assessment of spatial contextual factors from a *structural perspective* is less common than in the case of tree perspective. For example, in studies of the health benefits of visual exposure to urban greenery (including trees), the amount of visible greenery has been manually assessed by direct observations in the field (de Vries et al., 2013) or self-reported by the study participants (Hazer et al., 2018; Lottrup et al., 2015).

On the other hand, computer simulations and GIS are commonly used to measure spatial contextual factors from a structural perspective because they have the functionality to analyze spatial patterns and interactions and model the often complex spatial relationships in the factors. For example, various computer models have been developed to simulate the effect of trees on their surroundings, including the impact of trees on wind physics, solar radiation, air pollution deposition and similar specialized applications (Lin et al., 2019).

An extensive amount of GIS literature has focused on modelling the amount of tree canopy cover as a measure of spatial contextual factors reflecting the access and exposure to urban trees, for example, to study the recreation and health benefits of trees and their effect on housing values and safety. Commonly, the access and exposure to trees have been modelled as the amount of tree canopy within an accounting unit (a census tract, a parcel etc.) (e.g., Baró et al., 2019; Cho et al., 2008; Escobedo et al., 2018; Knobel et al., 2021; Kweon et al., 2017; Moreno et al., 2015; Troy et al., 2012; Vich et al., 2019; Volin et al., 2020). For example, to study the effect of greenery on cardiovascular health, Knobel et al. (2021) modelled the percentage of tree cover per census tract. An alternative metric of access and exposure to trees has been the percentage or amount of tree canopy within a defined radius of a structure under analysis (a residential location, a school, unit of open space etc.) (e.g., Mansfield et al., 2005; Mouratidis, 2019; Mouratidis and Yiannakou, 2022; Ng et al., 2021; Reid et al., 2017). For example, in a study of neighborhood satisfaction, Mouratidis and Yiannakou (2022) modelled the percentage of tree canopy within a 1km radius of residential housing. Fewer studies have modelled more complex metrics of access and exposure to tree canopy. For example, viewshed analysis has been used to model exposure to tree canopy from a human visual perspective (Cavailhès et al., 2009; Łaszkiewicz & Sikorska, 2020; Nutsford et al., 2016; Pecero-Casimiro et al., 2019; Sander & Zhao, 2015) and Paddle and Gilliland (2018) modelled the amount of tree canopy within walking distance instead of Euclidean radius, arriving at a more accurate estimate of access to tree canopy.

Few studies have applied GIS in modelling other spatial contextual factors. For instance, GIS has been used in modelling trees' shading effects on buildings and open space by measuring the position of trees towards buildings (Carver et al., 2004; Rafiee et al., 2019; Rafiee et al., 2016) or by modelling Sky View Factor (Aleksandrowicz et al., 2020). GIS has also been used to model the proximity of trees to infrastructure to study the potential collisions between trees and power lines and the effect of trees on road safety (Hartling et al., 2021; Marshall et al., 2018).

3.2.3 Advantages and limitations of modelling spatial context with GIS

Modelling spatial contextual factors of urban trees with GIS has several advantages compared to manual assessment. First, manual assessment of spatial contextual factors is prone to measurement errors (Lin et al., 2021; USDA Forest Service Research, 2021a), and GIS is thus expected to increase the overall *accuracy* of the measurements. Second, GIS as an *objective* means of measurement can reduce the uncertainties and biases of manual assessment caused by subjective judgements of the assessors and observers (Alonzo et al., 2016). Finally, manual assessment can be labor intensive, time-consuming and expensive, especially in large-scale assessments (A. Nielsen et al., 2014). By reducing per-tree assessment time, GIS can significantly increase the assessment *efficiency* in terms of time and monetary costs (Scholz et al., 2018).

Consequently, there are many cases where modelling spatial contextual factors with GIS can be advantageous compared to manual assessment. These include cases of access, time, spatial scale and complexity restrictions, need for special measurement tools, assessment of a large number of trees etc. (A. Nielsen et al., 2014; Scholz et al., 2018) (Table 3.4). For example, access restrictions may limit the possibility to directly measure a distance between a public tree and a building (to estimate indoor temperature regulation by the tree) if the building is on private property. While estimating the distance manually in the field would lead to lower accuracy, modelling the distance in GIS would enable accurate measurement of the factor regardless of access restrictions. Similarly, spatial modelling in GIS can be advantageous when the spatial relationship of the factor is complex, and manual assessment is likely to be biased by the assessor's subjective judgement, as in the case of estimating the amount of visible tree canopy (Falfán et al., 2018). Furthermore, GIS ensures efficiency and consistency in measuring spatial contextual factors. It thereby enables observing spatial variations in the factors across large areas and over time, which might benefit applications such as accounting and strategic tree planting (Falfán et al., 2018; Helbich, 2018; Scholz et al., 2018).

On the other hand, there are also limitations to measuring spatial contextual factors with GIS. In some cases, manual assessment is preferable to GIS. Objective spatial modelling in GIS is not suitable to cases where the factors reflect subjective qualities or perceptions of the assessed tree, which are difficult or impossible to reflect in a spatial model (Dzhambov et al., 2018; Falfán et al., 2018). For example, while spatial modelling can quantify the amount of objectively accessible urban trees canopy, this measure of the factor might not reflect the subjective, perceived access (Knobel et al., 2021).

Moreover, manual assessment may be preferable if the spatial relationship in the factor cannot be clearly translated into a geometrical representation in a spatial model. An example of such a factor is the "architectural context" in the VAT tree valuation method (Randrup, 2005; Randrup et al., 2019). Experience and knowledge of the tree assessors are needed to assess this factor because translating it into a geometrical representation cannot accurately capture the meaning of the factor.

Modelling spatial contextual factors can further be limited by the availability of data for modelling the factors at a required accuracy (A. Nielsen et al., 2014), either because such data do not exist or because they are not available due to data protection. For example, assessing micro-scale factors such as rooting conditions with GIS might be possible but likely impractical because of the difficulties to obtain detailed spatial data to model rooting conditions with sufficient accuracy.

Finally, manual assessment might be preferred in specific application purposes where the development and operation of GIS methods is limited by the lack of technical skills and knowledge.

Table 3.4: Cases benefiting from modelling spatial contextual factors with GIS

Case	Explanation	Example
Access restrictions	Manual assessment restricted by limited access to tree or structure/process due to ownership rights, safety issues etc.	E.g., measuring the distance from tree to building in private areas E.g., measuring tree visibility from tree perspective
Time restrictions	Manual assessment restricted by need for long-term monitoring	E.g., measuring the number of people who pass by a tree in a year E.g., measuring hourly air pollution at tree location over a year
Spatial scale restrictions	Manual assessment restricted by large spatial scale of the factor	E.g., measuring tree accessibility from residential areas
Complexity restrictions	Manual assessment restricted by complexity of spatial relationship in the factor	E.g., measuring tree visibility from open space
Need for special measurement tools	Manual assessment restricted by need for special measurement tools	E.g., measuring air pollution at tree location
Assessment of a large number of trees/structures	Manual assessment restricted by need for assessing large number of trees or structures in a large area	E.g., assessing all trees in a city extent
Assessment of future scenarios	Manual assessment not possible because the assessed tree or structure/process do not exist	E.g., comparing hypothetical tree planting scenarios in terms of spatial contextual factors
Observing temporal changes	Manual assessment restricted by need for consistency and comparability of measurements	E.g., assessing change in access to trees over several years

3.2.4 Assessment of existing GIS methods for modelling spatial context of urban trees

In this section, I will use five performance criteria (Table 3.5) to explore the suitability of the existing GIS methods for modelling spatial contextual factors of urban trees for the different application purposes outlined in Section 3.1. The performance criteria are loosely inspired by van Oudenhoven et al. (2018) criteria for developing ecosystem service indicators to inform decision making, but have been adjusted and supplemented to serve the purpose of assessing the use of GIS in modelling spatial contextual factors of urban trees.

Table 3.5: Performance criteria for assessment of existing GIS methods for modelling spatial contextual factors (matching criteria from van Oudenhoven et al. (2018) in parentheses)

Performance criterion	Definition
Accuracy (Legitimacy)	The degree to which the translation of the physical spatial contextual factor into a model reflects the meaning of the factor
Input data availability (Feasibility)	The ease of obtaining all necessary input spatial data for the method
Efficiency (Feasibility)	The computational resources (time) and hardware necessary to apply the method
Availability (Legitimacy, Salience, Feasibility)	The requirements to access and operate the method, including requirements for software and technical skills
Flexibility (Legitimacy, Flexibility, Credibility)	The ease of extending and modifying the method and its parameters

Accuracy

Accuracy characterizes the degree to which the modelling method reflects the meaning of the spatial contextual factor. Importantly, the demands for accuracy vary with application purposes (Zulian et al., 2018). While for example monetary valuation of individual trees for insurance claims demands high accuracy, in estimating ecosystem services of urban tree stock for awareness-raising, accuracy demands might be lower (Gómez-Baggethun & Barton, 2013). Moreover, in some application purposes, lower accuracy might be acceptable in return for decreased input data costs or improved computational efficiency.

One of the main drivers of the accuracy in the existing GIS methods for modelling spatial contextual factors is the spatial resolution of input data: higher spatial resolution generally leads to higher accuracy. Tree canopy rasters, used in modelling spatial contextual factors from a structural perspective, are commonly in very high resolution (e.g., 0.2m in Łaszkiewicz and Sikorska (2020), 0.3m in Knobel et al. (2021)), although some studies build on lower resolution maps (e.g., 30m in Mouratidis and Yiannakou (2022) and Sander and Zhao (2015)). On the other hand, modelling spatial contextual factors from a tree perspective is commonly based on detailed vector representations of individual trees, both in 3D (e.g., Zhang et al., 2015) and 2D (e.g., Cox et al., 2019; Scholz et al., 2018).

Moreover, accuracy is influenced by the choice of spatial analysis in modelling the factor's spatial relationship. Frequently, the spatial relationship is approximated and generalized by a simpler spatial operation. A typical example is modelling the access to tree canopy (a spatial contextual factor) as a proportion of tree canopy in a census tract (Baró et al., 2019) or within a radius (Ng et al., 2021) instead of using more complex accessibility measures. However, there are also examples of complex spatial analyses that more accurately reflect the spatial relationship in the factors, such as viewshed analysis in modelling tree visibility to people (Cox et al., 2019; Łaszkiewicz & Sikorska, 2020) and 3D modelling of tree shading (Zhang et al., 2015; Zhao et al., 2017).

Low spatial data resolution and simple spatial analyses do not always represent an accuracy issue. For example, factors varying on large spatial scales (e.g., climate) can undoubtedly be accurately modelled even with low-resolution data. However, in some instances, low resolution and simplifications of the spatial relationship have been shown to fail in accurately capturing the meaning of the factor. For example, aerial-perspective approaches for modelling the exposure to tree canopy (e.g., tree canopy cover in a census tract, within a radius) do not accurately reflect the actual amount of tree canopy visible from the perspective of people at ground level (Helbich et al., 2019; Larkin & Hystad, 2019; R. Wang et al., 2019). In addition, lower accuracy may cause problems in transferring the existing methods to different application purposes that require higher accuracy.

Input data availability

The methods for modelling spatial contextual factors are dependent on input spatial data. Input data availability then describes the ease of obtaining all necessary input spatial data for the methods.

In modelling spatial contextual factors, most studies build on raster or vector tree cover datasets with regional or municipal coverage, which could be easily available but might prevent the transfer of the methods beyond the original study areas. Mostly, tree cover data are derived from LiDAR (e.g., Aleksandrowicz et al., 2020; Pecero-Casimiro et al., 2019; Rafiee et al., 2016) or aerial optical imagery (e.g., Baró et al., 2019; Kim et al., 2018; Zhou and Kim, 2013) or their combination (e.g., Knobel et al., 2021; Kweon et al., 2017; Reid et al., 2017). Some studies also build on municipal tree inventories (e.g., Escobedo et al., 2018; Paddle and Gilliland, 2018; Scholz et al., 2018).

On the other hand, building on datasets with global coverage ensures that the methods can easier be applied in various study areas. Tree cover maps from high-resolution satellite imagery with global coverage (e.g., Quickbird, SPOT-6) have been used, for instance, in the studies of Shaker et al. (2020), Von Thaden et al. (2021) and Marshall et al. (2018).

Efficiency

Efficiency characterizes the computational resources necessary to apply the method. While computational efficiency does not have significant effects in analyzing small tree samples or small study areas, developing modelling methods with efficiency in mind is important for detailed analyses and processing large spatial extents such as entire cities. Long processing times or special hardware demands such as high-performance computing systems might decrease the practical applicability of the methods.

The efficiency of the developed methods is mostly influenced by the complexity of spatial analysis, the resolution of input spatial data and the technical aspects of the method's implementation in a GIS software. For example, while a simple buffer analysis is relatively fast, a viewshed analysis can be significantly slower. Similarly, analyzing high-resolution datasets requires larger computational resources than analyzing lower resolutions. Finally, implementation details such as parallel processing can substantially increase computational efficiency.

Most studies modelling spatial contextual factors do not report on the computational efficiency, likely because the methods are not intended for repeated processing or because computational efficiency was not an issue due to a smaller number of processed features (trees or structures). The number of processed features in most studies is indeed relatively low (in the order of thousands or less) (e.g., Cavailhès et al., 2009; Cho et al., 2008; Gangwisch et al., 2021), yet even studies that processed hundreds of thousands of features with complex spatial analyses often do not report any efficiency metrics (Cox et al., 2019). Few studies provide enough information to assess the methods' efficiency. For instance, in a study of visual exposure to urban greenery (including trees), Labib et al. (2021) report analyzing 86 807 875 features (observation locations) with viewshed analysis in 11.5 days on a high-performance computing system.

Availability

Availability reflects the requirements for software and technical skills to access and operate the methods. Availability can be ensured, for example, by implementing the method as a GIS tool or making available the source code of the analysis. In turn, availability ensures that the analyses can be repeated beyond the study scope.

However, most existing methods for modelling spatial contextual factors are only used once for the specific purpose of the analysis in the study and are not automatized and made available for repeated use. Exceptions in this regard are established methods such as FRAGSTATS (McGarigal et al., 2012), used, for instance, to measure the contribution of trees to habitat suitability (Von Thaden et al., 2021) or canopy cohesion and its effect on walkability (Shaker et al., 2020). Also, the method of Labib et al. (2021) mentioned above has been published together with a Python script.

Flexibility

Tightly connected to the availability criterion are the demands for the methods' flexibility, which refer to the ease of extending and modifying the method and its parameters. Similarly to the availability criterion, flexibility ensures that the method can be transferred beyond the original scope and adjusted to fit various application purposes. Flexibility can thus be ensured by providing the methods as scripts or GIS tools with user-specified settings. The flexibility of the few above-mentioned methods that have been made available is relatively good. For instance, the method of Labib et al. (2021) has recently been implemented as an R package with a range of user-specified settings (Brinkmann & Labib, 2021).

3.2.5 Knowledge gaps in current use of GIS for modelling spatial context of urban trees

The previous sections point out that measuring spatial contextual factors of urban trees is essential to enable accounting for them in various application purposes (Section 3.1). Numerous methods have been developed to measure specific factors, including a substantial number of GIS methods based on spatial analysis (Sections 3.2.1 and 3.2.2), which in many cases are more suitable than manual assessment (Section 3.2.3).

However, a closer look into the current use of GIS methods in Sections 3.2.1 and 3.2.2 shows that GIS methods have been developed for relatively few spatial contextual factors from the overview of 114 factors compiled in Paper I. This might be largely driven by the limitations of spatial modelling, as discussed in Section 3.2.3. Still, GIS might be suitable for modelling some of these factors.

Moreover, a closer look into the existing GIS methods in Section 3.2.4 shows that most existing methods are developed for specific study areas and purposes. Consequently, the transferability of the methods beyond this specific study scope might be limited. This is caused by multiple factors. First, the availability and flexibility of most of the existing methods is limited. This prevents the application of the methods beyond the original study areas and adjusting them for other application purposes. Second, the accuracy of many of the existing methods is limited by building on spatial analyses that simplify the spatial relationship in the factor. Although such simplifications might provide sufficient accuracy for the specific study scopes, they might prevent the application of the methods for purposes requiring higher accuracy. Third, most existing methods do not report on computational efficiency or require high-performance computing systems, often unavailable to practitioners and requiring specific technical skills. This prevents the estimation of the usability of the methods or applying them to large study areas. Finally, most existing methods build on national or regional datasets, which might limit their transferability to new study areas but will become less of an issue as these datasets are increasingly available for urban areas worldwide.

Consequently, the various application purposes that rely on measuring spatial contextual factors of urban trees (such as those presented in Section 3.1) often do not benefit from the existing methods. The lack of suitable methods for modelling the factors might then, for example, lead to the factors being assessed manually instead, which might lead to accuracy, objectivity and efficiency issues, as discussed in Section 3.2.3. Moreover, the lack of suitable modelling methods might lead to disregarding these factors in the various application purposes and, in turn, lower accuracy in accounting for the ecosystem services of urban trees (e.g., Szkop, 2020).

Therefore, there is a need for developing new GIS methods for modelling spatial contextual factors of urban trees for application purposes that cannot benefit from the existing methods. Preferably, such novel methods should then be developed with accuracy, input data availability, efficiency, availability and flexibility in mind to ensure that they can be transferred to a wide range of application purposes.

GIS methods for modelling spatial context of urban trees

4

In this chapter, I address the main objective of the thesis, i.e. develop GIS methods for modelling the spatial context of urban trees for the purpose of informing research and practical applications that aim at supporting the ecosystem services of urban trees. I open the chapter by formulating a research question to guide the selection and modelling of the spatial contextual factors. Next, I present the modelled factors and the developed methods. The chapter concludes with several practical examples of the potential use of the developed methods in specific practical tasks.

4.1 Research question

The background knowledge presented in Chapter 2 and Chapter 3 indicates that there are spatial contextual factors mediating ecosystem services of urban trees that are suitable for developing GIS methods in the thesis because

(i) they are important mediators of ecosystem services (they are multifunctional in terms of mediated ecosystem services), and thus there is a strong relevance in measuring and modelling these factors (Section 2.4),
(ii) modelling these factors is likely to require a complex and innovative spatial modelling approach because they explicitly describe the configuration between trees and structures/processes (Section 2.4),
(iii) modelling these factors with GIS is not restricted by unclear spatial relationships in the factors, data availability or the limitations of spatial modelling in GIS to accurately reflect subjective qualities (Section 3.2.3),
(iv) methods for modelling these spatial contextual factors are lacking because such methods have not been developed, or the developed methods are not transferable beyond the study-specific scope (Section 3.2.5).

Based on this premise, the following research question (RQ2) was formulated:

RQ2

How can spatial contextual factors of urban trees be modelled using GIS methods, given the following requirements?

(i) ***The factors are multifunctional in terms of mediated ecosystem services and thus more important to measure and model,***
(ii) ***Modelling the factors requires a complex and innovative spatial modelling approach,***
(iii) ***Modelling the factors with GIS is possible,***
(iv) ***Methods for modelling the factors are lacking.***

4.2 Selected spatial contextual factors of urban trees

In response to the research question and following the requirements, methods for modelling four spatial contextual factors of urban trees were developed. The factors were selected by successively filtering the overview of 114 spatial contextual factors developed in Paper I by the four requirements specified in the research question:

(i) Excluding all factors that are not multifunctional and are thus less important to measure and model. Excluded factors were, for instance, "soil perviousness" and "proximity of tree to noise source",

(ii) Excluding all factors with an implicit spatial relationship, which are not likely to require a complex and innovative spatial modelling approach. Excluded factors were, for example, "species diversity of tree composition", "climate" and "socio-economic status",

(iii) Excluding all factors where spatial modelling in GIS is restricted by unclear spatial relationships in the factors, data availability or the limitations of spatial modelling to accurately reflect subjective qualities. An excluded factor was "position in street canyon" because the spatial relationship "position" is not specific enough for spatial modelling,

(iv) Excluding the factor "connectivity of trees to other trees/tree aggregations" because this factor can be modelled with the established program FRAGSTAT (McGarigal et al., 2012).

Sixteen spatial contextual factors passed through the four criteria (Table 4.1).

4.2.1 Light condition of trees' crowns, distance from trees to buildings, direction from trees to buildings

The first three selected factors are "light condition of trees' crowns", "distance from trees to buildings" and "direction from trees to buildings". These three factors were selected because they are important inputs into the assessment of regulating ecosystem services of urban trees with a widely used software i-Tree Eco (presented in Section 3.1.1 (USDA Forest Service Research, 2021b). In i-Tree Eco, light condition indicates crown competition and is measured alongside other mediators of tree growth rate (e.g., growing season length, tree species) to estimate annual carbon sequestration (Nowak, 2020). Distance and direction to buildings are assessed together with, for example, tree species and climate region to estimate the trees' effect on building energy consumption and pollutant emissions from buildings (Nowak, 2020).

The three factors are *multifunctional* in terms of mediated ecosystem services. For example, the light condition of a tree's crown has been shown to mediate also outdoor temperature regulation (Bartesaghi Koc et al., 2018) and the ecosystem disservice of ozone and particular matter formation (Roeland et al., 2019; Salmond et al., 2016). Distance to nearest buildings also mediates several ecosystem disservices,

Table 4.1: Spatial contextual factors of urban trees considered for developing GIS methods in the thesis (*dist: distance, prox: proximity*)

Spatial contextual factor	(i) Multi-functional (no.services)	(ii) Explicit sp. relationship	(iii) Spatial modelling possible	(iv) Methods lacking	Developed in thesis
factors mediating single ecosystem service (43)	No	-	-	-	No
factors with implicit spatial relationship (53)	-	No	-	-	No
Position in street canyon	Yes (2)	Yes (position)	No	-	No
Connectivity to other trees/ tree aggregations	Yes (5)	Yes (connectivity)	Yes	No	No
Light condition of trees' crowns	Yes (5)	Yes (shadowing)	Yes	Yes	**Yes**
Dist. to buildings	Yes (4)	Yes (dist/prox)	Yes	Yes	**Yes**
Direction to buildings	Yes (2)	Yes (direction)	Yes	Yes	**Yes**
Visibility to people	Yes (2)	Yes (visibility)	Yes	Yes	**Yes**
Visibility from buildings	Yes (2)	Yes (visibility)	Yes	Yes	No
Proximity or visibility from hospitals	Yes (2)	Yes (dist/prox, visibility)	Yes	Yes	No
Proximity to other trees/tree aggregations	Yes (8)	Yes (dist/prox)	Yes	Yes	No
Proximity to green areas	Yes (2)	Yes (dist/prox)	Yes	Yes	No
Proximity to coast	Yes (2)	Yes (dist/prox)	Yes	Yes	No
Proximity to air pollution source	Yes (2)	Yes (dist/prox)	Yes	Yes	No
Proximity to infrastructure	Yes (8)	Yes (dist/prox)	Yes	Yes	No
Proximity to parking locations	Yes (3)	Yes (dist/prox)	Yes	Yes	No
Proximity to pavements	Yes (3)	Yes (dist/prox)	Yes	Yes	No
Proximity or accessibility to housing	Yes (5)	Yes (dist/prox, accessibility)	Yes	Yes	No
Accessibility to people	Yes (7)	Yes (accessibility)	Yes	Yes	No
Proximity to people	Yes (6)	Yes (dist/prox)	Yes	Yes	No

including accidents, damage to infrastructure and view blockage (Davies et al., 2017; Gómez-Baggethun & Barton, 2013). Therefore, there is a strong relevance in developing methods for modelling these factors.

At the same time, we have shown in the review in Paper IV that GIS methods for modelling these three factors are currently sparsely used, and the factors are commonly assessed manually, as suggested by the official i-Tree Eco field guide (USDA Forest Service Research, 2021a). In addition, the factors explicitly describe the spatial relationship (distance, direction, light condition) and are thus likely to require a more complex and innovative spatial modelling approach (this applies especially for "light condition of trees' crowns").

4.2.2 Visibility of trees to people

Out of the remaining factors, I decided to develop methods for modelling "visibility of trees to people". The visibility of urban trees is a key mechanism to receiving many recreation, health and aesthetic benefits. Amongst others, visibility of tree canopy and urban greenery in general has been shown to positively influence human psychological, cognitive and physiological health (Kaplan, 2001; Keniger et al., 2013; Lottrup et al., 2015; Velarde et al., 2007). Further, visible trees deliver aesthetic benefits (Goodness et al., 2016; Schroeder & Cannon, 1983) and can lead to numerous social benefits, including reduced crime rates (Troy et al., 2012; Wolfe & Mennis, 2012) and increased perceived safety (Mouratidis, 2019). Importantly though, the visual effects of trees can also be negative, for instance, due to view blockage (Lyytimäki et al., 2008). Tree visibility as an important determinant of ecosystem services is also recognized in various methods for valuing amenity trees (Doick et al., 2018; Helliwell, 2008b; Randrup et al., 2019).

Despite the relevance of the factor "visibility of trees to people", we have shown in the literature reviews in Papers II and III that GIS is sparsely used to model the factor. Commonly, the amount of tree canopy visible to people is measured from street view images (Helbich et al., 2019; Larkin & Hystad, 2019; W. Wang et al., 2019), which has limitations in coverage and image availability. From the tree perspective, individual tree visibility is usually estimated manually in field observations (Doick et al., 2018; Randrup et al., 2019). Few studies have begun experimenting with innovative spatial modelling approaches to model the spatial relationship "visibility" in the factor, namely viewshed analysis (Cox et al., 2019; Labib et al., 2021). However, the existing methods are often difficult to generalize beyond their specific application purpose, are inefficient in processing large spatial extents and have limited use due to demands for technical knowledge.

4.3 The developed methods

Five GIS methods (method A – method E) were developed to model the selected spatial contextual factors of urban trees:

A Visual exposure to tree canopy (Paper II),
B Individual tree visibility (Paper III),
C Crown light exposure (Paper IV),
D Distance to nearest residential buildings (Paper IV) and
E Direction to nearest residential buildings (Paper IV).

Each method is thoroughly described in the respective paper.

The objective of method A (Figure 4.1a, Figure 4.2) is to obtain a continuous raster map of visual exposure to tree canopy, where each pixel stores the amount of tree canopy visible from that pixel. The method is based on parametrized cumulative viewshed analysis and takes a raster map of tree canopy and a digital surface model on the input.

The objective of method B (Figure 4.1b, Figure 4.3) is to model, for each tree, the surface area from which that tree is visible. The method builds on method A in combination with overlay analysis. The input data to the method are a vector map of individual tree crowns, a digital surface model and a raster map of exposure wights.

The objective method C (Figure 4.1c) is to model for each tree the percentage of crown perimeter shaded by surrounding trees and buildings. The method is based on intersection analysis and constructing tangents between features. Input data to the method are a vector map of individual trees and tree crowns, a digital surface model and a vector map of building footprints.

Methods D and E (Figure 4.1d, e) aim at measuring the distance (method D) and direction (method E) from each tree to the three nearest residential buildings within an 18m radius. The methods build on calculating distance and direction between features and take a vector map of individual trees and a vector map of building footprints on the input.

The results of modelling spatial contextual factors with the developed methods in Oslo, Norway, are also illustrated in an interactive map on http://urban.nina.no/maps/407/view.

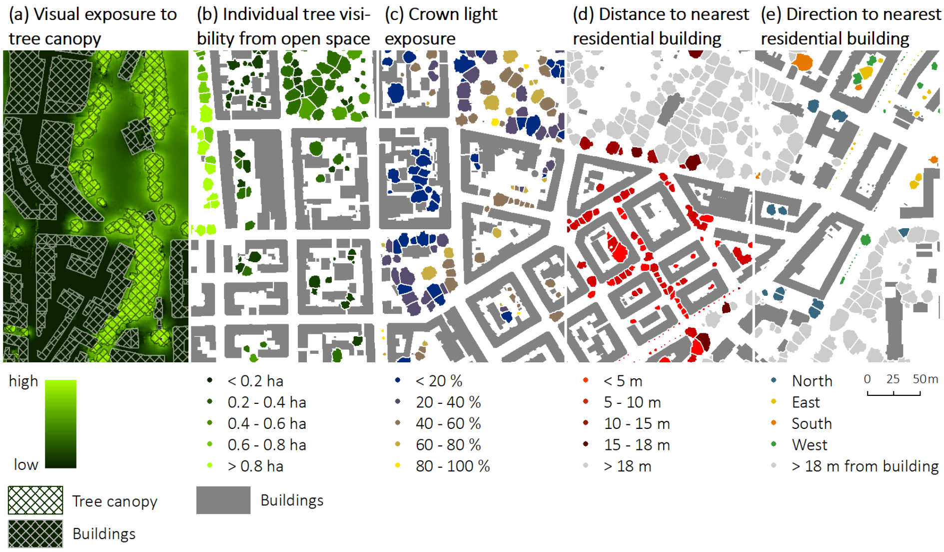

Figure 4.1: Examples of modelling spatial contextual factors of urban trees with the developed methods in a sample area in Oslo. (a) Visual exposure to tree canopy modelled with 100m exposure range, 25% sampling density and distance decay viewshed parametrization function; (b) Individual tree visibility from open space modelled with 100m exposure range, 100% sampling density and no viewshed parametrization; (c) Crown light exposure; (d) Distance to nearest residential building; (e) Direction to nearest residential building.

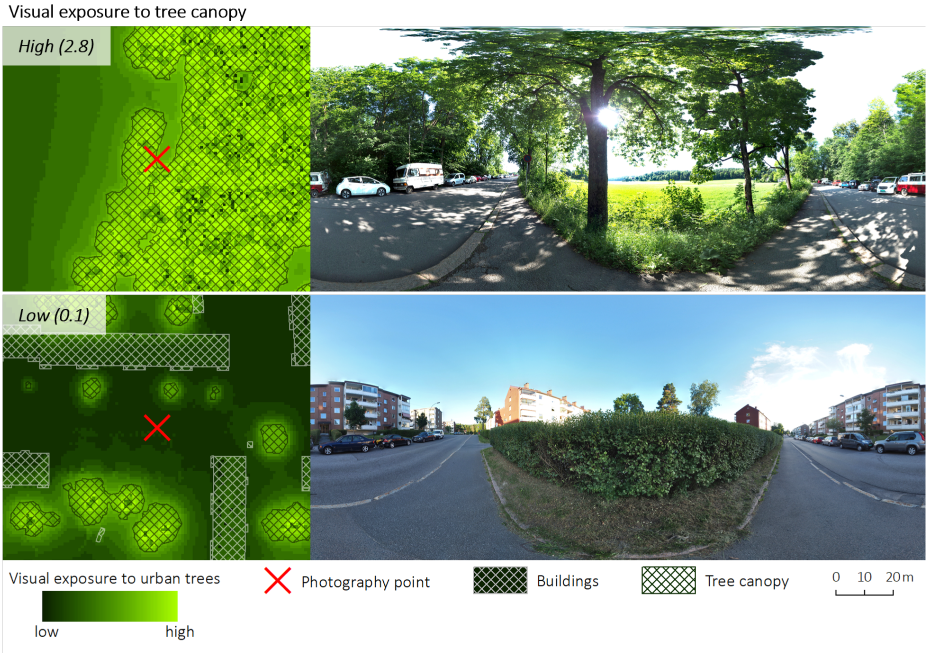

Figure 4.2: Comparison of modelling visual exposure to tree canopy with method A to photographs

Figure 4.3: Comparison of modelling individual tree visibility with method B to photographs

4.3.1 The developed methods in the ecosystem service framework

The five methods relate to the four selected spatial contextual factors: *visibility of trees to people*, *light condition of trees' crowns* and *distance* and *direction from trees to buildings*, which altogether mediate 12 ecosystem services (Figure 4.4).

Both method A for modelling visual exposure to tree canopy and method B for modelling individual tree visibility address the same spatial contextual factor: tree visibility. However, the two methods take two different perspectives. Method A models visual exposure to tree canopy as seen from all possible standpoints on the ground (i.e., structural perspective as discussed in Chapter 3). On the other hand, method B models the area from which each individual tree can be seen (i.e., tree perspective as discussed in Chapter 3). Methods C – E all model the spatial contextual factors from the perspective of a tree to enable per-tree quantification of regulating ecosystem services with the i-Tree Eco software.

In addition to the five developed methods, several other spatial contextual factors of urban trees were modelled in Paper IV, but no innovative GIS methods were developed for them. These are all factors with an implicit spatial relationship, which can be modelled by a simple intersection. The factors are land use, precipitation and air pollution levels at tree location and local benefit prices (social cost of carbon, electricity prices, stormwater and sewage treatment costs, air pollution costs).

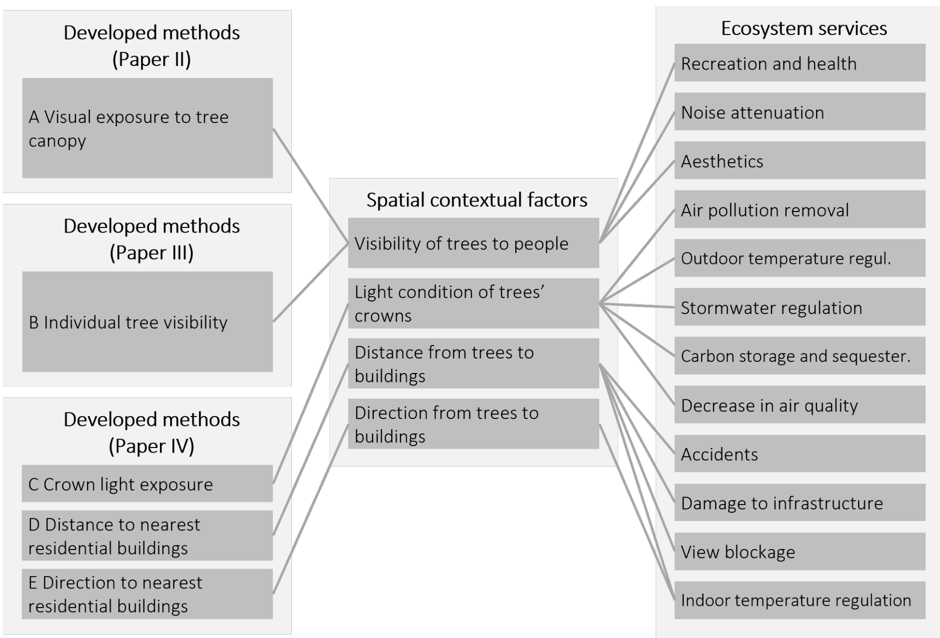

Figure 4.4: Relationship between the developed methods, selected spatial contextual factors and mediated ecosystem services. The relationship between spatial contextual factors and ecosystem services is based on findings of Paper I and literature reviews in Papers II – IV.

4.3.2 Developing the methods as applications for research and practice

The five methods were developed for a range of specified application purposes (Table 4.2), which form the background of the respective papers. The objective of method A was to develop a general, flexible and efficient tool for a broad range of purposes in research and practice, and a specific application purpose was not defined. Similarly, method B was developed as a general support tool for tree valuation methods and tree management and planning, and a specific application purpose was not defined. Finally, the objective of methods C, D and E was to develop alternative methods for measuring spatial contextual factors for i-Tree Eco analysis of existing municipal tree inventory in Oslo, Norway. The individual application purposes are described in detail in the respective papers.

The respective application purposes of methods A – E drove the choices made in designing the algorithms of the methods (e.g., selection of spatial modelling approach, representation of the physical environment) and choices made in implementing the methods in GIS (e.g., software selection, implementation of user-defined settings, user interface). In this section, I will present the developed methods through the choices made in the development and the consequences of the choices on the methods' applicability. In particular, I will present and discuss the choices made in response to the five performance criteria presented in Section 3.2.4 (Table 4.3).

Table 4.2: Application purposes of the five methods

Developed method	Application purposes
A Visual exposure to tree canopy	Flexible and efficient method for a broad range of application purposes in research and practice; specific application purpose not defined.
B Individual tree visibility	Support for general tree valuation methods and tree management and planning; specific application purpose not defined.
C Crown light exposure **D Distance to nearest residential buildings** **E Direction to nearest residential buildings**	Alternative method for computing selected spatial contextual factors to enable i-Tree Eco analysis of existing municipal tree inventory in Oslo, Norway.

Choices in algorithm design

The algorithms of the five developed methods are illustrated as workflow diagrams in Figure 4.6 – Figure 4.9 and thoroughly presented in the respective papers. In this section, I will explain the choices made in designing the algorithms to ensure that the methods accurately reflect the meaning of the modelled spatial contextual factors, build on available input spatial data, are computationally efficient, available and flexible. I will do so by describing the choices made in the representation of the physical environment, representation of urban trees, selection of other input spatial data, selection of spatial modelling approaches and validation of the methods.

Table 4.3: Demands on performance criteria considered in developing the methods

	Methods A and B	Methods C, D and E
Accuracy	The meaning of the spatial contextual factor was not defined by any specific application purpose. Based on the literature, the factor could be understood as the amount of visible greenery from any place where people can potentially move (method A) and as visibility of trees from various places (method B).	The meaning of the spatial contextual factors was defined by the i-Tree Eco field guide.
Input data availability	The input spatial data should be easy to obtain from national or municipal spatial datasets and not require difficult pre-processing.	The methods should operate on currently available spatial data in Oslo.
Efficiency	The methods should be computationally efficient so that large spatial extents and high-resolution datasets can be analyzed on commodity hardware.	The methods should be sufficiently efficient to analyze the municipal tree inventory on a personal computer.
Availability	The methods should be implemented as open-source GIS tools to foster availability and usability for end-users without technical skills.	No specific demands on flexibility.
Flexibility	The methods should be flexible to enable adaptation to various application purposes.	No specific demands on flexibility.

Representation of physical environment: An initial choice in the algorithm design of all five methods was whether to develop the methods in 2D, 2.5D or 3D representation of the physical environment (Figure 4.5). In methods A, B and C, we chose a 2.5D representation, i.e. all surface locations only have one elevation information. This choice was driven by the need to accurately model the impacts of a three-dimensional built environment on visibility and light conditions, while at the same time allowing to run the methods in widely used GIS software, which often do not support 3D data analysis, and utilize readily available input spatial datasets, which usually are not in 3D.

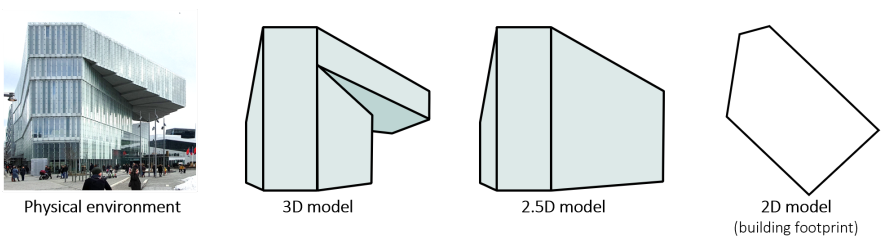

Figure 4.5: The difference between 3D, 2.5D and 2D representation of physical environment. Illustrated on the example of Oslo's Public Library main building.

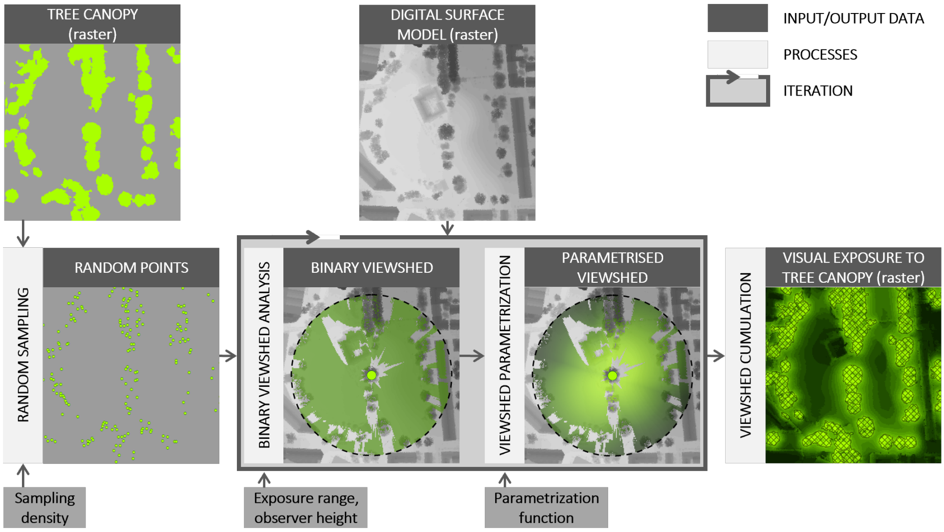

Figure 4.6: Algorithm of method A for modelling visual exposure to tree canopy (adapted from Paper II)

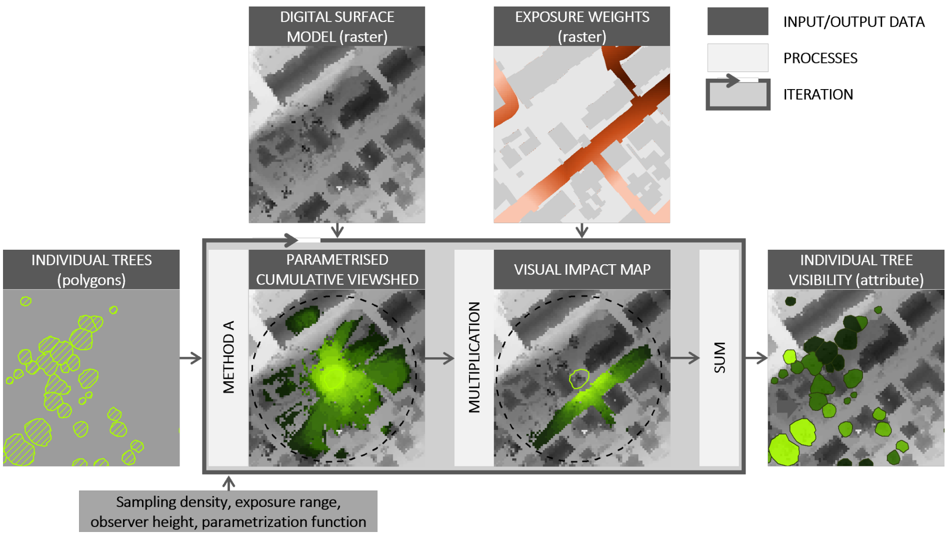

Figure 4.7: Algorithm of method B for modelling individual tree visibility (adapted from Paper III). Note that the method builds on method A.

Methods A, B and C thus build on high-resolution digital surface models (DSM). The availability of high-resolution DSM has been improving due to data from LiDAR missions and high-resolution satellite sensors (Gong & Fritsch, 2019; Gui & Qin, 2021; Ye et al., 2021). To illustrate and test the methods in Oslo, we used a DSM at 1m resolution provided by the Norwegian Mapping Authority (Norwegian mapping authority, 2017b). This initial choice of working in 2.5D had direct consequences on the used spatial modelling principles in methods A and B. The methods model tree visibility to people on the surfaces in the physical environment (i.e., not inside buildings or under trees) because such approach is compliable with the 2.5D representation in a raster GIS. In methods D and E, the physical environment is represented in 2D because including the third dimension does not increase the accuracy of modelled distance and direction.

Representation of urban trees: Different representations of the analyzed trees were chosen, depending on the perspective taken to model the spatial contextual factor. Methods B – E model the factors from a tree perspective, and thus each tree needs to be represented as a separate object. Therefore, individual urban trees in the methods are represented by vector data. Polygon representation was chosen when crown geometry was needed to accurately model the factor (methods B, C). Point representation was chosen when tree stem position was analyzed (methods C – E). For illustrating and testing the methods in Oslo, we used a LiDAR-based tree crown detection for Oslo (Hanssen et al., 2021) (methods B, C) and a spatially referenced tree inventory provided by Oslo's Urban Environment Agency (methods C – E).

In method A, the spatial contextual factor is modelled from the perspective of observers on the ground, i.e. from a structural perspective. For modelling from a structural perspective, it is not necessary to distinguish between individual trees. Therefore, in method A, a sufficient input is a high-resolution tree canopy raster. Importantly, the empirical assessment of method A in Paper II showed that input data quality (spatial resolution and accuracy) is crucial to accurately model visual exposure to urban trees. Therefore, the tree canopy map should be in high spatial resolution. To illustrate and validate method A in Oslo, we rasterized the LiDAR-based tree crown detection for Oslo (Hanssen et al., 2021) in 1m resolution. In addition, we manually corrected the dataset using an orthophoto to avoid inaccuracies that could affect the validation results.

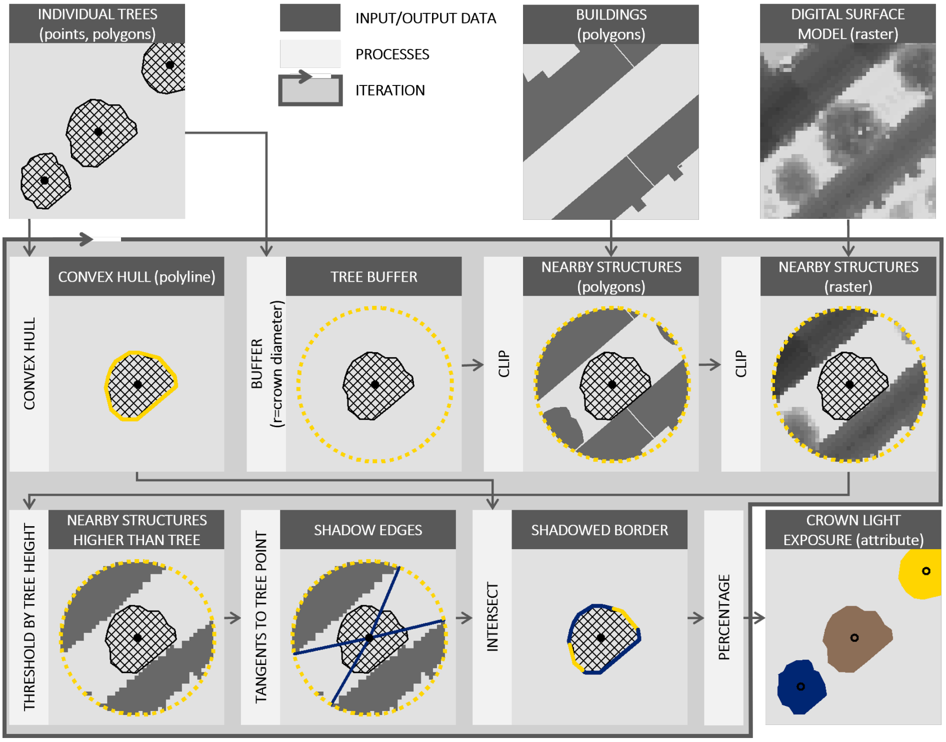

Figure 4.8: Algorithm of method C for modelling crown light exposure (adapted from Paper IV)

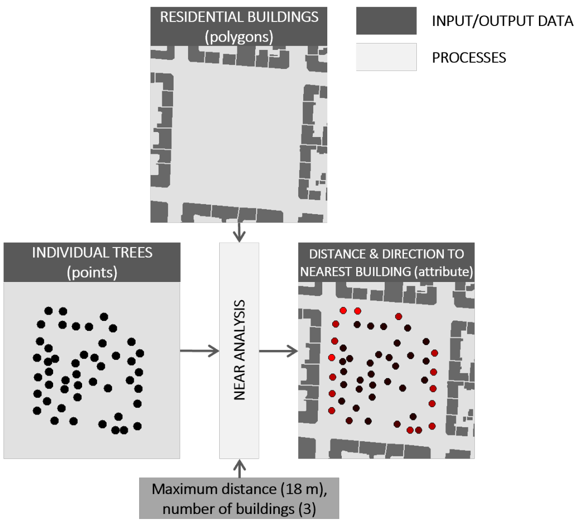

Figure 4.9: Algorithm of methods D and E for modelling distance and direction to nearest residential buildings

Other input spatial data: Other input data to the methods include a raster map of so-called "exposure weights" in method B and a vector map of building footprints in method C. The raster map of exposure weights in method B is a user-defined map of continuous or discreet values representing the relative or absolute importance of each surface pixel on the tree visibility. Including the exposure weights map enables modelling individual tree visibility from specific areas (e.g., private/public areas) or weighting tree visibility by specific phenomena (e.g., pedestrian frequency), which is often considered in tree valuation methods. Thus, this option also increases the flexibility of the method. In illustrating method B in Oslo, the exposure weights map was represented by a binary map of public open spaces, a binary map of private open spaces and a map of pedestrian and bike trip counts derived from Strava Metro (Strava Metro, 2021).

A vector map of building footprints is used in method C to model the shading of tree crowns by surrounding buildings. Vector representation of building footprints is common in, for example, municipal cadastral data. To analyze crown light exposure of trees in Oslo, we used a vector FKB-Buildings map in reference scale 1:5 000 (Norwegian mapping authority, 2017a). The individual input spatial datasets for the five developed methods are summarized in Table 4.4.

Table 4.4: Overview of input spatial datasets used in the developed methods

Input spatial dataset		Used in method
Urban trees	**Tree canopy (raster)**	A Visual exposure to tree canopy
	Individual trees (points)	C Crown light exposure
		D Distance to nearest residential buildings
		E Direction to nearest residential buildings
	Individual trees (polygons)	B Individual tree visibility
		C Crown light exposure
DSM (raster)		A Visual exposure to tree canopy
		B Individual tree visibility
		C Crown light exposure
Buildings (vector)		C Crown light exposure
		D Distance to nearest residential buildings
		E Direction to nearest residential buildings
Exposure weights (raster)		B Individual tree visibility

Spatial modelling approach: A major modelling challenge in methods A and B was to choose a spatial modelling approach that enables accurate modelling of the human visual perspective. Both methods are thus based on viewshed analysis, a spatial analysis method that delineates the areas of a terrain model visible from a given observer pixel (Petrasova et al., 2015). However, a significant drawback of traditional viewshed analysis in modelling human visual perspective is that the output binary raster (i.e., visible and non-visible pixels) does not reflect the variable visual significance of the observed objects (pixels) from the point of view of the observer (Chamberlain and Meitner, 2013; Ervin and Steinitz, 2003;

Nutsford et al., 2015; Ogburn, 2006). The variable visual significance may be caused, for instance, by the characteristics of the observed objects (e.g., the contrast between the object and its surroundings), observer characteristics (e.g., how well we see), characteristics of the environment between the observed object and the observer (e.g., light and atmospheric conditions) and their spatial configuration (e.g., distance, slope and aspect) (Domingo-Santos & De-Villarán, 2017; Ogburn, 2006).

To accurately reflect human visual perspective in methods A and B, we, therefore, went beyond the standard binary viewshed analysis and implemented *viewshed parametrization functions* that weight the binary viewshed by the relative distance, slope and aspect between the observer and the observed pixel. In particular, we implemented visual magnitude (Chamberlain & Meitner, 2013), solid angle (Domingo-Santos et al., 2011) and distance decay viewshed parametrization functions (Chamberlain & Meitner, 2013; Grêt-Regamey et al., 2007). The individual viewshed parametrization functions are described in detail in Paper II. In method B, the viewshed is further weighted (multiplied) by the input exposure weights map.

The choice of viewshed analysis to model human visual perspective in methods A and B had significant consequences on the computational efficiency of the methods. In designing the algorithms, repeated viewshed analysis was identified as the most computationally demanding operation. Therefore, we applied two approaches to reduce the number of viewshed operations. First, in method A, we used a cumulative viewshed approach with viewsheds constructed from tree pixels, rather than analyzing the contents of viewsheds constructed at all possible observation points. This approach decreases the total number of viewshed operations if the total number of possible observed pixels (i.e., tree pixels) is smaller than the number of observation points. By building on method A, method B inherits this efficient algorithm. Second, we explored the possibility of reducing the total number of viewshed operations by sampling the tree canopies with points, i.e. not computing the viewsheds from all tree canopy pixels. We observed that for example 25% sampling density reduces the total computation time by 50% with a negligible reduction in the accuracy.

In methods C, D and E, the modelling choices were driven by the objective to accurately translate the measurement instructions from the i-Tree Eco field guide (USDA Forest Service Research, 2021a) into a set of spatial modelling steps. Method C slightly diverges from the original measurement instructions but keeps the measurement principle. In particular, crown light exposure is modelled as the percentage of tree crown perimeter covered by the projection of surrounding trees and buildings, while in the field, the number of tree sides blocked by surrounding trees and buildings is counted. Methods D and E are based on simple analyses of distance and direction, which accurately reflect the measurement instructions of the i-Tree Eco field guide.

Validation: Method A was empirically validated against ground-truth data to assess how well it captures the amount of visible tree canopy as seen from a human visual perspective. Importantly, in method A, we modelled and validated the amount of visible tree canopy *potentially* seen from a human perspective. Assessing how this measure corresponds to the subjective, self-reported amount of visible tree canopy is a possible direction for further research. To validate the method, we distributed 94 validation points across the extent of the Oslo built-up zone and then took full-view panoramic photographs at these points. We then observed the Spearman correlation coefficient between the visual exposure to tree canopy modelled at these points and the proportion of tree canopy in these photographs, which is assumed to be a reliable measure of the amount of greenery observed from a human perspective (Yang et al., 2009).

The validation showed that the method is highly accurate in modelling the amount of tree canopy visible from a human perspective ($\rho = 0.96$). In addition, the validation confirmed that viewshed parametrization is crucial to accurately model human visual perspective. Without viewshed parametrization, validation accuracy dropped from $\rho = 0.94 - 0.96$ to $\rho = 0.50 - 0.79$, depending on other parameters such as exposure range. However, more complex viewshed parametrization functions (solid angle, visual magnitude) did not substantially increase the validation accuracy compared to parametrizing with distance decay. The validation of method A also showed that input data quality (spatial resolution and accuracy) affects validation accuracy significantly more than viewshed parametrization and exposure range.

In methods B – E, validation against ground-truth data was not conducted. The accuracy of method B was ensured by building on the validated algorithm from method A. Accuracy of methods D and E was ensured by strictly following the measurement instructions from i-Tree Eco field guide. In addition, the accuracy of distances and directions computed with GIS might be higher than the accuracy of manual assessment. In the case of method C, we slightly diverged from the measurement instructions. Therefore we discussed the methodology with i-Tree Eco developers, who confirmed its suitability for i-Tree Eco analysis.

Choices in method implementation

In this section, I explain the choices made in implementing the methods in GIS to ensure that the methods are computationally efficient, available and flexible. The criteria for availability and flexibility were not considered in methods C – E because these methods were developed for the specific purpose of computing i-Tree Eco attributes for municipal trees in Oslo. A detailed description of the method implementation can be found in the respective papers.

Methods A and B were implemented as tools (“AddOns”) called *r.viewshed.exposure* and *v.viewshed.impact* in GRASS GIS (Neteler et al., 2012) (Figure 4.10). The choice of GRASS GIS was driven by several reasons. First, GRASS GIS offers the underlying functionality necessary to develop the methods, namely an efficient tool for viewshed analysis (Toma et al., 2020), comprehensive Python API and integration with NumPy. Second, GRASS GIS enables easy implementation of a graphical user interface to the tools, making the developed methods accessible to users with limited GIS or programming skills. Third, implementing the tools as AddOns to an open-source GIS software ensures that the tools can be easily accessed, integrated in the users' processing workflows and adjusted if necessary.

In each method A and B, we implemented a range of user-specified parameters that control the modelling accuracy and processing time of the methods. At the same time, the user-specified settings increase the flexibility of the methods by allowing the users to control the methods' behavior and thus define the "meaning" of the modelled spatial contextual factor for specific application purposes. The user-specified parameters correspond to the non-spatial parameters shown in Figure 4.6 and Figure 4.7 and include, for instance, exposure range, viewshed parametrization function and sampling density.

A consequence of the user-specified parameters is that the resulting value ranges of visual exposure to tree canopy and individual tree visibility in methods A and B vary with the parameter specification. This might be a complication for using the methods in applications where we want to know "how much is a lot" and "how much is too little". For instance, when using method B to value trees based on their visibility, a possible solution would be to compute the visibility of all trees across the entire valuation area to obtain a possible value range.

The user-specified parameters also significantly influence the computational efficiency of the methods because they determine the number of viewshed operations (e.g., sampling density), the amount of processed data (e.g., exposure range) and the complexity of the analysis (e.g., viewshed parametrization function). For example, in the validation of method A, the highest validation accuracy was achieved with a relatively long exposure range (200m), 100% sampling density and complex parametrization function (solid angle). However, by decreasing the exposure range to 100m, reducing sampling density to 25% and using a less complex viewshed parametrization function (distance decay), the processing time could be decreased substantially (almost 55 times) while the validation accuracy dropped negligibly (from $\rho = 0.96$ to $\rho = 0.94$).

The right choice of parameter settings in methods A and B is thus important to ensure a good trade-off between accuracy and computational efficiency, for example, when processing large areas in high resolution with limited computational resources. Therefore, we provide default parameter settings in the tools based on the accuracy assessment findings (default values correspond to the combination of settings that gave the best tradeoff between accuracy and processing time in the validation of method A). This further simplifies the use of the methods.

Two additional adjustments were made in implementing methods A and B to improve their computational efficiency: parallelizing the iterative operations and conducting selected operations in memory, thus reducing the time for writing and reading operations. Therefore, both methods can be run on a personal computer or server even when analyzing large areas and large numbers of trees in high resolution. For instance, running the two methods in the entire extent of Oslo built-up zone (1m resolution, extent 152km^2, out of which 49.5km^2 is tree canopy formed by 390 000 individual trees) took 134 hours for method A and 172 hours for method B[4].

Methods C – E were implemented as ArcPy scripts in ArcGIS, which enabled an automatic computation of the three spatial contextual factors for a large number of trees[5]. The methods' efficiency was improved by conducting the individual operations in memory. The i-Tree Eco field guide determines the parameter settings, and therefore these parameters were fixed in the methods.

[4] *r.viewshed.exposure* was run on 25 cores of an HPE ProLiant DL360 Gen10 server with two Intel(R) Xeon(R) Gsold 6134 CPU @ 3.20GHz Central Processing Units, 256GB Random Access Memory and three 960GB Solid State Storage Devices with 6Gbps bandwidth and ext4 file system running Ubuntu 18.04.5 LTS.

v.viewshed.impact was run on 40 cores of an HPE ProLiant DL360 Gen10 server with two Intel(R) Xeon(R) Gold 6146 CPU @ 3.20GHz Central Processing Units, 384GB Random Access Memory and four 960GB Solid State Storage Devices with 6Gbps bandwidth and ext4 file system running Ubuntu 18.04.5 LTS.

[5] The ArcPy scripts of methods C – E are available from https://doi.org/10.5281/zenodo.6138850.

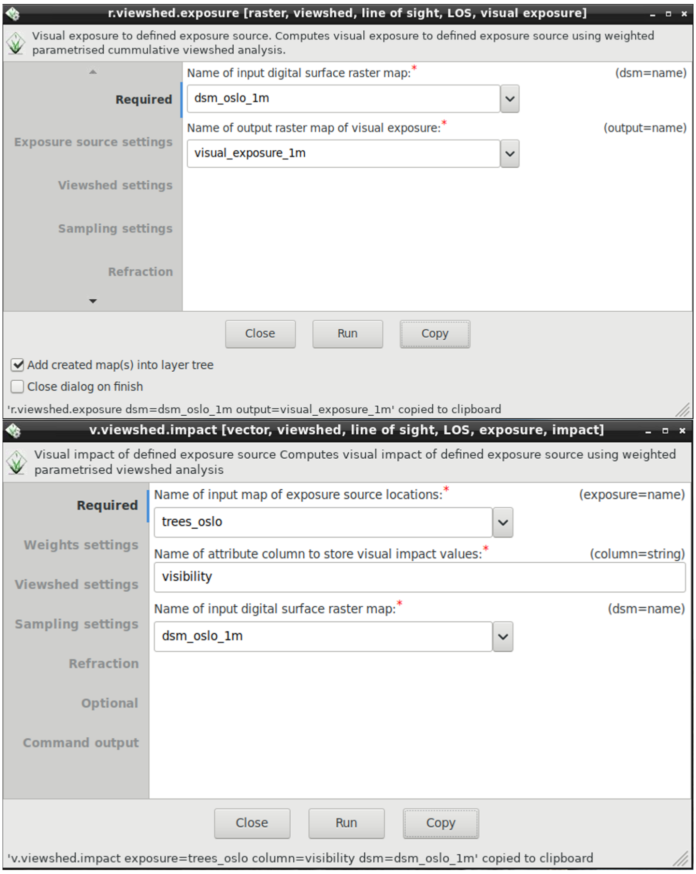

Figure 4.10: Graphical user interface of *r.viewshed.exposure* and *v.viewshed.impact* in GRASS GIS

4.4 Examples of potential use of the developed methods

While the potential application areas of the developed methods are comprehensively discussed in the respective papers (Paper II – Paper IV), in this section, I will provide concrete examples of the potential use of the methods in specific practical tasks. The examples were formulated based on the overview of application purposes provided in Section 3.1, Table 3.2 and Table 3.3.

The analyses in the examples are based on a map of individual tree crowns detected by LiDAR (Hanssen et al., 2021), a DSM in 1m resolution (Norwegian mapping authority, 2017b) and a vector map of building footprints (Norwegian mapping authority, 2017a). The map of individual tree crowns was manually adjusted in each example to avoid inaccuracies at an individual tree level.

4.4.1 Example 1: Modelling changes in visual exposure to tree canopy with method A

The objective of Example 1 was to demonstrate how method A can aid in assessing change in visual exposure to tree canopy due to change in tree canopy or view-obstructing structures. In particular, the example shows how visual exposure to tree canopy has changed after simulating a tree and a building removal in a yard in Oslo.

The change in visual exposure to tree canopy was analyzed in two steps. First, visual exposure to tree canopy was modelled with method A using a 100m exposure range, distance decay viewshed parametrization, 25% sampling density and data of existing situation (a DSM and a map of tree canopy) (Figure 4.11a). Second, the analysis was recomputed with adjusted data – a tree was deleted from the tree canopy map, and the DSM at the tree and building location was adjusted to the altitude of the surrounding terrain to simulate tree and building removal (Figure 4.11b). Finally, the change in visual exposure to tree canopy was modelled as a difference between the two maps (Figure 4.11c). In the resulting change map, negative values represent a net decrease in visible tree canopy (in areas where the removed tree was visible). Positive values represent a net increase in visible tree canopy (in areas where the removed building blocked the tree view).

This example illustrates the potential of method A to aid scenario modelling and impact assessment in observing temporal changes following building and tree removal in both existing and hypothetical situations. For instance, landscape architects could use the method to compare different tree planting or felling scenarios by manipulating the tree canopy map (adding or removing trees) and select those that result in the largest increase or smallest decrease in visual exposure to tree canopy. Similarly, urban planners could use the method to assess the effect of planned construction projects on tree visibility in the surroundings. In addition, conducting the change analysis on a city scale could contribute to more accurate urban ecosystem accounting by providing an account of temporal changes of visual exposure to tree canopy due to changes in tree cover and surrounding urban structures.

To successfully analyze the change in visual exposure to tree canopy with method A, it is necessary to ensure that the input data remain consistent in the compared situations to limit noise and inaccuracies in the change map. For example, the tree canopy maps should be based on the same detection technique so that changes in the canopy map reflect actual changes in the physical tree canopy and not changes due to the detection technique.

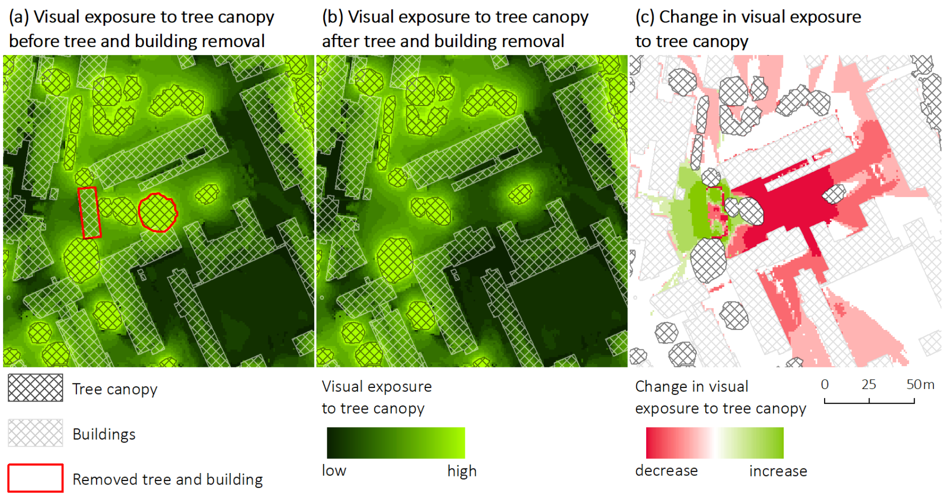

Figure 4.11: Example of using method A to model change in visual exposure to tree canopy due to tree and building removal. (a) Visual exposure to tree canopy before removing a selected tree and building (highlighted in red), modelled with method A; (b) Visual exposure to tree canopy after the selected tree and building have been removed, modelled with method A; (c) Net change in visual exposure to tree canopy modelled as a difference of maps (a) and (b).

4.4.2 Example 2: Evaluating tree planting scenario with methods B, C, D, E

The objective of Example 2 was to show the use of methods B, C, D and E to evaluate tree planting scenarios. The example shows a hypothetical situation in which a range of possible locations was selected for tree planting in an urban block in the suburbs of Oslo. The aim was to choose a location where a tree would provide the most ecosystem services to the block's residents. The spatial contextual factors modelled in methods B – E were thus used here as ecosystem service indicators: tree visibility from open space (method B) as an indicator of the health and recreation benefits (Keeler et al., 2019; Nesbitt et al., 2017), crown light exposure (method C) as an indicator of the growth conditions and the capacity of the tree to sequestrate carbon and mitigate air pollution (Keeler et al., 2019; Nowak, 2020) and distance and direction to a nearest residential building (methods D, E) as indicators of reducing heating costs due to wind protection (Nowak, 2020; Y. Wang et al., 2014).

In the analysis, 609 regularly spaced points (in 5m distance) were distributed to represent all possible planting locations in the urban block (i.e., all locations outside buildings and existing tree canopy). It was assumed that a tree planted at the location would be 5m tall with a 2m crown diameter. Therefore, the input DSM was adjusted at each planting location to reflect the planted tree and tree crowns of the simulated trees were represented as 2m buffers of the planting locations. For each simulated tree, four spatial contextual factors were computed using methods B – E.

The values in the four resulting maps (Figure 4.12a – d) represent how each planting location supports the delivery of the respective ecosystem service. For aesthetic and health benefits, the preferred planting locations would be those where the tree would be more visible, for instance, in the open areas in the northeast part of the block (Figure 4.12a). Most planting locations provide 100% crown light exposure to support carbon sequestration and air pollution mitigation, except planting the trees directly next to building façades and existing trees (Figure 4.12b). Preferred planting locations for reducing heating costs are those closer to residential buildings and located to the north and western building façades. On the other hand, planting locations near the southern façades might increase heating costs due to sun blockage in winter (Figure 4.12c, d).

Following the modelling results from methods B – E, the four factors were combined in a naïve (equal criteria weights, no ecosystem service valuation) multicriteria analysis to illustrate how a preferred planting location could be selected. The factors were first scaled to 0 – 1 range (direction to nearest residential building scaled north: 0, west: 0.5, east: 1, south: 1). The final tree planting suitability score was then computed from the factor average, classified into five equally sized classes scored 1 – 5 (Figure 4.12e). The result suggests that planting trees close to the northwest building façades, especially in the urban block's northwest corner, would provide the largest benefits to the residents.

The example illustrates the potential of methods B – E to provide information for targeting planting locations that can best support the delivery of specific ecosystem services. Importantly, the methods B – E model only several ecosystem service indicators. In a real-world case, it would be necessary to first select the ecosystem services in question and the indicators to model them. Furthermore, combining the individual indicators in a multicriteria analysis requires decisions on indicator scaling and weighting. It is also important to note that modelling spatial contextual factors from the perspective of possible planting locations does not consider the ecosystem services already provided by other trees in the location. The evaluation of tree planting priority in terms of lacking ecosystem service supply is illustrated in Example 3.

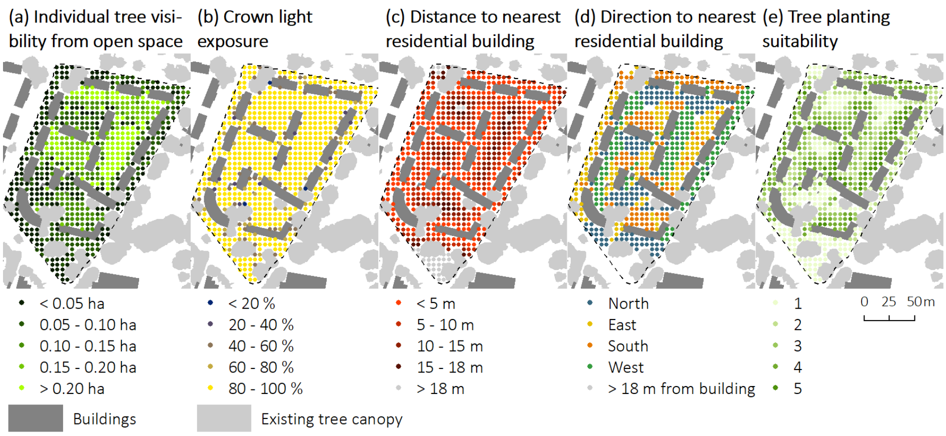

Figure 4.12: Example of using methods B – D to evaluate possible tree planting locations in terms of ecosystem service indicators. Each point corresponds to a place where a tree could be planted. (a) Visibility of the trees from open space in the urban block; (b) Crown light exposure of the trees; (c) Distance from the trees to the nearest residential building; (d) Direction from the trees to the nearest residential building; (e) Tree planting suitability indicator modelled by combining maps (a) – (d).

4.4.3 Example 3: Identifying priority locations for tree planting with method A

The objective of Example 3 was to illustrate how method A can support the identification of priority locations for tree planting in several streets in the center of Oslo (Kvadraturen). These streets currently have only little greenery but relatively high pedestrians density. Method A was used to identify locations with low visual exposure to tree canopy, i.e. low supply of visually perceived benefits such as aesthetics and mental health benefits (Kaplan, 2001; Lottrup et al., 2015; Schroeder & Cannon, 1983). The results were then combined with spatially explicit demand information to identify priority locations for tree planting.

The analysis consisted of three steps, illustrated in Figure 4.13. First, visual exposure to tree canopy was modelled with method A using a 100m exposure range, distance decay viewshed parametrization and 25% sampling density. Second, areas with no visible tree canopy were selected (visual exposure to tree canopy = 0) (Figure 4.13a). Finally, the map of zero visible tree canopy was multiplied with a map of pedestrian density (Figure 4.13b), representing the demand for the visually perceived benefits of urban trees. The result is a map of tree planting priority (Figure 4.13c). In the map, high values correspond to high tree planting (low supply and high demand), and low and null values correspond to low tree planting priority (low supply and low demand, or high supply).

This example illustrates the potential of method A to inform strategic tree planting by detecting areas that have a deficit of visually perceived tree benefits. In the example, only areas with no visible greenery were considered. However, non-zero values up to a certain threshold could also be regarded as a deficit. As shown in the example, the deficit map can be combined with various layers representing demand to identify locations with a mismatch between supply and demand for visually perceived tree benefits. Planting trees in these locations would thus have the largest impact in terms of delivering visually perceived benefits. In this example, I used a pedestrian density map derived from available Strava Metro data as a proxy for demand (Strava Metro, 2021). However, the Strava Metro data only capture a fraction of the total pedestrian volumes and are thus not representative of pedestrian density. In addition, other criteria such as population demographics could be used to model demand. A real-world case study would have to investigate what further data to consider in modelling tree planting priority and how to weigh these in a multicriteria analysis.

Figure 4.13: Example of applying method A to identify areas of tree planting priority. (a) Map of visual exposure to tree canopy modelled with method A, areas of no visible tree canopy are highlighted in red; (b) Map of pedestrian density as an example of demand criteria that could be considered in prioritizing tree planting; (c) Map of tree planting priority modelled by multiplying the areas of no visible tree canopy from map (a) with a map of pedestrian density from map (b).

4.4.4 Example 4: Assessment of visual exposure to tree canopy along paths with method A

The objective of Example 4 was to illustrate the use of method A to compare different paths in terms of visual exposure to tree canopy. In particular, visual exposure to tree canopy was mapped along two possible routes from the Royal Palace to Central Station in the center of Oslo (Figure 4.14). The first path (marked in blue in Figure 4.14) takes an east direction from the Royal Palace through the Palace Park, follows Kristian IVs gate and Grensen towards Oslo Cathedral and Biskop Gunnerus gate towards the Central Station. The second path (marked in red in Figure 4.14) takes a southeast direction from the Royal Palace through the Palace Park and then follows Karl Johans gate towards the Central Station. The paths are comparable in length (1.51km and 1.48km, respectively).

In the analysis, visual exposure to tree canopy was modelled with method A using a 100m exposure range, distance decay viewshed parametrization and 25% sampling density. A profile graph of the resulting visual exposure to tree canopy was then plotted for each path. Several sections of the first path (blue in Figure 4.14) pass under the tree canopy. As discussed in Paper II, method A is not capable of modelling visual exposure to tree canopy for observation points under trees because of the 2.5D representation of the physical environment. Instead, visual exposure is modelled as if standing on top of the tree crowns, leading to extreme values. Therefore, in the profile graph of the first path, visual exposure values for path sections under the tree canopy were replaced by a constant, reflecting a visual exposure maximum.

The potential of method A to accurately model the amount of visible tree canopy along paths can benefit a range of application purposes. For example, in epidemiological research and exposure studies, recent reviews have called for higher resolution modelling of exposure to urban nature to assess health benefits (Bratman et al., 2019; Remme et al., 2021). Accurately modelling the visual exposure to tree canopy along people's tracks of daily movement could enable a more in-depth and detailed insight into their exposure to further advance our knowledge on the relationship between visible greenery and various health benefits of urban trees.

Furthermore, street greenery, including tree canopy, has been shown to increase street walkability (Ki & Lee, 2021; Lu, 2018; Lu et al., 2018). The profile graphs of visual exposure to tree canopy constructed from method A outputs could be used in walkability studies to compare different paths and justify path choices or explore walking speeds. However, a limitation of method A in this regard is that it models the amount of visible tree canopy in a full view (360 x 180 degrees). In contrast, when walking, the field of view is limited to one direction, and thus the amount of visible tree canopy might be lower.

Figure 4.14: Example of applying method A to assess visual exposure to tree canopy along two paths. The top panel shows a map of visual exposure to tree canopy and the two assessed paths. The bottom panel shows profile graphs of visual exposure to tree canopy along the respective paths.

Concluding remarks 5

The scope of the thesis has been defined on the intersection between four bodies of knowledge: Geographical information science (GISc), urban planning, urban forestry and ecosystem service assessment (Figure 5.1). However, the thesis findings can contribute to various areas beyond the thesis scope (shown in grey in Figure 5.1). In this chapter, I will briefly recall the main findings of the thesis and then focus on discussing the contributions and limitations of the findings beyond the thesis scope. I conclude the chapter by providing directions for future research in modelling spatial contextual factors.

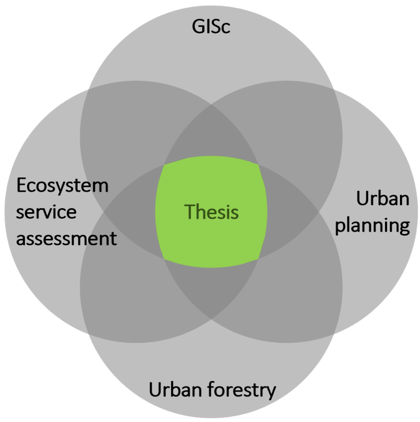

Figure 5.1: The scope of the thesis on the intersection between four bodies of knowledge: Geographical information science (GISc), urban planning, urban forestry and ecosystem service assessment

5.1 The supporting objectives of the thesis

Supporting objectives

S1: Review and synthesize existing knowledge on spatial context in ecosystem services of urban trees.

S2: Review and assess the current use of GIS in modelling the spatial context of urban trees.

RQ1

Within the ecosystem service framework, what specific tree location characteristics mediate ecosystem services of urban trees?

- ***What ecosystem services are mediated by the individual tree location characteristics and by what mechanisms?***
- ***How can tree location characteristics be represented as a conceptual model?***
- ***What are the implications of such conceptual representation of tree location characteristics for spatial modelling?***

The first supporting objective of the thesis (S1) and the respective research question (RQ1) were addressed in a dedicated Paper I by reviewing and synthesizing the current knowledge on spatial contextual factors mediating ecosystem services of urban trees. The findings, presented in Section 2.4, supported reaching the main objective of the thesis. In particular, the resulting comprehensive overview of spatial contextual factors justified the selection of the specific factors for which modelling methods were developed. Moreover, clarifying the conceptual understanding of spatial contextual factors provided guidelines for approaching the modelling tasks.

The second supporting objective of the thesis (S2) was addressed in Section 3.2 by reviewing and assessing the current use of GIS in modelling spatial contextual factors of urban trees. The findings supported reaching the main objective of the thesis by identifying knowledge gaps in the current use of GIS for modelling spatial contextual factors.

5.1.1 Contributions beyond the thesis scope and limitations

The work conducted to address the first supporting objective and the respective research question may further contribute beyond the thesis scope. The work complements other studies in emphasizing the importance of spatial context for the delivery of ecosystem services by trees and ecosystems in general (e.g., Andersson et al., 2015; Salmond et al., 2016; Wilkerson et al., 2018; Bruckmeier, 2016) and contributes to a better understanding of spatial context in ecosystem service delivery. In particular, the findings provide insight into what types of structures and processes represent the spatial context and clarify how spatial context participates in the ecosystem service delivery process.

The review and synthesis conducted in Paper I collected the fragmented literature on the various spatial contextual factors influencing the numerous ecosystem services of urban trees along the entire ecosystem service cascade and organized it into a systematic overview. Such an overview can benefit various application purposes. For example, it can help tree planners, landscape architects and other professionals to find specific factors that should be considered when planting trees for a particular ecosystem service. It can also help them identify the ecosystem services that could be affected by specific changes in the trees' context. This, in turn, contributes to supporting and maintaining ecosystem services of urban trees and brings more insight into developing tree planting strategies that are effective in providing ecosystem services. Similarly, the overview can inform environmental benefit (value) transfer used in cost-benefit analysis (Brander et al., 2012; De Valck & Rolfe, 2018; Johnston et al., 2021) because it provides a concrete set of variables that should be considered to control for spatial heterogeneity when generalizing, scaling and transferring ecosystem service value estimates from local studies to larger extents or new sites.

Importantly, the findings highlight that planning and design have an essential role in supporting ecosystem services of urban trees. Many factors describe the built environment around the tree (e.g., position of the tree towards a building, land use, urban form) or relate the tree to the potential beneficiaries and their characteristics (e.g., configuration of the trees to people, their socio-demographic profile). Finally, the findings also highlight the need for integrative planning approaches. The spatial contextual factors come from many different domains, and cooperation between professions is needed to support the ecosystem services effectively.

Note on temporal context

Research has shown that apart from the *spatial* dimension of trees' context, the *temporal* dimension might be just as important (Andersson et al., 2015; Martín-López et al., 2009). For example, the aesthetic benefits of trees due to flowering can only be enjoyed in some seasons (Martín-López et al., 2009), and the potential of trees to regulate air pollution is limited during leaf-off periods (Eisenman et al., 2019). Similarly, the benefits obtained from exposure to trees might depend on the exposure duration (Helbich, 2018). Considering temporal context is also important when selecting tree species resilient to future climate scenarios (Esperon-Rodriguez et al., 2022).

During the thesis, the focus has been put on the spatial context of urban trees, while the temporal dimension of trees' context had been considered only partially. For example, we provided temporally disaggregated air quality and precipitation data to enable i-Tree Eco analysis of regulating ecosystem services in Paper IV. In addition, all the developed methods enable dynamic assessment of the spatial context of trees if applied to datasets from different time points, as shown in Example 1 in Section 4.4. Exposure duration could also be considered in the exposure weights layer in method B. However, further work would be necessary to establish a more solid understanding of the effects of temporal context on the ecosystem services of urban trees.

5.2 The main objective of the thesis

Main objective

Develop GIS methods for modelling the spatial context of urban trees for the purpose of informing research and practical applications that aim at supporting the ecosystem services of urban trees.

RQ2

How can spatial contextual factors of urban trees be modelled using GIS methods, given the following requirements?

(i) ***The factors are multifunctional in terms of mediated ecosystem services and thus more important to measure and model,***
(ii) ***Modelling the factors requires a complex and innovative spatial modelling approach,***
(iii) ***Modelling the factors with GIS is possible,***
(iv) ***Methods for modelling the factors are lacking.***

The main objective of the thesis and the respective research question were addressed in Papers II – IV, where five GIS methods for modelling four distinct spatial contextual factors were developed to support specified application purposes. The five methods are presented in Chapter 4 [6].

The development of the five methods addressed a knowledge gap in terms of missing methods for modelling important spatial contextual factors for specified application purposes. Therefore, the developed methods also add to the emerging number of quantitative methods supporting ecosystem service quantification and assessment tailored to urban settings (e.g., Suárez et al., 2020; van Oorschot et al., 2021; Venter et al., 2020) and highlight the potential of GIS for high-resolution, large-scale ecosystem service assessment.

5.2.1 Contributions beyond the thesis scope and limitations

Although the methods A – E were developed for the purpose of modelling the spatial context of urban trees in specified application purposes and illustrated in the study area of Oslo, they could be adjusted relatively easily to enable modelling spatial context in other study areas, for different application purposes and even model spatial context of structures other than trees. In this section, I will outline several possible directions for the applicability of the methods beyond their original scope.

[6] A: Visual exposure to tree canopy,
B: Individual tree visibility,
C: Crown light exposure,
D: Distance to nearest residential buildings,
E: Direction to nearest residential buildings.

In addition, I will discuss the limitations of the methods' transferability to these application areas, using the five performance criteria proposed in Table 3.5.

Modelling spatial contextual factors of urban trees in other study areas

The methods were developed for general application in any urban area. However, they were applied, illustrated and tested (in the case of method A) in the study area of Oslo. This has consequences for the transferability of the methods to other study areas.

The transferability of the methods to other study areas might be limited by the methods' accuracy. Caution would have to be paid especially in methods A and B, because the findings regarding a suitable combination of viewshed parametrization functions and exposure ranges in these methods are based on an assessment conducted in the conditions of Oslo and might not apply to urban areas with significantly different urban morphology. Therefore, exploring the methods' performance in other study areas might be an important pathway for future research. On the other hand, the accuracy of methods C – E is expected to be more robust to changes in study areas because their settings were driven by the i-Tree Eco field guide and were not fitted to a specific study area.

Furthermore, the transferability of the methods to other study areas might be limited by the availability of input spatial data. Although the methods build on relatively few datasets (Table 4.4), these might not be available in other study areas. The availability of high-resolution tree canopy data (raster or vector, depending on the method) is a prerequisite for applying all five methods and might represent a bottleneck to the methods' transferability. Therefore, the technical advances in individual tree detection from high-resolution LiDAR and hyperspectral imagery are promising in this regard (e.g., Hanssen et al., 2021; Mohan et al., 2021; Ramiya et al., 2019). In addition, municipalities might maintain tree inventories created for management purposes, which can be used as the input data if spatially referenced, although they might represent only a fraction of all trees in the urban forest. The input raster data on tree canopy (used in method A) could, to a certain extent, be replaced by lower-resolution freely available satellite data (e.g., from Sentinel-2 mission). However, the assessment of method A in Paper II showed that using a low-resolution tree canopy map significantly reduces the method's accuracy. A high-resolution DSM (required in methods A, B and C) is currently available for large parts of Scandinavia [7]. The worldwide availability of high-resolution surface data increases with advances in high-resolution satellite sensors such as Pleiades or WorldView-2 (Gong & Fritsch, 2019; Gui & Qin, 2021; Ye et al., 2021) but might still represent an issue.

[7] Norway: https://hoydedata.no/LaserInnsyn/,
Sweden: https://www.lantmateriet.se/globalassets/kartor-och-geografisk-information/hojddata/quality_description_dem.pdf,
Denmark: https://datafordeler.dk/dataoversigt/danmarks-hoejdemodel/overflade/.

The transferability of the methods to other study areas might also be limited by the computational efficiency of the methods. Most importantly, the computational efficiency of method C would have to be improved to enable analyzing city-wide datasets in a reasonable time. On the other hand, methods A and B were designed to provide high computational efficiency and could successfully analyze the extent of Oslo on commodity hardware. Similarly, the simple algorithms of methods D and E do not require further optimization.

Modelling spatial contextual factors of urban trees for other application purposes

The methods were developed for specified application purposes (Table 4.2) but could be adjusted to model spatial contextual factors of urban trees beyond these defined purposes. In this regard, further adjustments of the methods might be needed to accurately reflect the meaning of the modelled factors given the new application purposes. Importantly, different application purposes might also have different accuracy tolerance.

Applying methods A and B in specific tasks might require investigating which methods settings best fit the specific purpose. For example, adjusting method B to fit the particular needs of tree valuation with the VAT or CAVAT methods (Doick et al., 2018; Randrup et al., 2019) might include setting a fixed viewshed parametrization function, exposure range and exposure weights. New viewshed parametrization functions could also be implemented to reflect the various aspect of visual perspective. Further work is also needed to explore how the objective measure of the visible amount of tree canopy modelled with method A corresponds to subjectively perceived visible tree canopy. Such knowledge would enable transferring the method to a wider range of applications such as environmental psychology (Velarde et al., 2007).

On the other hand, methods C – E were developed specifically to provide information to i-Tree Eco analysis. Therefore, the methods might not accurately reflect the meaning of the individual factors in other application purposes. In addition, the methods do not offer the flexibility for adjustments. This is especially relevant in method C, where crown light exposure is modelled following the i-Tree Eco field guide. For example, the method could use solar irradiance analysis instead to model crown light exposure more realistically (Hofierka & Suri, 2002) in practical tree management applications, such as those shown in Example 2 in Section 4.4.

The transferability of the methods to other application purposes might further be limited by the software requirements and technical skills needed to use the methods. For example, methods C – E are currently only available as scripts in proprietary software but could be further implemented as open-source GIS tools to lower the demands for user technical skills and increase availability. The methods could even be integrated with i-Tree Eco to ensure automatic computation of the factors. The availability of methods A and B is currently ensured by implementation as open-source GIS tools. However, for specific application purposes such as tree valuation with the VAT or CAVAT methods (Doick et al., 2018; Randrup et al., 2019), the methods might in the future be implemented as for example mobile applications, ensuring easy access to tree assessors with limited GIS experience.

Modelling other spatial contextual factors of urban trees

The methods were developed to model four specific spatial contextual factors of urban trees. However, they could easily be adjusted to model other spatial contextual factors of urban trees, provided that the factors have a similar spatial relationship. The overview of 114 factors created in Paper I can provide an idea of the factors that could be modelled (Table 5.1). For example, method D, developed originally for modelling the direction from a tree to the nearest residential building, could be used to model other factors that describe the "distance" or "proximity" from a tree to surrounding structures and processes. The input map of residential buildings would only be replaced, for example, by a map of pavements or parking locations. Methods A and B, on the other hand, provide a starting point for modelling other visibility-related factors such as visibility from offices or hospitals. Moreover, the principles developed in the methods could be used as a foundation for modelling more complex determinants of urban tree benefits, such as view blockage by trees (Lyytimäki et al., 2008).

However, adjustments might be needed to ensure that the methods accurately capture the meaning of the new factors. For example, method D measures the Euclidean distance between a tree and a building, but the measure of "proximity" in other factors might mean other distance metrics such as walking distance. For instance, in the case of "proximity to hospitals", proximity might better be measured in terms of accessibility or visibility. Similarly, the transferability of methods A and B might be limited by building on a 2.5D representation of the physical environment. While this representation showed sufficient accuracy for modelling visual exposure to tree canopy from open spaces and surfaces (e.g., building roofs), the representation might limit the method's applicability to model visual exposure from inside buildings. For example, research suggests that visual exposure to urban greenery from inside residential houses, hospitals and offices is important (Kaplan, 2001; Lottrup et al., 2015; Ulrich, 1984), and so the methods might have to be adjusted to operate on a 3D representation of the physical environment to model these factors.

Modelling spatial context of built and natural structures other than urban trees

The literature on ecosystem service assessment suggests that spatial context is an important mediator of ecosystem services of biophysical structures other than urban trees, both within and beyond urban areas (Andersson et al., 2015; Wilkerson et al., 2018). Therefore, the methods developed in the thesis could be applied for modelling the spatial context of such biophysical structures. For example, in urban settings, grass and shrubs could be included in methods A and B to study

Table 5.1: Spatial contextual factors from the overview created in Paper I that can potentially be modelled with the developed methods if minor changes are made to the input data or method algorithms

Method	Potentially relevant for spatial contextual factor	Change
A Visual exposure to tree canopy **B Individual tree visibility**	Visibility of trees from buildings Visibility of trees from offices Visibility of trees from hospitals	Change from 2.5D to 3D representation to enable modelling visibility from inside buildings
D Distance to nearest residential buildings	Proximity from trees to housing Proximity from trees to other trees/tree aggregations Proximity from trees to hospitals Proximity from trees to green areas Proximity from trees to infrastructure Proximity from trees to parking locations Proximity from trees to pavements Proximity from trees to air pollution source Proximity from trees to noise source Proximity from trees to people	(Assuming that proximity is measured in terms of distance)

the visual benefits of urban greenery in general (e.g., Kaplan, 2001; Lottrup et al., 2015; Schroeder and Cannon, 1983; Thayer and Atwood, 1978). In forests beyond urban areas, trees are often valued for timber production and carbon sequestration (Schwenk et al., 2012; Triviño et al., 2015). Method C could thus be applied to model the crown light exposure of individual forest trees to estimate their growing conditions, affecting carbon sequestration rates and timber production (Nowak, 2020). Furthermore, methods A and B could support landscape aesthetic studies in modelling visual landscape quality, view composition or visual exposure to landmarks if land cover maps are used on the input instead of urban tree canopy maps (Dramstad et al., 2006; Grêt-Regamey et al., 2007).

Moreover, the methods could provide information to model spatial context in urban planning applications beyond the domain of urban nature. In this regard, method A could be used to compare different locations in terms of their visual exposure to one or more structures. For example, running method A with an input exposure map representing a visual pollution source (e.g., transport infrastructure, outdoor advertisements) would help to identify locations most exposed to the visual detriment (similarly to e.g., Chmielewski et al. (2016)). On the other hand, method B could contribute to modelling the visual impact of various structures. Potential applications are, for instance, modelling of the visual impact of high-rise building proposals (similarly to e.g., Rød and van der Meer (2009)) or modelling the visibility of the city's landmarks from different viewpoints (similarly to e.g., Pyka et al. (2021)). Finally, method C, originally developed for modelling the exposure of tree crown to sunlight, could be used to model the percentage of building perimeter blocked by surrounding trees and buildings to assess view blockage or shadowing.

The transferability of the methods to modelling the spatial context of other built and natural structures might be limited by the methods' capacity to accurately reflect the meaning of such new spatial context measures. Caution would thus have to be paid especially in methods A and B, where the findings regarding accuracy, viewshed parametrization functions and exposure ranges are based on an assessment conducted for the case of urban trees and might not apply to structures other than trees. For example, urban trees have a specific visual impact due to their vertical dimension. In contrast, other types of urban greenery (e.g., grass, shrubs) are mostly horizontal and might have a different visual impact. Therefore, testing the method's performance on built and natural structures other than trees would be necessary.

Furthermore, applying the methods in modelling the spatial context of other built and natural structures might be limited by the methods' flexibility. Methods A and B, which were developed without a specific application purpose[8], already support visibility analyses of various structures at various resolutions and various scales. However, further improvements could be made. For instance, applications such as visual impact assessment might benefit from a new option to modify the height from which viewsheds are generated. In the current implementation, viewsheds are generated from the top of the DSM, which might be problematic if the analyzed structures are not reflected in the DSM. On the other hand, methods C – E currently are implemented with fixed settings (e.g., the definition of a maximum distance at which surrounding structures are considered to shade the tree crown). To enable using these methods beyond urban tree assessment, they would benefit from implementation as GIS tools with flexible settings.

[8] The terminology in the tools *r.viewshed.exposure* and *v.viewshed.impact* was also kept general to increase the methods' flexibility (e.g., the input map is called "exposure source", not "tree canopy map").

5.3 Directions for future research in modelling spatial context of urban trees

The work conducted in the thesis could be followed up, built on and extended by future research in multiple directions. First, there are many options for technical improvements of the five developed methods, some of which were outlined in the previous section. Such improvements could be minor additions increasing the methods' flexibility (e.g., implementing new viewshed parametrization functions in method A), as well as more substantial adjustments in the methods' design (e.g., enabling visibility modelling from inside buildings in methods A and B).

Second, further steps could advance the availability and usability of the methods for concrete practical applications and use cases. For example, methods C – E, which model inputs into the i-Tree Eco analysis of regulating ecosystem services, could be integrated into the i-Tree Eco software to compute the three spatial contextual factors automatically. Similarly, method B could be implemented as a mobile application for tree assessors working with the VAT or CAVAT tree valuation methods. Moreover, the methods could be integrated into decision support tools for strategic tree planting. For example, following the application examples shown in Section 4.4, a multicriteria tree planting prioritization tool could be developed, where method A would be included along with other maps and models of ecosystem service deficits and demands. Similarly, the practice could benefit from a tool for tree planting scenario evaluation, where methods B – E could be used amongst the input criteria. Such tools could then inform, for instance, the various tree planting campaigns in major European and American cities [9].

Finally, more spatial contextual factors of urban trees might benefit from spatial modelling in GIS. Filtering the overview of 114 factors based on the four requirements specified in RQ2 (Table 4.1) can provide a suggestion of the other factors potentially suitable for spatial modelling in GIS. While some of these factors can build on the methods developed in the thesis (e.g., those with "visibility" or "distance" as a spatial relationship), other factors are unrelated to those addressed in the thesis. For example, many factors specify the accessibility of trees from various structures and processes (e.g., "proximity or accessibility from trees to housing", "accessibility of trees to people"). There are relatively many studies in which accessibility of trees has been modelled (e.g., Baró et al., 2019; Mouratidis and Yiannakou, 2022; Zhou and Kim, 2013), but research and practice could benefit from developing methods that are more available, flexible and efficient. Together with the knowledge and methods presented in the thesis, these future advances would then help to better account for the spatial context of urban trees and thereby aid in ensuring, maintaining and supporting ecosystem services in the urban environments.

[9] New York (*Million Trees NYC* https://www.milliontreesnyc.org/); Paris (*L'arbre à Paris* https://www.paris.fr/pages/l-arbre-a-paris-199); Oslo (*Oslotrær* https://www.oslo.kommune.no/slik-bygger-vi-oslo/oslotrar/); Berlin (*Stadtbäume für Berlin* https://www.berlin.de/sen/uvk/natur-und-gruen/stadtgruen/stadtbaeume/stadtbaumkampagne/); Prague (*Zastromuj Prahu* https://zastromujprahu.cz/)

6 Summary of Papers I – IV

6.1 Summary of Paper I: Location matters. A systematic review of spatial contextual factors mediating ecosystem services of urban trees

Background Spatial context is recognized as an important mediator of the ecosystem services of urban trees. Accounting for the different aspects of tree location that mediate urban tree ecosystem services, here called spatial contextual factors, is important especially in strategic tree planting for supporting ecosystem service delivery. However, little research has been done on synthesizing the currently recognized spatial contextual factors of urban trees into a comprehensive overview. Moreover, there is little common understanding of what spatial context is conceptually and how it participates in the co-production of ecosystem services in general.

Objectives The paper's objective is to develop a comprehensive overview of spatial contextual factors recognized by research as relevant for ecosystem service delivery by urban trees.

Methods To support creating the overview, we conduct two systematic literature reviews. The first review aims to gain insight into the current common understanding of what spatial context is conceptually and how it participates in the co-production of ecosystem services in general. The second review aims at identifying the spatial contextual factors recognized by research as relevant for ecosystem services of urban trees. The knowledge established in the first review is then used to organize and synthesize the findings of the second review.

Results In the first review, we find that generally, spatial context is represented by both social and ecological structures and processes and that it mediates ecosystem services by four mechanisms along the ecosystem service cascade. The paper's main result is the overview of spatial contextual factors mediating the ecosystem services of urban trees created in the second review. The overview contains 114 unique spatial contextual factors mediating 31 ecosystem services of urban trees. By synthesizing the overview, we find that of all factors, people, represented by physical location, socio-demographics or building functions, mediate the highest number of services. Furthermore, many spatial contextual factors are multifunctional in terms of mediated ecosystem services. For example, factors describing the configuration of trees to land use and building function mediate the highest number of ecosystem services.

Conclusions The overview developed in the paper makes explicit the individual spatial contextual factors and links them directly to specific ecosystem services. Thereby, the overview is directly usable in both research and practical planning applications. Furthermore, the findings from the overview synthesis support other studies that emphasize that spatial context is an important mediator of the ecosystem services of urban trees. Besides, the findings point out the general importance of design and planning in supporting the ecosystem services of urban trees. Finally, through the findings from the first review, the paper also contributes to a better conceptual understanding of spatial context in ecosystem service assessment in general.

6.2 Summary of Paper II: Viewshed-based modelling of visual exposure to urban greenery – An efficient GIS tool for practical planning applications

Background Visual exposure is an important pathway in receiving aesthetic, social and health benefits from urban greenery. Measuring green visual exposure is central for understanding the relations between green visual exposure and associated benefits and applying these findings in practice. Spatial modelling with viewshed analysis has been successfully used to model and map green visual exposure from a human perspective in continuous representation and places of missing street view imagery for widely used photography-based methods. However, existing viewshed-based methods suffer from limited applicability in research and practice due to limited generalizability beyond their specific scope, inefficiency in processing large spatial extents and demands for advanced technical knowledge.

Objectives The paper's objective is to develop a viewshed analysis-based method for modelling visual exposure to urban greenery with a special focus on the method's applicability in research and practice.

Methods and results The paper's main result is a method for modelling visual exposure to urban greenery. The method is based on parametrized cumulative viewshed analysis to reflect human visual perspective. The method is implemented as a practical and flexible tool called *r.viewshed.exposure* in GRASS GIS. Extensive validation and assessment of the method on the specific case of urban trees in Oslo, Norway, confirms that the method is a highly accurate alternative to modelling visual exposure from street view imagery ($\rho = 0.96$). However, data quality and viewshed parametrization are essential for achieving accurate results. Thanks to parallel processing and effective implementation, the method is applicable for city-wide scale analysis with high-resolution data on commodity hardware.

Conclusions The paper supports the use of spatial modelling with viewshed analysis as a reliable and highly accurate means of measuring visual exposure to urban greenery from a human perspective. Furthermore, implementing the method as a tool in open-source GIS software makes the method available as a practical and flexible tool for a broad range of research and practical applications, including strategic tree planting, scenario modelling and urban ecosystem accounting, as well as ecosystem service research. Therefore, the paper adds to the emerging number of quantitative methods that enable easier modelling of cultural ecosystem services that otherwise are often challenging to include in ecosystem accounting or landscape management.

6.3 Summary of Paper III: Making trees visible: a GIS method and tool for modelling visibility in valuation of urban trees

Background Tree visibility as a key mechanism in benefiting from cultural ecosystem services of urban trees is recognized in various methods for valuing amenity trees. Measuring individual visibility is a precondition for including it in tree valuation methods and other practical and research applications. However, little research has been done on modelling individual tree visibility in GIS, which could address the limitations of field-based assessment that is often used in current practice.

Objectives The paper's objective is to develop a flexible, efficient and easy-to-use GIS method for modelling individual tree visibility to support tree valuation methods and tree management and planning.

Methods and results The paper's main result is a method for modelling individual tree visibility. The method is based on parametrized viewshed analysis weighted by user-defined spatially explicit weights to reflect the tree's spatial context that is often considered in the tree valuation methods. The method is implemented as a GRASS GIS AddOn tool called *v.viewshed.impact* with flexible user-specified settings. Furthermore, thanks to empirically validated underlying algorithms and parallel processing, the method is accurate and fast even for analyzing high-resolution datasets and large numbers of trees. These features render the method available for a wide spectrum of users and purposes. The method's capabilities are demonstrated in modelling two tree visibility indicators from commonly used tree valuation methods in Oslo, Norway.

Conclusions The paper shows that modelling tree visibility with viewshed analysis provides an alternative to field-based assessment of visibility indicators in current tree valuation methods. Furthermore, the method facilitates accounting for complex visibility indicators not possible to assess in the field. Finally, implementing the method as a tool in open-source GIS software makes the method available as an easy-to-use and flexible tool for a broad range of research and practical application areas beyond the scope of tree valuation, including ecosystem accounting and epidemiological research.

6.4 Summary of Paper IV: The potential of geospatial analysis and Bayesian networks to enable i-Tree Eco assessment of existing tree inventories

Background Valuing ecosystem services of urban nature is important for gaining public and political support for its conservation and maintenance. i-Tree Eco is a software application for quantifying and valuing the regulating ecosystem services of individual urban trees. It calculates ecosystem service indicators by putting a range of tree attributes (tree species, dimensions, spatial context) into a functional relationship. Subsequently, it estimates the trees' monetary value based on local benefit prices. However, existing municipal tree inventories may not contain the attributes necessary for i-Tree Eco analysis. Furthermore, manual field surveys to supplement these attributes or establish specialized i-Tree Eco inventories are costly and time-consuming.

Objectives The paper's objective is to demonstrate the potential of GIS and machine learning methods to supplement missing and incomplete attributes in existing municipal tree inventories to enable i-Tree Eco analysis.

Methods We use a municipal tree inventory of Oslo, Norway, as an example. Th inventory contains tree location and incomplete attributes on species and stem diameter. Therefore, only 19% of the inventory is suitable for i-Tree Eco analysis. We compute the missing tree dimensions (stem diameter, crown diameter, tree height) using allometric equations and by overlaying the inventory with LiDAR-detected tree crowns. We use other available spatial data to derive missing attributes of the trees' spatial context (crown light exposure, distance and direction to building, land use) and include differentiation of air pollution levels. Integrating Oslo's tree inventory with available spatial datasets enables i-Tree Eco analysis for 54% of the trees. In addition, we use machine learning with Bayesian networks to extrapolate i-Tree Eco outputs and infer the value of the entire municipal inventory.

Results Using statistical and GIS methods to compute missing attributes in Oslo's tree inventory increases the proportion of trees suitable for i-Tree Eco analysis from 19% to 54%. Missing information on tree species (in the inventory and in available spatial data) is the main reason for 46% of trees not suitable for i-Tree Eco. Bayesian networks enable inferring the expected asset value of the entire municipal inventory, which is 38.5 – 43.4 million USD, depending on modelling assumptions.

Conclusions Our findings show a potential for greater use of spatial data and GIS methods in creating urban tree inventories to enable tree valuation. GIS methods are especially useful to model location-specific tree characteristics. However, given the available data in our case, we question the accuracy of values inferred by Bayesian networks for ecosystem accounting and tree compensation valuation.

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Part II: Publications

Paper I

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Review Paper

Location matters. A systematic review of spatial contextual factors mediating ecosystem services of urban trees

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ABSTRACT

To ensure and maintain ecosystem service delivery in cities undergoing densification, strategic tree planting is important. The effects of tree location on ecosystem service delivery have been emphasised. However, there is no integrated overview of the different aspects of tree location, here called spatial contextual factors, that mediate urban tree ecosystem services. This paper presents the results of a systematic literature review and provides a comprehensive overview of spatial contextual factors recognised by research as relevant for ecosystem service delivery by urban trees. To support creating such an overview, we first gain insight into the current common understanding of what spatial context is conceptually and how it participates in the co-production of ecosystem services. We find that generally, spatial context is represented by both social and ecological structures and processes and that it mediates ecosystem services by four mechanisms along the ecosystem service cascade. In the next step, we identify 114 unique spatial contextual factors mediating 31 ecosystem services of urban trees. Of all factors, people, represented by physical location, socio-demographics or building functions, mediate the highest number of services, highlighting the importance of urban planning and design in mediating urban tree ecosystem services.

1. Introduction

1.1. Background

Rapid urban growth accompanied by climate change is associated with problems such as air and noise pollution, urban heat island effect, increased stress levels, habitat loss and flash floods (Ahlfeldt and Pietrostefani, 2017; Bazaz et al., 2018; Berghauser Pont et al., 2020; Gren et al., 2018). Research suggests that urban trees, i.e. trees in both public and private areas (parks, streets, urban forest and gardens respectively), have the potential to contribute to mitigating these problems and contributing to the well-being of urban citizens by delivering a range of benefits. These benefits that nature can provide to humans have been conceptualized by the framework of ecosystem services (ES) (Daily, 1997; De Groot et al., 2002; Millennium Ecosystem Assessment, 2003; TEEB, 2010). Urban trees deliver provisioning, regulating, cultural and supporting ecosystem services (Escobedo et al., 2011; Salmond et al., 2016; Säumel et al., 2016) with a variety of economic, social and health benefits (Roy et al., 2012). In addition, urban trees might also lead to nuisances, harms and costs, collectively referred to as ecosystem disservices (Lyytimäki, 2017; von Döhren and Haase, 2015).

At the same time, urbanization puts pressure on green spaces in and around cities and in consequence influences the ES they deliver (European Environment Agency, 2006; Haaland and van den Bosch, 2015). Land-use competition caused by densification and compact city development leads to urban green space losses and fragmentation within cities, but at the same time can safeguard open space outside cities (Gren et al., 2018). While the latter can be supportive for biodiversity, the loss of green areas within cities negatively impacts living quality, recreation opportunities and biodiversity (Haaland and van den Bosch, 2015).

Urban trees demand relatively little ground surface space while making effective use of vertical space to provide vegetative surface and can therefore be easier integrated in cities than larger green areas, even in high-density neighbourhoods. Tree planting and tree management are therefore vital to ensure, maintain and support the delivery of ES and associated benefits in cities where space by definition is scarce (Haaland and van den Bosch, 2015; Vogt et al., 2017). In this paper, we therefore use the individual tree as our study object (i.e. service providing unit

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(Andersson et al., 2015)).

The amount of ES delivered by individual urban trees varies depending on characteristics of the tree itself and contextual factors[1], which should be accounted for in tree planting strategies and tree management aiming to support the benefits obtained from trees (Davies et al., 2017; Roeland et al., 2019; Roy et al., 2012; Salmond et al., 2016). An example of tree characteristic is stem diameter, which, by influencing tree dry-weight biomass and growth rates, determines for instance the rate of carbon sequestration, an important ES (Nowak et al., 2002; Nowak and Crane, 2002). An example of a contextual factor is the position of the tree towards other trees and structures, which, together with a range of other contextual factors such as local growing conditions or length of growing season, determines how much carbon a tree really will sequester (Nowak et al., 2008; Nowak and Crane, 2002). Unlike tree characteristics, contextual factors co-determine the delivery of ES through their interaction with the tree (Andersson et al., 2015; Palomo et al., 2016; Spangenberg et al., 2014). The importance of contextual factors in ES delivery in general has been discussed on a theoretical and practical level (e.g. Andersson et al., 2015; Luederitz et al., 2015; Bruckmeier, 2016; Wilkerson et al., 2018). Specifically, it extends the scope for variables to be considered in ecosystem accounting and environmental benefit transfer (Luederitz et al., 2015; Keith et al., 2019).

The common denominator of contextual factors, as defined for this paper, is that they can be associated with a geographic location and their relationship to the tree can be described and measured in a spatially explicit manner. For instance, in the previous example of carbon sequestration, the contextual factor "length of growing season" varies with geographical location and the contextual factor "position of a tree towards other trees or structures" can be described in terms of their co-location in space which leads to crown competition. Therefore, we adapt the term "contextual factor" (Andersson et al., 2015; Reyers et al., 2013) and add a prefix "spatial" to emphasize the role of space.

There are various ways in which spatial contextual factors mediate or co-produce the delivery of ES by urban trees. Looking again at the example of carbon sequestration, a change in growing conditions or crown competition will lead to a change in the supply of the service, while ongoing climate changes might influence the demand for or appreciation of the service, as reflected for instance in an increase of the social cost of carbon (Nordhaus, 2017). Thus, spatial contextual factors can mediate various aspects of the ES delivery process – both its supply and demand (Burkhard et al., 2012). A helpful conceptualization of the ES delivery process in this regard is the ES cascade framework (Haines-Young and Potschin, 2010). In this framework[2], the ES delivery process is decomposed into a linked set of five key components, which span both the supply and demand aspect of the ES delivery process (i.e. biophysical structure, function, service, benefit, value). To highlight how spatial contextual factors participate in the co-production of each of these five components, Fedele et al. (2017) further adjusted the cascade by making explicit the four mediating mechanisms (i.e. management, mobilization, allocation-appropriation, appreciation), which lead from one component of the cascade to the next.

1.2. Identified gaps and paper objectives

From the above, we can conclude that spatial context is an important aspect in the ES delivery process, necessary to better understand, assess and measure ES delivery. However, to our best knowledge, a comprehensive overview of spatial contextual factors for urban trees is not available. Papers presenting reviews of factors mediating ES of urban trees do not explicitly discuss the role of tree location and the spatial relationship between trees and surrounding structures and processes in delivering ES (Davies et al., 2017; Keeler et al., 2019). Furthermore, they often focus only on a single ES such as air quality or microclimate regulation (Abhijith et al., 2017; Salmond et al., 2016) or specific factors such as institutional barriers (Biernacka and Kronenberg, 2018) or do not link tree location characteristics to individual ES (Vogt et al., 2017).

The *main objective* of this paper is therefore to develop such comprehensive overview of spatial contextual factors using a systematic literature review guided by the following two research questions: (i) What are the spatial contextual factors participating in the delivery of ES by urban trees and (ii) By what mechanisms do these spatial contextual factors mediate the delivery of ES by urban trees? However, in scientific literature on ES assessment, there is no common conceptual understanding of what spatial context is or which kinds of structures and processes represent spatial context. This hinders the immediate development of such an overview. Furthermore, the mechanisms by which spatial context mediates ES delivery seem not to be agreed upon. For example, Andersson et al. (2015) explore socio-technological, ecological and cultural contexts and how these affect the transfer from ecological functions to services. Wilkerson et al. (2018), for instance, investigate the influence of context on the supply, demand and benefits of urban ES – but focus on socio-economical context only.

Therefore, a *sub-objective* of this paper necessary to reach its main objective is to gain insight into the current common understanding of what spatial context is conceptually, i.e. what structures and processes represent spatial context, and how it participates in the co-production of ES, i.e., what are the mechanisms (Fedele et al., 2017) by which these spatial contextual factors mediate ES delivery.

2. Methods

2.1. Workflow

The method consisted of two systematic literature reviews[3] (Review 1 and Review 2), where the second literature review addressed the main objective of the study and the first literature review addressed the sub-objective of the study. The knowledge established in Review 1 was used to organise and synthesize the findings of Review 2, resulting in an overview of spatial contextual factors currently recognised by research as mediating the delivery of ES by urban trees (Fig. 1). In this overview, individual spatial contextual factors are grouped by the structures and processes they represent and, through mediating mechanisms, linked to the ES they mediate (Results box in Fig. 1).

2.2. Literature review 1

We conducted a systematic database search (Web of Science, Google Scholar) using predefined search terms, which were formulated to find articles focusing on the role of spatial context in ES delivery. We did not use "spatial context" as a single search term because researchers might not specify the spatial component of context explicitly. On the other hand, the simpler term "context" has a too broad meaning, which was reflected in more than 3.000 hits when applying the search term *"context*" AND "ecosystem service*"*. Therefore, we used a series of more specific terms, namely *("contextual factor*" OR "context depend*" OR*

[1] Contextual factors (Andersson et al., 2015; Reyers et al., 2013) are also referred to as "mediating factors" that co-produce the delivered ES (Fedele et al., 2017), but we will use the term "contextual factors" to avoid confusion with the term "mediating mechanisms" used later in the article.

[2] The interpretation of individual components in the ES cascade and the links between them differs with the purpose of use, analysed ecosystem and scale (Heink and Jax, 2019). Acknowledging the diversity of interpretations, in this paper, we understand the individual cascade components as presented in the Supplementary Material (sheet "ES cascade").

[3] By a "systematic literature review" we understand a review following pre-defined review steps (definition of search terms, reading identified articles using pre-defined exclusion criteria, extracting specific information), as used for instance in Czúcz et al. (2018) or Heyman et al. (2018).

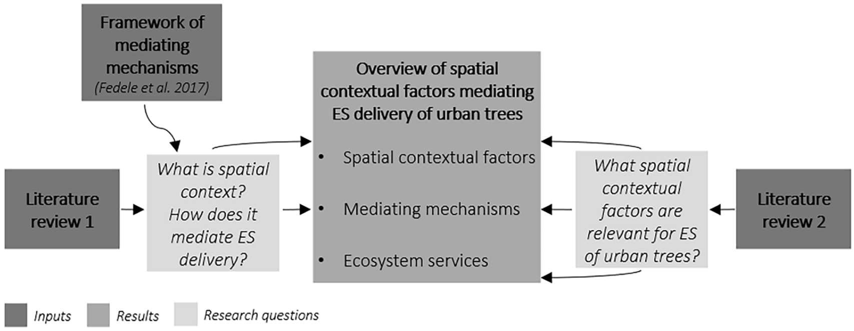

Fig. 1. Methodology workflow.

"mediating factor" OR "spatial context*") AND "ecosystem service*"*. We also used the combination *"context*" AND "cascade" AND "ecosystem service*"* to find articles relating spatial context to the ES cascade. For Web of Science, we did not restrict the timespan of the articles; for Google Scholar, we used the first 20 hits, sorted by relevance.

The database search was conducted on September 17, 2019 and revealed 159 articles from Web of Science and 20 articles from Google Scholar. We complemented the result with four articles recommended by experts in the field.

In the next step, titles and abstracts of the 183 articles were systematically screened using the following three exclusion criteria that narrowed down the selection to 27 articles:

- We excluded duplicate articles,
- We excluded articles that did not use the term "context" in direct relation to ES delivery (e.g., an article stating that "the study is carried out in the context of urban area" would be excluded), or which only vaguely emphasized the effect of spatial context in relation to ES delivery (e.g., an article stating that "considering the context in ES quantification is important" would be excluded),
- We excluded articles that study the concept of spatial context for a particular ES only, or provide concrete examples of spatial contextual factors without the possibility to generalise for all services (e.g. air pollution removal by trees is mediated by pollution concentrations, but this cannot be generalized). However, in case those articles studied urban trees, they were kept as input to Review 2.

In the following step, the full texts of the 27 articles were screened to identify the distinct notions of spatial context related to the mediation of ES delivery. In correspondence with the focus of this paper, we recorded the following information for each notion of spatial context:

- The term used to refer to spatial context,
- The structures or processes that represent spatial context,
- Description of the ways in which spatial contextual factors mediate ES delivery,
- The studied ecosystem,
- An example.

Of the 27 articles, 19 articles did not specify any concrete notion of spatial context in relation to ES delivery (see sheet "Review 1 – ref" in the Supplementary Material for a list of the individual articles). From the remaining 8 articles, we identified 57 distinct notions of spatial context in relation to ES delivery. These were recorded in a table where each row represents one notion and the columns represent the recorded information (see sheet "Review 1" in the Supplementary Material).

In the next step, these 57 notions were manually grouped based on similarities in the structures and processes that can represent spatial context. We identified five general domains of structures and processes and labelled them as *aggregation of biophysical structures*, *natural structures and processes*, *built structures and processes*, *individuals and society* and *maintenance and governance* (see sheet "Domains" in the Supplementary Material for an overview of the identified domains of structures and processes).

Based on the description of the ways in which spatial contextual factors mediate ES delivery, we then associated each notion with one of the four mediating mechanisms from the conceptual framework of mediating mechanisms developed by Fedele et al. (2017), i.e. management, mobilization, allocation-appropriation, appreciation (see sheet "Mechanisms" in the Supplementary Material for an overview of the individual mediating mechanisms). This framework was created to study how humans co-produce ES. To fit this framework to all five identified domains of structures and processes, we used the recorded descriptions of the ways in which spatial contextual factors mediate ES delivery and interpreted the original meaning of the individual mechanisms suggested by Fedele et al. (2017) to capture this wider scope.

2.3. Literature review 2

Relevant literature was primarily identified by a systematic search on the Web of Science database using predefined search terms, limited to peer-reviewed journal articles. Additional articles were identified through recommendations by experts in the field, by reference follow-up and from articles that were kept from Review 1. The following search terms were used to include all articles on trees in urban environments: *("urban tree*" OR "street tree*" OR "urban forest*" OR "green space*" OR "green infrastructure*" OR "park") AND ("urban*" OR "city" OR "cities")*. To limit the search to articles related to quantification or valuation of ES, which are likely to investigate spatial contextual factors mediating ES delivery, the following search terms were used: *("quanti*" OR "valu*")*. To further limit the search to cover literature that investigates tree benefits both with and without an explicit link to the ES framework, we included the search terms: *("ecosystem service*" OR "benefit*")*. Finally, we only included secondary sources (i.e. review articles using the search terms *"review*" OR "literature" OR "synthesi*" OR "meta-analysis"*) to more efficiently gain an overview of the spatial contextual factors used in scientific literature.

The timespan of the articles was not restricted. The database search, conducted on October 23, 2019, resulted in 320 articles in total; 50 additional relevant articles were identified through the reference follow-up, from articles that were kept from Review 1 and from recommendations by experts in the field.

In the title, abstract and full text screening, the following five exclusion criteria were used:

- We excluded articles that did not have urban areas as their primary focus,
- We excluded articles that did not specifically study individual trees or trees as components of larger green areas,
- We excluded articles reporting on original (primary) research (i.e. not being review articles),
- We excluded articles that did not quantify or value ES,
- We excluded articles that did not specify any spatial contextual factors.

Of the 370 articles, the title and abstract screening narrowed down the selection to 118 articles (see sheet "Review 2 – ref" in the Supplementary Material for a list of the individual articles). The full text screening of the 118 articles resulted in a final sample of 52 articles because 66 articles did not specify any spatial contextual factors. This final sample of 52 articles was then screened to identify spatial contextual factors. For each notion of spatial contextual factor identified, we recorded the following information:

- The term used to refer to the spatial contextual factor,
- ES mediated by the spatial contextual factor,
- Text from the paragraph or group of sentences explaining how the spatial contextual factor mediates the ES.

We extracted 861 notions of spatial contextual factors and organised them in a table where each row corresponds to one identified factor and columns correspond to the recorded information (see sheet "Review 2" in the Supplementary Material).

To enable a systematic approach towards the synthesis of the literature review, the recorded information was categorized according to the spatial contextual factor, ES and mediating mechanism.

The identified spatial contextual factors were hierarchically labelled on three levels of aggregation. On the most disaggregate first level, we listed the spatial contextual factors adapted from the individual articles, where factors with similar meaning but different names were assigned a common label. For instance, "distance to adjacent buildings" and "space between trees and buildings" were both relabelled as" distance to building". On the second level of aggregation, we grouped the spatial contextual factors based on the structure or process that is in focus, such as "building" in the case of "distance to building". Further, a distinction was made between factors that explicitly describe the spatial relationship with a tree such as "*distance* to building" or "*visibility* from building" and those where this is only implicit such as "building geometry" or "building type". Finally, on the most aggregate third level, we distinguished between the five general domains of structures and processes representing spatial context as was identified in Review 1: *aggregation of trees* (we adjusted the general name *aggregation of biophysical structures* to fit specifically urban trees), *natural structures and processes*, *built structures and processes*, *individuals and society* and *maintenance and governance*. On all three levels, label "other" was used for factors mentioned in a single article only and label "unspecified" was used for factors that did not specify any concrete description of tree location. See sheet "Factors" in the Supplementary Material for an overview of the identified spatial contextual factors and hierarchical labels and number of citing articles.

The identified ES were hierarchically labelled on two levels. The first level differentiates between the widely used categories of provisioning, regulating, cultural and supporting services (Millennium Ecosystem Assessment, 2003; TEEB, 2010) and ecosystem disservices (Lyytimäki, 2017; von Döhren and Haase, 2015); the second level differentiates between specific services/disservices such as food provisioning, air pollution removal, recreation and health or view blockage. The names of specific services/disservices were adapted from the individual articles and the final list of individual ES is comparable to those used e.g. by Escobedo et al. (2011), Roy et al. (2012), Gomez-Baggethun and Barton (2013) or Säumel et al. (2016). In most cases, it was also possible to find an equivalent ES in the Common International Classification of Ecosystem Services (CICES) (Haines-Young and Potschin, 2018). Label "unspecified" was used in case a spatial contextual factor was mentioned without a link to a particular ES. See sheet "ES" in the Supplementary Material for an overview of the identified ES.

Finally, we associated one of the four mediating mechanisms identified in Review 1 with each identified spatial contextual factor using the recorded information explaining how individual spatial contextual factors mediate ES. If the provided information in the article was unclear at this point, we recorded "unspecified" mechanism.

This strategy of hierarchical labelling allowed us to present the results in more general terms to provide an overview and discuss specific spatial contextual factors in relation to specific ES and the mediating mechanisms related to this.

3. Results

3.1. Conceptual understanding of spatial context and mediating mechanisms in ES delivery

Review 1 showed that in the current ES literature, spatial context is represented by five general domains that together encompass both ecological and social structures and processes (Reyers et al., 2013). We labelled them as *aggregation of biophysical structures*, *natural structures and processes*, *built structures and processes*, *individuals and society* and *maintenance and governance* (see the upper section of Fig. 2). Spatial contextual factors related to *aggregation of biophysical structures* specify the case when the analysed biophysical structure is part of a larger service providing unit, i.e. when the characteristics of the unit or the configuration between the biophysical structures mediate the provided service (Andersson et al., 2015; Keeler et al., 2019). *Natural structures and processes* contain e.g. the position of the biophysical structure in the landscape, various environmental processes such as climate, flooding or air pollution at the location of the biophysical structure, as well as the relationship of the biophysical structure to other organisms (Andersson et al., 2015; Chiabai et al., 2018; Keeler et al., 2019). Spatial contextual factors labelled as *built structures and processes* include man-made infrastructure, land use, urban form or technological solutions, among others (Andersson et al., 2015; Keeler et al., 2019). The domain *individuals and society* contains for instance socio-economical, demographic or cultural context, as well as individually held values or perceptions (Andersson et al., 2015; Fedele et al., 2017; Keeler et al., 2019). Finally, rules, policies or maintenance influencing the biophysical structure are included in the *maintenance and governance* domain (Burkhard et al., 2014; Fedele et al., 2017; Fischer and Eastwood, 2016).

Integrating Review 1 in the framework of Fedele et al. (2017) resulted in a new interpretation of the mediating mechanisms (see the middle section of Fig. 2). In this interpretation, the first mechanism – *management* – can be understood as altering the functioning of the biophysical structure, thereby mediating its capacity (or potential) to provide ES. The name of the mechanism – *management* – might evoke mediation by humans such as protecting or establishing biophysical structures or their maintenance (Burkhard et al., 2014; Fischer and Eastwood, 2016), but in our interpretation, other structures and processes – topography, soils or spatial configuration (Andersson et al., 2015; Keeler et al., 2019) – can alter the functioning of the biophysical structure as well. The second mechanism – *mobilization* – mediates how much of the capacity is turned into a service. By service here we mean the final output of ecosystem function, still linked to the ecosystem. The allocation of this output to potential beneficiaries is mediated by the third mechanism – *allocation-appropriation*. Finally, the fourth mechanism – *appreciation* – mediates the demand for the output and thereby determines the value associated with it.

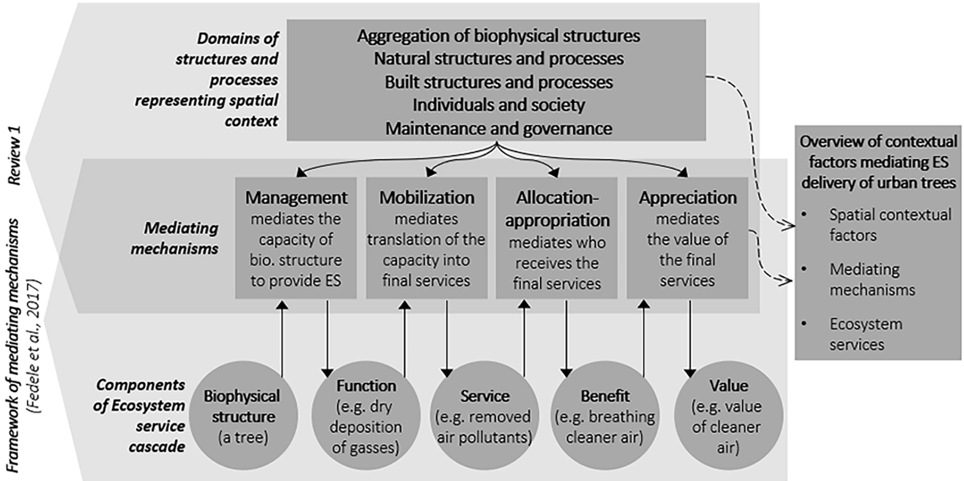

Fig. 2. Review 1 indicated that spatial context can be represented by five domains of structures and processes (upper section). Spatial context mediates ecosystem services by four mediating mechanisms (Fedele et al., 2017), newly interpreted using the findings of Review 1 (middle section). The solid arrows illustrate the linkage between spatial contextual factors, mediating mechanisms and components of the Ecosystem service cascade (bottom section). The dashed arrows illustrate how the results of Review 1 link to the overview of spatial contextual factors developed in this study.

3.2. Spatial contextual factors mediating ecosystem services of urban trees

In Review 2, we identified 861 notions of spatial contextual factors from 52 peer-reviewed journal articles that were categorised into 114 unique spatial contextual factors. These unique spatial contextual factors are organised into an overview that enables filtering the factors by mediated ES and provides information on the mediating mechanisms as well as underlying references. The resulting overview is provided in the Supplementary Material (sheet "Result"). Here, we present findings revealed by a synthesis of the overview.

3.2.1. Spatial contextual factors and the domains of structures and processes

The identified spatial contextual factors cover all five broad domains

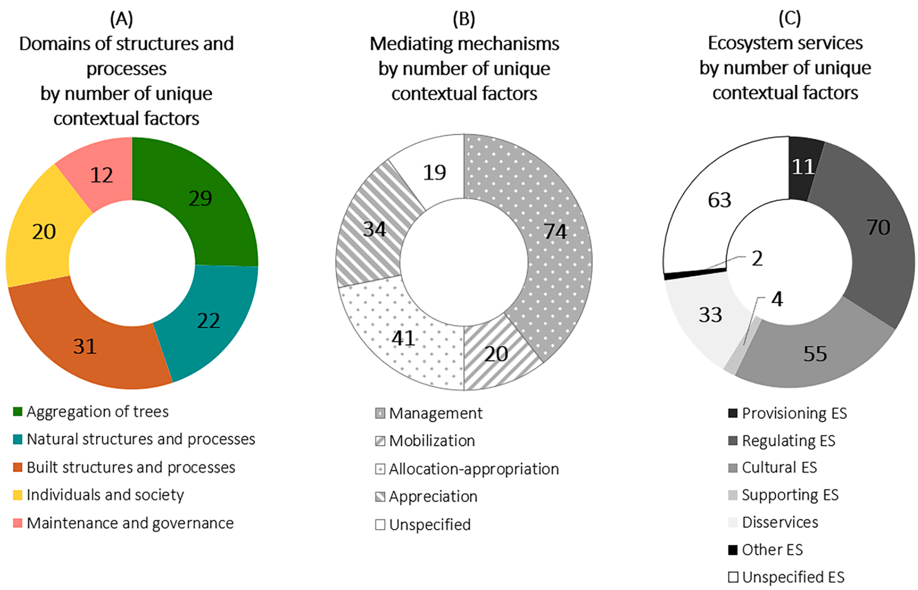

Fig. 3. Domains of structures and processes, mediating mechanisms and ecosystem services summarised by the number of spatial contextual factors within the respective category. In figure (B), category "unspecified" was used when the mediating mechanism of a spatial contextual factor was not explicitly described. In figure (C), category "unspecified" was used when a spatial contextual factor was mentioned without any link to a particular ecosystem service. Numbers of factors in figures (B) and (C) do not sum up to the total number of spatial contextual factors (114) because one factor might be related to more than one mediating mechanism or mediate more than one ecosystem service.

of structures and processes identified in Review 1. These are *aggregation of trees*, *natural structures and processes*, *built structures and processes*, *individuals and society* and *maintenance and governance*. Fig. 3A illustrates the number of spatial contextual factors found in each domain[4]. The largest number of spatial contextual factors is found in the domain *built structures and processes*, followed by *aggregation of trees*.

Spatial contextual factors from the domain *aggregation of trees* are descriptors of the structure and qualities of larger tree aggregates (such as parks, alleys or green corridors) that serve as service providing units. While many ES are delivered by single trees (e.g. air pollution removal), other ES can only be delivered if trees exist in larger aggregations (Andersson et al., 2015). For example, the potential of a tree to provide opportunities for outdoor recreation depends on the tree belonging to a larger green area, as well as on the size and shape of this area, its perceived qualities (safety, auditory environment) and its equipment or infrastructure (trails, benches, playgrounds) (Biernacka and Kronenberg, 2018; Bratman et al., 2019; Keeler et al., 2019).

The domain *natural structures and processes* contains spatial contextual factors related to characteristics of climatic and microclimatic conditions at tree location (e.g. temperature, wind conditions, precipitation), as well as characteristics of soils (e.g. chemical and physical characteristics, soil moisture), land cover (e.g. perviousness), terrain (e.g. site aspect) or water system (e.g. availability of water).

Within the domain *built structures and processes*, spatial contextual factors are related to buildings (e.g. building geometry and orientation), land use/building function (e.g. housing, hospital, but also private or public property), urban form (e.g. street canyon width, sky view factor), configuration of tree to building (e.g. visibility from building, direction to building) or configuration of tree to land use/building function (e.g. proximity or accessibility from housing, accessibility or visibility from hospitals). Included are also man-made environmental problems such as air pollution.

Included in the domain *individuals and society* are descriptors of socio-demographic and personal characteristics of individuals and society such as socio-economic status, cultural background, preferences and attitudes. Included are also spatial contextual factors related to the configuration of trees towards people, such as proximity, accessibility and visibility.

Finally, the domain *maintenance and governance* contains characteristics of maintenance (e.g. fertilization, pruning), institutional characteristics such as planning, policies and regulations and costs and values (e.g. pollutant costs, energy costs).

3.2.2. Mediating mechanisms

All four mediating mechanisms, as adopted from Fedele et al. (2017) and interpreted using the findings of Review 1, participate in the mediation of urban tree ES by the identified spatial contextual factors. In Fig. 3B, the individual mechanisms are compared in terms of the number of spatial contextual factors. *Management* is the most common way in which spatial contextual factors mediate ES, followed by *allocation-appropriation* and *appreciation*. *Mobilization* is the least common mechanism in which spatial contextual factors mediate ES and for 19 spatial contextual factors, the mediating mechanism is unspecified.

3.2.3. Relation between spatial contextual factors and ecosystem services

The identified spatial contextual factors are related to 31 unique ES, which cover the five main groups of ES – *provisioning*, *regulating*, *supporting* and *cultural services* and *ecosystem disservices*. In Fig. 3C, the groups of ES are compared in terms of the number of mediating spatial contextual factors. Most spatial contextual factors are related to regulating services, followed by cultural services. Many spatial contextual factors are also mentioned without any link to a particular ES. In many cases, these factors mediate tree growing conditions and might therefore be relevant for all ES (Jim et al., 2018; Steenberg et al., 2017; Vogt et al., 2017), but because specifications are not given, they are categorized as "unspecified".

The review further showed that some spatial contextual factors can mediate more than one ES. 69 spatial contextual factors mediate more than one ES and the median number of ES mediated by a spatial contextual factor is two. Species diversity is the single spatial contextual factor mediating the largest number of ES (11). ES mediated by species diversity include for instance outdoor temperature regulation (Jim and Chen, 2009), recreation and health (Bratman et al., 2019; Keeler et al., 2019), habitat provisioning (Roeland et al., 2019) and allergy disservice (Goodness et al., 2016).

Fig. 4 shows a ranking of spatial contextual factors on the second level of aggregation (i.e. grouped by the structures or processes in focus) based on the number of mediated ES. Configuration of tree to land use/building function from the domain *built structures and processes* mediates the highest number of ES (15); four groups of ES are mediated (provisioning, regulating and cultural ES and ecosystem disservices). There is no obvious pattern in the sense of a dominant domain that mediates more ES, but three of the five highest-ranked groups of spatial contextual factors exemplify the importance of people as a spatial contextual factor, either through their characteristics (i.e. socio-demographics) or through their spatial relationship with trees (i.e. configuration of tree to land use and building function, configuration of tree to people). Furthermore, three other highly ranked groups relate to the domain *aggregation of trees*, including its natural qualities, configuration and dimensions.

Besides ranking the spatial contextual factors using the number of ES they mediate, we can also investigate the dependency of individual ES on spatial contextual factors. Fig. 5 shows the 10 ES that are associated with the highest number of spatial contextual factors (a full list of ES is provided in sheet "ES" in the Supplementary Material). Recreation and health is mediated by the largest number of spatial contextual factors (53), mostly from the domain of *aggregation of trees* (e.g. its dimensions, perceived qualities or natural qualities mediating the suitability of the aggregation of trees for recreation) and *individuals and society* (e.g. personal characteristics and socio-demographics mediating the demand for/appreciation of the recreation service). This is followed by four regulating ES, all mediated by more than 15 spatial contextual factors, while the median number of spatial contextual factors mediating an ES is five.

3.2.4. Relation between domains of structures and processes, mediating mechanisms and ecosystem services

Fig. 6 summarises the resulting overview while making explicit the relationships between domains of structures and processes representing spatial context, mediating mechanisms and ES, which are illustrated as nodes in the graph. The width of edges between the nodes is proportional to the number of spatial contextual factors between the respective nodes. The colour of the edges corresponds to the colour of the respective domains. Reading the graph from the left side provides insight into which groups of ES the literature has identified as being mediated by a particular domain of structures and processes. For instance, spatial contextual factors from the domain *aggregation of trees* mediate all five groups of ES, but cultural ES are associated with the largest number of spatial contextual factors from this domain. On the other hand, *natural structures and processes* mediate only three groups of ES – regulating ES, cultural ES and ecosystem disservices. Starting from the right side of the graph, the figure also shows which domains of structures and processes the literature identifies as mediating a particular group of ES. For instance, cultural ES are predominantly mediated by the domain *aggregation of trees* and to a smaller extent by *natural structures and processes*, *built structures and processes* and by a few factors from the remaining domains. Supporting ES, on the other hand, are only

[4] Domains labelled as "unspecified" and "other" are not included in the figure. Factors included in these domains were not assigned with a common label and therefore cannot be counted.

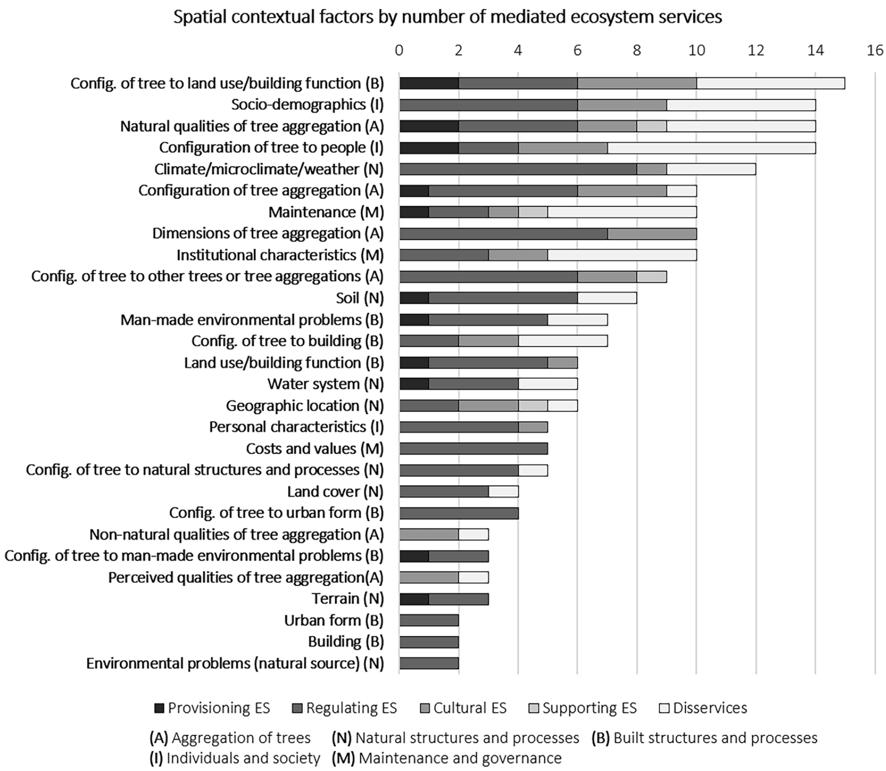

Fig. 4. Spatial contextual factors aggregated by similar structures and processes and ordered by the number of mediated ecosystem services. number of citations was used to determine the order in case of an equal number of mediated ecosystem services.

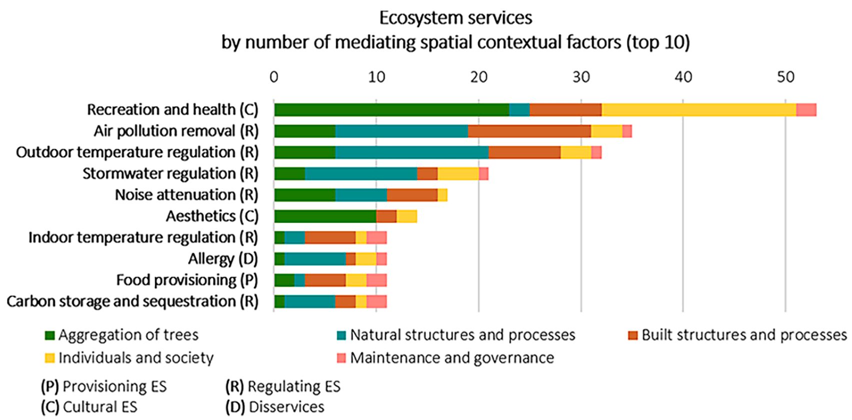

Fig. 5. Top 10 ecosystem services of urban trees ordered by the number of spatial contextual factors that mediate them. Unspecified services are not included in the diagram.

mediated by factors from the domain *aggregation of trees*. Finally, reading the graph from the perspective of mediating mechanisms makes it possible to see that *management* is the most common mechanism by which spatial contextual factors mediate all groups of ES of urban trees. The highest number of spatial contextual factors that mediate ES through *management* is within the domains *aggregation of trees* and *natural structures and processes*. *Built structures and processes* mostly mediate through *allocation-appropriation* and *management*, while for *individuals and society* and *maintenance and governance*, *appreciation* is the most common mediating mechanism. Only two spatial contextual factors mediate ES through *management* within the domain *individuals and society*, namely “proximity to people” and “knowledge”; because these two factors mediate two different services (fear and stress and carbon storage and sequestration, respectively), the width of respective edges between

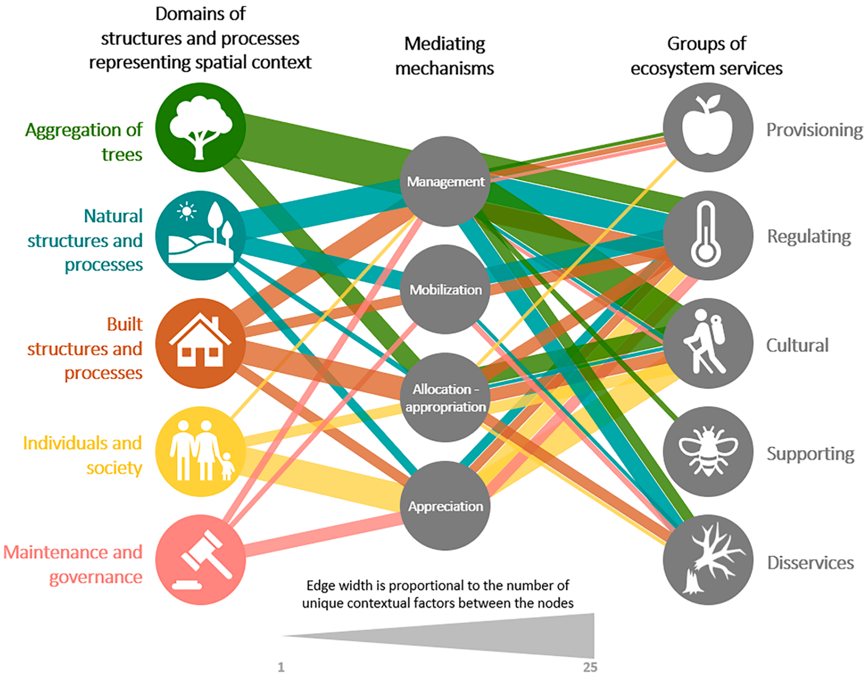

Fig. 6. Relationship between domains of structures and processes representing spatial context, mediating mechanisms and groups of ecosystem services (visualised as nodes). The width of edges between the nodes is proportional to the number of spatial contextual factors between the respective nodes. The colour of the edges corresponds to the colour of the respective domains. Edges containing only one spatial contextual factor (width equal to one) or related to other and unspecified factors, mechanisms or services are not shown.

mediating mechanisms and groups of ES is equal to one and therefore the edges are not shown.

4. Discussion

Our findings support other studies that emphasize the role of spatial context in the delivery of ES by urban trees and urban ecosystems (e.g. Andersson et al., 2015; Salmond et al., 2016; Wilkerson et al., 2018). Our findings complement these earlier studies by providing an overview of concrete spatial contextual factors that previously was missing and further linking the spatial contextual factors to specific ES of urban trees while keeping explicit the ways in which the factors mediate the ES (i.e. mediating mechanisms). The overview contains 114 unique spatial contextual factors related to 31 ES of urban trees and mediating through all four mechanisms introduced by Fedele et al. (2017).

Besides the overview, the results presented in this paper also help to draw more general conclusions on how tree location affects ES delivered by urban trees. For instance, species diversity is the single spatial contextual factor mediating the largest number of ES (11), which might be an important finding given the ongoing biodiversity loss in urban areas (Elmqvist et al., 2013). Most spatial contextual factors were found within the domain *built structures and processes*, which makes the understanding of where to plant trees an important question for architects and planners involved in urban development.

The review showed that *management* is the most common mechanism by which spatial contextual factors mediate all groups of ES of urban trees. In the ES cascade, this mechanism mediates the link between biophysical structure and ecosystem function, altering the functioning of the biophysical structure and thereby mediating its capacity to provide ES. All the consecutive components of the cascade, i.e. service, benefit and value, are therefore also affected by spatial contextual factors that mediate through *management*, which makes these spatial contextual factors particularly important for the delivery of ES by urban trees.

We have further shown that spatial contextual factors are often multifunctional in terms of the ES they mediate – one spatial contextual factor can affect many ES. These multifunctional factors could be described as the more important ones to include in tree planting strategies because they affect more than one ES and can thus represent an efficient use of resources. They are also potentially cost-effective points for measuring ecosystem condition for the purpose of urban ecosystem accounting (Keith et al., 2019; Wang et al., 2019). Our findings suggest that people are highly multifunctional spatial contextual factors, directly through their physical location or socio-demographic profile and indirectly through different land uses or building functions. This finding, in turn, highlights the significance of whom the user of the service is, such as specific groups in society or specific building functions. This highlights again the importance of planning and design in tree planting strategies.

Our results can be used to give insight into the dependency of individual ES on spatial contextual factor, where ES mediated by many spatial contextual factors can be interpreted as highly dependent on design and planning. The number shows a large variation. The most spatial context-dependent ES of urban trees is recreation and health, followed by various regulating services such as air pollution removal and outdoor temperature regulation. Without having direct evidence, a hypothesis further derived from these results is that this highlights the need for integrative planning approaches, because of the risk that such highly mediated and spatial context-dependent ES are more easily neglected in sectorized or 'siloed' urban planning processes. It also highlights a need for tools to measure the complex impact of spatial context on tree performance.

4.1. Relevance for urban planning and tree planting strategies

Besides the better understanding of how tree location affects ES delivered by urban trees as discussed above, the information in the resulting overview is aggregated at a level we believe could be useful for providing planning practice with knowledge to develop tree planting strategies that better support the delivery of ES. For instance, planting strategies can become more effective in delivering ES through a better understanding of where trees are most needed or where tree planting should be avoided because the spatial context endangers tree survival or substantially increases management costs. The overview developed in this paper can support planting strategies by allowing planners and other professionals and researchers to query the overview in different ways. For example, the results can help to answer a question such as "which spatial contextual factors need to be taken into account when planting trees for a particular ES?". For example, to support air pollution removal, there are 29 spatial contextual factors to be considered, sorted by the domain of structures and processes (Table 1).

Table 1
Spatial contextual factors mediating air pollution removal by urban trees, obtained by querying the resulting overview and sorted by the domain of structures and processes.

Domains of structures and processes	Spatial contextual factors	Mediating mechanisms
Aggregation of trees	Height of tree aggregation	Management
	Width of tree aggregation	Management
	Species diversity	Management
	Density of tree aggregation	Management
	Connectivity to other trees/ aggregations of trees	Management
	Proximity to other trees/ aggregations of trees	Management
Natural structures and processes	Climate	Management
	Humidity	Management, Mobilization
	Light conditions	Management
	Precipitation	Management
	Temperature	Management, Mobilization
	Ventilation	Management
	Weather	Management
	Wind direction	Management, Mobilization, Unspecified
	Wind speed	Management, Mobilization, Unspecified
	Proportion of canopy cover to other land covers	Management
	Soil moisture	Management
	Water availability	Management
	Proximity to coast	Appreciation
Built structures and processes	Traffic density	Mobilization
	Proximity or accessibility from housing	Allocation-appropriation
	Proximity or visibility from hospitals	Allocation-appropriation
	Proximity to green areas	Allocation-appropriation
	Proximity to infrastructure	Appreciation, Management, Mobilization
	Proximity to parking locations	Allocation-appropriation
	Air quality	Management, Mobilization
	Proximity to air pollution source	Mobilization
	Street canyon aspect ratio	Management
	Street canyon width	Management
	Urban form type	Management
	Position in street canyon	Management
Individuals and society	Behaviour	Appreciation
	Health	Appreciation
	Age	Appreciation
Maintenance and governance	Pollutant costs	Appreciation

The overview can also be used to understand how a specific spatial contextual factor affects ES delivery by urban trees, i.e. it can help to answer the question "which ES provided by a particular tree would be altered by changes in the surrounding structures and processes?". For example, "area of tree aggregation" mediates six different ES including regulating and cultural services and changing the area of tree aggregation will affect carbon storage, outdoor temperature and wind regulation, aesthetics, recreation and health, and social cohesion (Table 2). Further, "visibility from building" mediates two cultural services, and "socio-economic status" mediates 10 different ES including regulating and cultural services and ecosystem disservices.

The range of applications based on the overview presented in this paper is potentially much wider. Apart from scoping strategic tree planting, the overview could serve as a checklist in urban open space design processes (Jansson and Randrup, 2020). Furthermore, the overview provides useful information for generalizing valuation studies to entire urban accounting areas, where some form of benefit transfer is required (Johnston et al., 2020). Benefit transfer assumes that the contextual factors are constant, or possible to control for, between the reference and transfer site and that there are value function and meta-analytic transfer methods to deal with known differences. The overview presented in this study provides a systematic list of contextual factors that need to be considered to minimize the risks for over- or underestimations with benefit transfers.

Table 2
Ecosystem services mediated by spatial contextual factors "area of tree aggregation", "visibility from building" and "socio-economic status", obtained by querying the resulting overview.

Spatial contextual factors	Ecosystem services		Mediating mechanisms
Area of tree aggregation	Regulating services	Carbon storage and sequestration	Management
	Regulating services	Outdoor temperature regulation	Management
	Regulating services	Wind regulation	Management
	Cultural services	Aesthetics	Management
	Cultural services	Recreation and health	Allocation-appropriation, Management
	Cultural services	Social cohesion	Management
Visibility from building	Cultural services	Aesthetics	Allocation-appropriation
	Cultural services	Recreation and health	Allocation-appropriation
Socio-economic status	Regulating services	Outdoor temperature regulation	Appreciation, Unspecified
	Regulating services	Stormwater regulation	Appreciation
	Regulating services	Water supply	Appreciation
	Cultural services	Education	Appreciation
	Cultural services	Recreation and health	Appreciation
	Disservices	Allergy	Appreciation
	Disservices	Damages to infrastructure	Appreciation
	Disservices	Decrease in air quality (ozone and PM formation)	Appreciation
	Disservices	Fruit and leaf fall	Appreciation
	Disservices	Maintenance emissions	Appreciation

4.2. Limitations and future research

The overview of spatial contextual factors revealed by the review and its synthesis presented here does not claim to cover the full range of spatial contextual factors mediating ES of urban trees. First, the review did not include grey literature such as research reports, design guidelines or policy reports. This might have influenced the results towards dominance of factors where data are available, while design guidelines or policy reports might have been more focused on factors that can be influenced through design. Second, due to a so-called "street light effect", spatial contextual factors that are more often discussed in the scientific literature might be overrepresented, while spatial contextual factors that are less studied might not have been revealed. It should therefore be noted that if a particular link between ES, mediating mechanism and spatial contextual factor was not uncovered, it does not mean that such a link does not exist or is not important, but rather that it was not addressed in the literature. Moreover, when identifying spatial contextual factors, we intended to distinguish between all small nuances available from the reviewed articles. In consequence, ES of urban trees studied in larger detail are likely to reveal larger numbers of more detailed spatial contextual factors. For instance, we found a great number of spatial contextual factors related to regulating ES and only a small number of factors related to supporting ES. However, this does not necessarily mean that supporting ES are less context-dependent, but rather that the current research focuses more on regulating ES of urban trees.

Furthermore, the results are also affected by the categorization choices made when aggregating spatial contextual factors. This is a general issue relevant to any categorization task. We acknowledge that some spatial contextual factors may be categorised differently or placed in between two categories. For instance, we placed the factor "air quality" in the domain *built structures and processes*, because it can be considered a consequence of human activity. However, one might argue that this factor can also be placed in the domain *natural structures and processes*. Similarly, associating some spatial contextual factors with mediating mechanisms was not always straightforward. For example, various environmental problems such as air pollution can be interpreted as either *mobilization* (i.e. mediating how much of the capacity to provide an ES is turned into an actual service) or *appreciation* (i.e. mediating the demand for the ES). To be transparent about our choices and allow for future modifications based on new insights, we, therefore, provide all data used in the process of our categorization choices in the Supplementary Material.

For the aggregate presentation of the resulting overview of spatial contextual factors, we have summarized the spatial contextual factors by the number of ES they mediate and domains of structures and processes, ecosystem services and mediating mechanisms by the number of spatial contextual factors. However, caution must be paid when drawing conclusions from these relative frequencies, as they do not aim to express the relative importance of individual spatial contextual factors. This information can be found by searching the individual articles, but a meta-analysis quantifying the effect of individual spatial contextual factors in ES delivery by urban trees would be an important next step for developing the understanding of ES of urban trees.

Future research could also investigate how spatial contextual factors are currently addressed in urban planning practices to assess the ease of implementing the different factors in planning, as well as explore how to make practitioners in different sector agencies more aware of factors that are currently not addressed. Another direction for future research considers the quantification and modelling of spatial contextual factors to make ES assessments of existing urban environments and evaluate design proposals. For example, quantifying spatial contextual factors can provide empirical evidence for planning practice in assessing various tree planting strategies. Furthermore, quantification of tree characteristics, including spatial contextual factors, is in many cases the foundation for tree valuation based on the delivered ES using tools such as i-Tree Eco or VAT03 ("i-Tree Eco v.6," n.d.; Randrup et al., 2018). Cost-effective ecosystem condition accounting could further be improved by including actual mediators of ES, rather than ad hoc compilation of available environmental monitoring data. Therefore, future work should also investigate methods for quantification and modelling spatial contextual factors.

The resulting overview presents spatial contextual factors – however, the spatiality of the individual factors varies. For example, the factors "management practices" or "personal characteristics" are not explicitly spatial but can be understood as occurring in space and vary across different locations. On the other hand, the factor "visibility of tree to people" is a clear example of high spatiality. We believe that this distinction can be useful for addressing the spatial context of urban trees in urban planning practice. For example, the largest number of spatial contextual factors explicitly mentioning the spatial relationship between a tree and a structure or process was found within the domain *built structures and processes*, which highlights the complexity of the design question at hand – it is not only the presence of buildings or transport which is relevant for the delivery of ES by urban trees but also the proximity or visibility of them. Thinking of the spatial component of the identified factors on a gradient between absolute and relative space (Harvey, 2004) might be useful for this purpose. Similar variability can be found in the spatial and temporal resolutions and scales of the identified spatial contextual factors. For example, while climate describes the global spatial context, weather describes a more local spatial context; in a similar manner, climate and weather describe two very different temporal scales. We consider these ways of thinking worth further exploration. In addition, we also see a potential for further research in the development of advanced spatial analysis methods that will enable to quantitatively assess and model these highly-spatial or large-scale contextual factors.

Given the relatively small number of articles identified in Review 1 (8), there is uncertainty in the proposed categorisation of domains of structures and processes representing spatial context and in the interpretation of mediating mechanisms. In consequence, the result of Review 1 should not be interpreted as the final defined set of categories and relations. Instead, it should be understood as a proposal for organising the links between ES, mediating mechanisms and spatial contextual factors. Further research is needed to establish a more solid conceptual understanding of spatial context in the ES delivery process. In this paper, we have chosen to build our conceptual understanding of spatial context around the ES cascade framework developed by Haines-Young and Potschin (2010) and Fedele et al. (2017), but other conceptual frameworks could possibly have been used instead (for an overview of various ES frameworks, see e.g. Fisher et al. (2013)). However, the choice of a framework was not at the core of this study and merely used to reach the main objective of this paper. To build a solid conceptual understanding of spatial context in ES delivery, future research should explore and discuss the effect of the various ES frameworks. The insight developed in this study can be used as a starting point.

5. Conclusions

The influence of spatial context on the delivery of ES has been highlighted before (e.g. Andersson et al., 2015; Wilkerson et al., 2018; Bruckmeier, 2016). In this paper, we have developed a systematic overview of spatial contextual factors that are currently recognised by research as being relevant for the delivery of ES by urban trees, in order to support tree planting strategies effective at the delivery of ES.

Our findings point out the importance of design and planning in supporting ES delivery by urban trees. First, of all spatial contextual factors, people are found to mediate the highest number of ES of urban trees. Second, the highest number of spatial contextual factors was found within the domain *built structures and processes.*

The overview developed here enables researchers as well as urban planners and tree managers to identify the spatial contextual factors that are of importance to a particular ES and see which ES are mediated by a particular spatial contextual factor. This, in turn, will provide the knowledge needed to ensure, support and maintain ES of urban trees and bring more insight into developing tree planting strategies that are more effective in providing ES.

The overview might further benefit other practical applications such as environmental benefit transfer (Johnston et al., 2020) or ecosystem condition accounts (Keith et al., 2019; Wang et al., 2019) in the context of experimental ecosystem accounting. A meta-analysis of the importance of individual spatial contextual factors in terms of their impact on ES delivery remains to be addressed by future research.

Finally, by uncovering which structures and processes represent the spatial context in general and then associating the role of spatial context, through mediating mechanisms, with the ES cascade, we have also contributed to a better conceptual understanding of what spatial context is in relation to ES delivery in general.

CRediT authorship contribution statement

Zofie Cimburova: Conceptualization, Methodology, Formal analysis, Writing - original draft, Writing - review & editing, Visualization. **Meta Berghauser Pont:** Conceptualization, Writing - original draft, Writing - review & editing, Supervision.

Declaration of Competing Interest

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

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Appendix A. Supplementary data

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Paper II

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Research Paper

Viewshed-based modelling of visual exposure to urban greenery – An efficient GIS tool for practical planning applications

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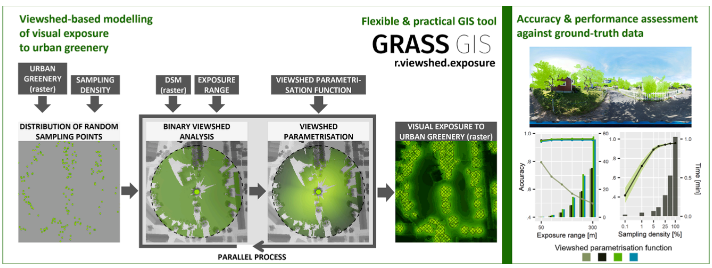
HIGHLIGHTS

- We developed a geospatial method for modelling visual exposure to urban greenery.
- Implementing the method in GRASS GIS ensures its wide applicability and flexibility.
- High computational efficiency enables city-wide assessment on commodity hardware.
- Viewshed parametrisation and high-quality data needed for high modelling accuracy.

GRAPHICAL ABSTRACT



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ABSTRACT

Quantifying green visual exposure is necessary to assess aesthetic, social and health benefits from urban greenery. Viewshed analysis has been successfully used to model and map green visual exposure from human perspective in continuous representation and in places where street view imagery for widely-used photography-based methods is not available. However, current viewshed-based methods for modelling green visual exposure are often difficult to generalise beyond their specific application purpose, inefficient in processing large spatial extents and have limited use due to demands on technical knowledge. This hampers their wider use in research and practice. In this paper, we develop a viewshed analysis-based method for modelling visual exposure to urban greenery with special focus on the method's applicability in research and practice. The method is implemented as a tool in GRASS GIS which makes it available as a practical and flexible tool. Extensive validation and assessment of the method on the specific case of urban trees confirm that the method is a highly accurate alternative to modelling visual exposure from street view imagery ($\rho = 0.96$) but that data quality and viewshed parametrisation are essential for achieving accurate results. Thanks to parallel processing and effective implementation, the method is applicable for city-wide scale analysis with high-resolution data on commodity hardware (here illustrated on the case of Oslo, Norway). Therewith, the method has potential application in many areas including strategic tree planting, scenario modelling and urban ecosystem accounting, as well as ecosystem service research.

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1. Introduction

Urban greenery has the potential to mitigate urban issues associated with rapid urban growth and climate change (Demuzere et al., 2014) by providing numerous ecosystem services (Millennium Ecosystem Assessment, 2003; TEEB, 2010), including temperature regulation, air and noise pollution mitigation, recreation opportunities and habitat for biodiversity (Bolund & Hunhammar, 1999; Gomez-Baggethun & Barton, 2013). This leads to economic, social, physical and mental health benefits and increases the wellbeing of urban citizens (Keniger et al., 2013; Office for National Statistics (ONS), 2019). An important pathway in receiving many benefits from urban greenery is visual exposure. Green visual exposure contributes to psychological, cognitive and physiological wellbeing (Kaplan, 2001; Lottrup et al., 2015; Ulrich, 1984). Further, visible greenery has aesthetic and amenity benefits (e.g., Schroeder & Cannon, 1983; Thayer & Atwood, 1978), thereby increasing neighbourhood walkability and property prices (Ki & Lee, 2021; Tyrväinen & Miettinen, 2000). Finally, green visual exposure leads to numerous social benefits, including reduced crime rates and increased perceived safety (e.g. Troy et al., 2012; Wolfe & Mennis, 2012; Mouratidis, 2019). Central to better understanding the relations between green visual exposure and associated benefits and applying these findings in practice is the possibility to quantitatively assess green visual exposure.

1.1. State of the art in quantitative assessment of green visual exposure

The amount of green visual exposure has traditionally been assessed manually. For instance, to study how street greenery affects health, De Vries et al. (2013) quantified visible greenery by direct observation in the field, while in the studies of Hazer et al. (2018) and Lottrup et al. (2015), the amount of visible greenery was self-reported by the study participants. Such manual approaches have been discussed as labour intensive and thus inefficient in large-scale field assessments and prone to human errors and bias due to observer subjectivity (Helbich et al., 2019). This hampers applying these approaches in e.g. dynamic green visual exposure assessment across space and time (Helbich, 2018) or urban planning applications.

In recent years, automatic methods for quantitative assessment of green visual exposure have been developed, focusing mainly on assessment from photographs and geospatial modelling. To our best knowledge, Aoki et al. (1985) were the first to measure the proportion of vegetation pixels in street photographs obtained from a human perspective and finding that it is an efficient measure of how much urban greenery people observe from a fixed observation point. The method has later been referred to as a Green View index (Yang et al., 2009) and gained attention and has been technically further developed thanks to the increased availability of street view images from databases of Google, Tencent or Baidu that minimise the need for manual photography (Helbich et al., 2019; Larkin & Hystad, 2019; W. Wang et al., 2019). However, the dependency on street images hinders applying the method in places and regions where street view imagery is not yet available (Rzotkiewicz et al., 2018) or where it usually is not obtained, such as backyards (Villeneuve et al., 2018). Because the green view index values are only available at photography points, the method is not suitable for purposes where continuous representation of green visual exposure is desired. Moreover, although the type of greenery affects the benefits obtained (Reid et al., 2017), photography-based methods usually do not enable such differentiation (Sun et al., 2021).

An alternative method that addresses many shortcomings of the photography-based methods is geospatial modelling of green visual exposure. It is not dependent on the availability of street view imagery and scales easily to large spatial extents. Raster-based geospatial analyses enable continuous representation of green visual exposure and can be used to analyse various types of urban greenery e.g., available from landcover maps provided by remote sensing (Yan et al., 2018). Numerous studies modelled green visual exposure with geospatial analysis as green coverage within properties, within specific radii from residence place or within census tracts (e.g., Troy et al., 2012; Ward Thompson et al., 2016; Wolfe & Mennis, 2012). Unlike photography-based methods, such aerial-perspective approaches however often fail to capture the amount of urban greenery visible from the perspective of people at ground level. The correlation between the amount of urban greenery observed from human versus aerial perspective is likely low (Helbich et al., 2019; Larkin & Hystad, 2019) or insignificant (R. Wang et al., 2019), and these two measures might capture different aspects of urban greenness (Falfán et al., 2018; Villeneuve et al., 2018).

A potentially powerful tool to reflect human visual perspective in geospatial modelling is viewshed analysis, which delineates the area visible from a given observation point, taking into account the surrounding terrain features (Petrasova et al., 2015). However, in green visual exposure modelling, viewshed analysis has been used sparsely (e.g., Łaszkiewicz & Sikorska, 2020; Nutsford, Pearson, Kingham, & Reitsma, 2016; W. Wang et al., 2019), and the potential for modelling green visual exposure in continuous representation remained largely unused, likely due to high computational workloads and dependency on high-resolution spatial data (Qiang et al., 2019; Tabrizian et al., 2020). Only recently have first studies begun experimenting with viewshed analysis to model green visual exposure in continuous representations and large-scale study areas. For example, Tabrizian et al. (2020) analysed the visibility of various vegetation classes from 39,321 viewpoints regularly displaced in a grid, and Labib et al. (2021) used viewshed analysis to assess visibility of greenery at all 86 million pixels of a region-wide raster map. The latter approach has recently been made available as an R-package (Brinkmann & Labib, 2021). These studies showed that geospatial modelling with viewshed analysis can successfully be used to model green visual exposure from human perspective, in continuous representation, in large spatial extents and at places where street view imagery is unavailable.

However, several challenges hinder wider applicability of these novel methods. First, the method settings (e.g., exposure range) have often been fixed for specific application purposes, which hampers their generalisation outside the original scope. In addition, the sensitivity of modelling accuracy to those settings has not been systematically studied (Labib et al., 2021), and current methods do not offer the flexibility to conduct such assessment. Second, the methods are often provided as scripts, and their usage requires a higher degree of technical knowledge, which limits their practical applicability. Third, analysing large spatial extents, such as entire cities, in large detail can take significant amount of time, even when using high-performance computing systems which are not commonly available to practitioners and require significant technical skills (Labib et al., 2021).

1.2. Paper objectives

Our aim in this paper is to build on the work of Labib et al. (2021) and Tabrizian et al. (2020) and develop a viewshed-based method for modelling visual exposure to urban greenery with special focus on the method's general applicability in research and practice. In particular, the method should be (i) integrated as a tool in open-source geographical information system (GIS) to lower the threshold for usage and to increase the method's flexibility, thus enabling adjusting the method to different application purposes and simplifying empirical assessment of the method's settings in relation its performance, (ii) empirically assessed against ground-truth to demonstrate how the settings influence the method's performance in terms of accuracy and processing time, which also provides guidelines for application of the method in praxis and (iii) computationally efficient so that large spatial extents and high-resolution datasets can be analysed on commodity hardware.

The method is assessed on the specific case of urban trees but can be applied similarly to analyse visual exposure to other types of urban greenery. Urban trees are used for three reasons. First, trees are an urban asset often managed and valued separately from other greenery (Nowak, 2017). Second, the benefits obtained by visual exposure to trees might be different from those of other types of urban greenery (Reid et al., 2017). Finally, trees significantly impact green visual exposure due to their vertical dimension and are thus an effective way of creating green views in urban areas where space is often limited (Yang et al., 2009).

2. Methods

2.1. Background of visibility modelling in geospatial analysis

The method for modelling visual exposure to urban greenery is based on viewshed analysis, a geospatial analysis method applied to a digital surface or terrain model that delineates the area (viewshed) visible from a given pixel (observation point) by determining whether the view between the observation point and all other pixels (target points) within a given radius is obstructed. The analysis returns a map where visible and non-visible pixels are usually coded as 1 and 0, respectively (Petrasova et al., 2015).

Research suggests that a binary viewshed representation – with visible and non-visible pixels – does not accurately reflect visibility from human perspective because it fails to account for the variable visual significance of the observable objects from the observer's point of view (Chamberlain and Meitner, 2013; Ervin and Steinitz, 2003; Nutsford et al., 2015; Ogburn, 2006). The visual significance is affected by the properties of the observed objects (e.g. size, contrast between the object and surroundings), observer's characteristics (e.g. visual acuity and resolving capacity of human eye), the environment between the observed objects and the observer (e.g. light and atmospheric conditions) and their relative spatial configuration (e.g. distance, slope and aspect) (Domingo-Santos, 2017; Groß, 1991; Ogburn, 2006).

Therefore, various viewshed parametrisation functions have been developed, where focus was put mainly on accounting for the effect of spatial configuration between the observed objects and the observer (e.g. Chamberlain and Meitner, 2013; Domingo-Santos et al., 2011; Grêt-Regamey et al., 2007; Nutsford et al., 2015). These functions build on the concepts of solid angle (Groß, 1991), visual magnitude (Iverson, 1985; Travis et al., 1975) and vertical visual angles (Llobera, 2003). Visual magnitude and vertical visual angle quantify the portion of the observer's field of view occupied by the observed object, depending on its slope, aspect and distance relative to the observer. Solid angle is a direct measure (in steradians) of the surface area of the observer's eye retina covered by the projection of the observed object. Another approach is fuzzy viewshed analysis which simulates the decreasing clarity of the observed objects with increasing distance from the observer due to atmospheric and lighting conditions (Fisher, 1994; Ogburn, 2006).

In this paper, we implement the visual magnitude algorithm of Chamberlain and Meitner (2013) and the solid angle algorithm of Domingo-Santos et al. (2011). We further implement a simple exponential distance decay function used in the visual magnitude algorithms of Chamberlain and Meitner (2013) and Grêt-Regamey et al. (2007) to see whether the sole effect of distance (i.e. omitting slope and aspect) can adequately capture the visual impact of greenery. We do not implement the fuzzy viewshed function because atmospheric extinction is likely a minor issue for green visual exposure in urban areas. The individual viewshed parametrisation functions are described in the Supplementary Material.

Of specific relevance for modelling visual exposure is analysing the composition of the viewshed, i.e. the portion of viewshed made up by the studied exposure source, here urban greenery. This analysis, also referred to as viewscape analysis (Tabrizian et al., 2020), has been used previously in landscape aesthetics assessment (Grêt-Regamey et al., 2007), hedonic pricing studies (Bishop et al., 2004) or to study how view characteristics affect mental health (Nutsford et al., 2016; Tabrizian et al., 2020). To achieve an area-wide, continuous representation of visual exposure, the analysis of viewshed composition is usually calculated for all possible observation points (pixels) that make up the study area (Labib et al., 2021; Tabrizian et al., 2020). However, such a procedure is computationally intensive, especially if the spatial extent or resolution of the analysed area is large. If the number of possible observation points is larger than the number of pixels representing the exposure source, the computational efficiency can be increased by reversing the perspective and taking the observation points as targets and the exposure source pixels as observers, assuming their mutual visibility. Viewsheds calculated from the exposure source pixels represent the areas visually exposed to that pixel. Such an approach is often used in visual impact assessment (e.g. Minelli et al., 2014; Ogburn, 2006). Adding up the individual viewsheds then results in a continuous representation of visual exposure, referred to as a cumulative viewshed (Wheatley, 1995). Such modelling approach also seems suitable for the method developed in this paper, as in urban areas, the number of possible observation points is often larger than the number of green pixels. In addition, we hypothesise that computing visual exposure from a random sample of all exposure source pixels can yield adequate accuracy while decreasing processing times significantly, especially when analysing large-extent, high-resolution datasets.

2.2. Method development

2.2.1. Processing workflow

Input spatial datasets to the developed method are (i) a raster map of urban greenery and (ii) a high-resolution digital surface model (DSM). A DSM is a continuous representation of surface heights, including built and natural structures such as trees. Importantly, a DSM is a 2.5D representation of space, i.e. all surface locations have single elevation information. The processing workflow of the method consists of four steps (Fig. 1). First, the input map of urban greenery is randomly sampled by vector points in specified sampling density. The second and third step are executed iteratively for each sampling point. In the second step, a binary viewshed is generated from the sampling point. The point height above the DSM is 0 m (i.e. the viewshed is generated from surface of the greenery). The user can control the height of the observer on the ground and viewshed radius (i.e. range of visual exposure). In the third step, the binary viewshed can be parametrised by one of the three implemented viewshed parametrisation functions (solid angle, visual magnitude, distance decay). Finally, visual exposure values from viewsheds generated from all sampling points are added, resulting in a continuous raster map of visual exposure to urban greenery.

2.2.2. Method implementation

The method was implemented as a tool ("AddOn") called *r.viewshed.exposure* to the Geographic Resources Analysis Support System (GRASS) GIS, which is a cross-platform multi-purpose GIS software offering more than 300 analytical tools and a growing number of AddOns that extend the core functionality. The source code of GRASS GIS is available under the GNU General Public License (Neteler et al., 2012). GRASS GIS offers the underlying functionality that makes it a suitable platform for implementing the method developed in this paper, namely an efficient tool for viewshed analysis *r.viewshed* (Toma et al., 2020) and a comprehensive Python API, including integration with NumPy.

We wrote the algorithm of *r.viewshed.exposure* with computational efficiency in mind. For example, many operations of the algorithm are conducted in memory, reducing the time needed for writing and reading operations. Computational efficiency was further increased by parallelizing the iterative operations. To enable wide usage of *r.viewshed.exposure* in practical applications, sampling density, observer height, visual exposure range and viewshed parametrisation function were implemented as user-specified settings.

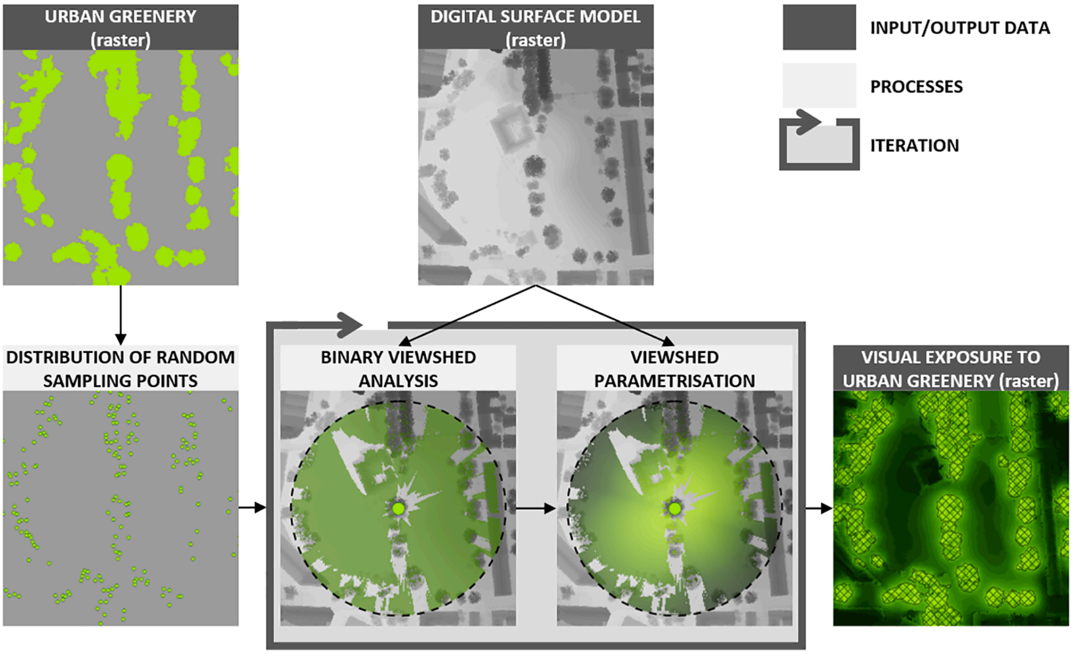

Fig. 1. Processing workflow of the developed method for modelling green visual exposure. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2.3. Method assessment

The method was assessed on the specific case of urban trees from two perspectives. First, we assessed the method against ground-truth data to see how the method's accuracy and processing time vary in response to the method's settings. Second, we assessed the computational efficiency of the method in a city-wide application with high-resolution data.

2.3.1. The effect of variation in the method's settings

The method was assessed by comparing values of visual exposure to urban trees modelled with *r.viewshed.exposure* against percentage of tree canopy manually delineated in full view (360° × 180°) panoramas obtained at 94 validation points, randomly distributed in sampling areas stratified across 11 urban form types of Oslo, Norway. Measuring the percentage of greenery in photographs is a common method to assess the amount of greenery observed from a human perspective (Yang et al., 2009). Each validation point was associated with accurate geographic coordinates to extract the modelled values of visual exposure and obtain the validation photographs at the same location. A detailed description of the process of obtaining validation data is provided in the Supplementary Material.

The settings of *r.viewshed.exposure* (viewshed parametrisation function, exposure range, sampling density, input data quality) were systematically tested in three steps (Table 1). In the first step, accuracy and processing time were recorded for all possible combinations of viewshed parametrisation functions and exposure ranges between 50 m and 300 m with 50 m steps. This was done to determine the method's highest possible accuracy and see how these settings affect the trade-off between accuracy and processing time. Exposure ranges larger than 300 m were not tested due to increased processing time and observable saturation with regards to accuracy. Sampling density was 100%. The input exposure source map was a tree canopy dataset in 1 m resolution obtained by laser scanning in 2017 (Hanssen et al., 2021). This is the most precise spatial representation of tree canopy currently available for the built-up area of Oslo. However, due to low accuracy at individual tree level, we manually corrected the dataset around the validation points using an updated orthophoto.

In the second step, we varied sampling density between 0.1%, 1%, 5%, 10%, 25%, 50% and 100% and observed its effect on the accuracy/processing time trade-off. We used the combination of viewshed parametrisation function and exposure range identified in the first step as a good trade-off between accuracy and processing time. For sampling densities lower than 100%, the modelling was repeated 50 times to account for randomness in sampling point distribution and provide a more robust accuracy estimate. The average accuracy and standard deviation across the 50 repeats were reported.

Table 1
Settings of r.viewshed.exposure used in method assessment.

	Viewshed parametrisation	Exposure range	Sampling density	Tree canopy map resolution	DSM resolution
Step 1: Test of viewshed parametrisation & exposure range	None; Distance decay; Visual magnitude; Solid angle	50 m; 100 m; 150 m; 200 m; 250 m; 300 m	100%	1 m	1 m
Step 2: Test of sampling density	Determined by step 1	Determined by step 1	0.1%; 1%; 5%; 10%; 25%; 50%; 100%	1 m	1 m
Step 3: Test of input data quality	Determined by step 1	Determined by step 1	100%	10 m	1 m

Finally, in the third step, we run *r.viewshed.exposure* with a 10 m tree canopy map derived from Sentinel-1 and Sentinel-2 imagery (Venter and Sydenham, 2021) to assess how input data resolution affects accuracy. Sampling density was set to 100%, and except for the tree canopy map, the same settings as in the previous steps were used.

In all three steps, the input surface model was a 1 m DSM obtained by laser scanning (Norwegian mapping authority, 2019) and exposure receiver height was 150 cm, consistently with the shooting height of validation panoramas. *r.viewshed.exposure* was run on 25 cores of an HPE ProLiant DL360 Gen10 server with two Intel(R) Xeon(R) Gold 6134 CPU @ 3.20 GHz Central Processing Units, 256 GB Random Access Memory and three 960 GB Solid State Storage Devices with 6Gbps bandwidth and ext4 file system running Ubuntu 18.04.5 LTS. Accuracy was assessed by Spearman correlation coefficient (ρ) between the percentage of tree canopy pixels in the validation panoramas and values extracted from the maps modelled with *r.viewshed.exposure*. Processing time was measured as a per-point elapsed time, i.e. the average elapsed time of running *r.viewshed.exposure* within the specified exposure range of one validation point, where the grid size to process in number of pixels is the square of exposure range.

2.3.2. City-wide application

To assess the method's computational efficiency in a practical city-wide application with high-resolution data, we ran *r.viewshed.exposure* for the entire study area of Oslo. We used the same input data (1 m tree canopy map and DSM) and server as in the first assessment phase. The total extent of the study area was 19603 × 18486 pixels, covering 152 km^2, i.e. 152 million non-null pixels, out of which 49.5 million pixels was tree canopy. For viewshed parametrisation function, exposure range and sampling density, we used the combination identified as a good trade-off between accuracy and processing time in the first assessment phase.

3. Results

3.1. *r.viewshed.exposure*

The developed tool *r.viewshed.exposure* (Fig. 2) is available through the GRASS GIS Addons repository. The default values of viewshed parametrisation function, exposure range and sampling density are set to the combination identified as a good trade-off between accuracy and processing time in the method assessment. Fig. 3 provides examples of maps of visual exposure to urban trees calculated with the tool using the different viewshed parametrisation options, 200 m exposure range and 100% sampling density. While all three viewshed parametrisation functions lead to visually similar output, the map created without viewshed parametrisation is significantly different. The range of numerical values of visual exposure depends on viewshed parametrisation, exposure range, sampling density and spatial resolution of the analysis. We include detailed information about theoretical value ranges of the individual functions in the Supplementary Material.

3.2. Method assessment

3.2.1. The effect of variation in the method's settings

The highest Spearman correlation coefficient between values of visual exposure to urban trees modelled with *r.viewshed.exposure* and the percentage of tree canopy in validation panoramas is 0.96 (solid angle function, 200 m exposure range, 100% sampling density). This means that the developed method captures visual exposure to urban trees almost as accurately as street view photographs. In Fig. 4, the modelled values are plotted against the tree canopy percentage. At visual inspection, the relationship is clearly monotonic. The scatter plot also identifies cases where the modelled values considerably under- and over-estimate the tree canopy percentage (points O1 and O2). In these outlying validation points, tree canopy percentage was measured in photographs taken from under the tree canopy, while visual exposure was modelled on the surface of the tree canopy due to the 2.5D character

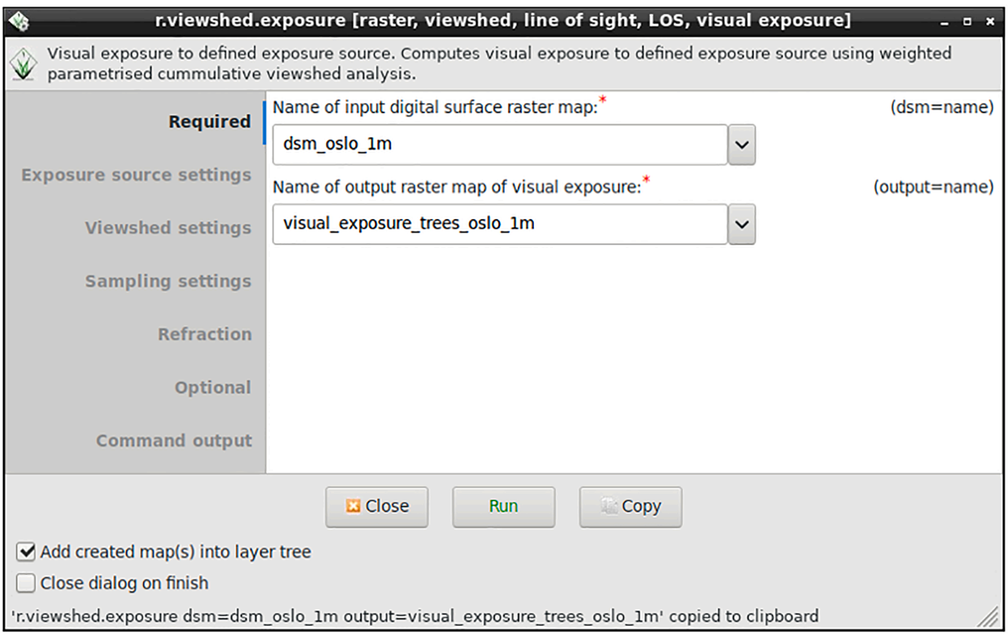

Fig. 2. Graphical user interface of *r.viewshed.exposure* in GRASS GIS.

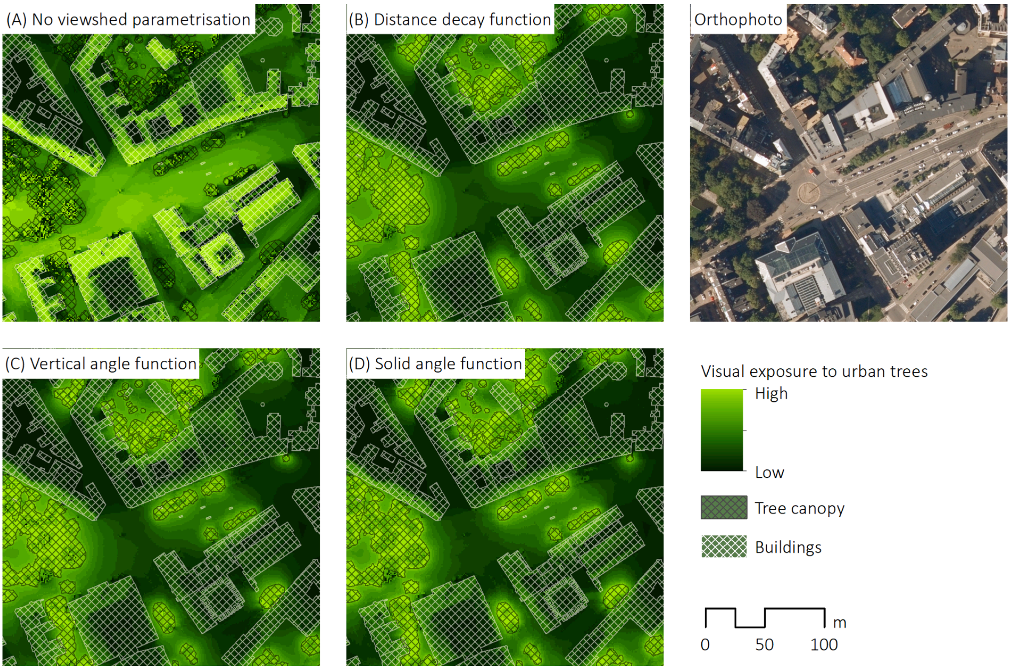

Fig. 3. Visual exposure to urban trees modelled with *r.viewshed.exposure* (200 m exposure range, 100% sampling density). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

of the DSM. Fig. 4 further illustrates the range of modelled visual exposure values across the validation points, along with output maps and validation panoramas.

Fig. 5A illustrates that the accuracy differs little between viewshed parametrisation functions (ρ = 0.94–0.96) while omitting viewshed parametrisation leads to significantly lower accuracy (ρ = 0.50–0.79). This underpins the importance of viewshed parametrisation when modelling visual exposure to urban trees. Solid angle and visual magnitude functions increase processing time roughly 1.6x compared to no parametrisation and distance decay function (Fig. 5A). Considering that both former functions do not significantly improve accuracy, the simpler distance decay function can be a good choice for many applications.

Fig. 5A further shows that exposure range has minimal effect on accuracy if viewsheds are parametrised (ρ = 0.94–0.96), although 50 m exposure range has slightly lower accuracy in all three parametrisation functions. Yet, without viewshed parametrisation, accuracy clearly decreases with increasing exposure range. This is likely caused by the disproportional increase in visual exposure due to increasing number of visible pixels at longer exposure ranges. The relationship between exposure range and per-point elapsed time follows a power function across all viewshed parametrisation options. Therefore, lower exposure ranges can be a good choice for reliable and efficient modelling of visual exposure to urban trees from human perspective. Considering the abovementioned findings, we used distance decay function and 100 m exposure range to assess the effect of sampling density and input data accuracy.

Fig. 5B shows that low sampling density (0.1%, 1%) leads to low accuracy with high uncertainty due to the randomness in sampling point distribution (ρ = 0.42 + -0.079 and 0.72 + -0.051, respectively). However, with sampling density 25% and higher, accuracy is comparable to 100% sampling density and the uncertainty is low (ρ = 0.94 + -0.009). Processing time increases exponentially with increasing sampling density and e.g. with 25% sampling density, the processing time is nearly four times shorter compared to 100% sampling density.

Using a low-resolution tree canopy map, the accuracy dropped considerably (ρ = 0.53). This indicates that input data quality impacts the result accuracy even more than viewshed parametrisation and exposure range (except for extreme settings without viewshed parametrisation).

3.2.2. Visual exposure to urban trees in Oslo

The result of running *r.viewshed.exposure* for the extent of Oslo with distance decay parametrisation function, 100 m exposure range and 25% sampling density is illustrated in Fig. 6 and also provided as an interactive map at http://urban.nina.no/maps/400/view. The total elapsed time was 133.8 h.

4. Discussion

In this paper, we built upon the work by Labib et al. (2021) and Tabrizian et al. (2020) and developed a viewshed-based method for modelling visual exposure to urban greenery. The method supports the potential of geospatial modelling to address shortcomings of photography-based methods for quantifying visual exposure to urban greenery (Helbich et al., 2019; Larkin & Hystad, 2019; W. Wang et al., 2019; Yang, Zhao, McBride, & Gong, 2009). In particular, the method developed here can model visual exposure to various types of urban greenery (here illustrated on the case of urban trees), which usually is not possible with photography-based methods (Sun et al., 2021). In addition, the method enables modelling green visual exposure in continuous representation and in places and regions where street view imagery is not available (Rzotkiewicz et al., 2018; Villeneuve et al., 2018).

The method has been developed with particular focus on its usability in research and practical applications. It was implemented as a GIS tool

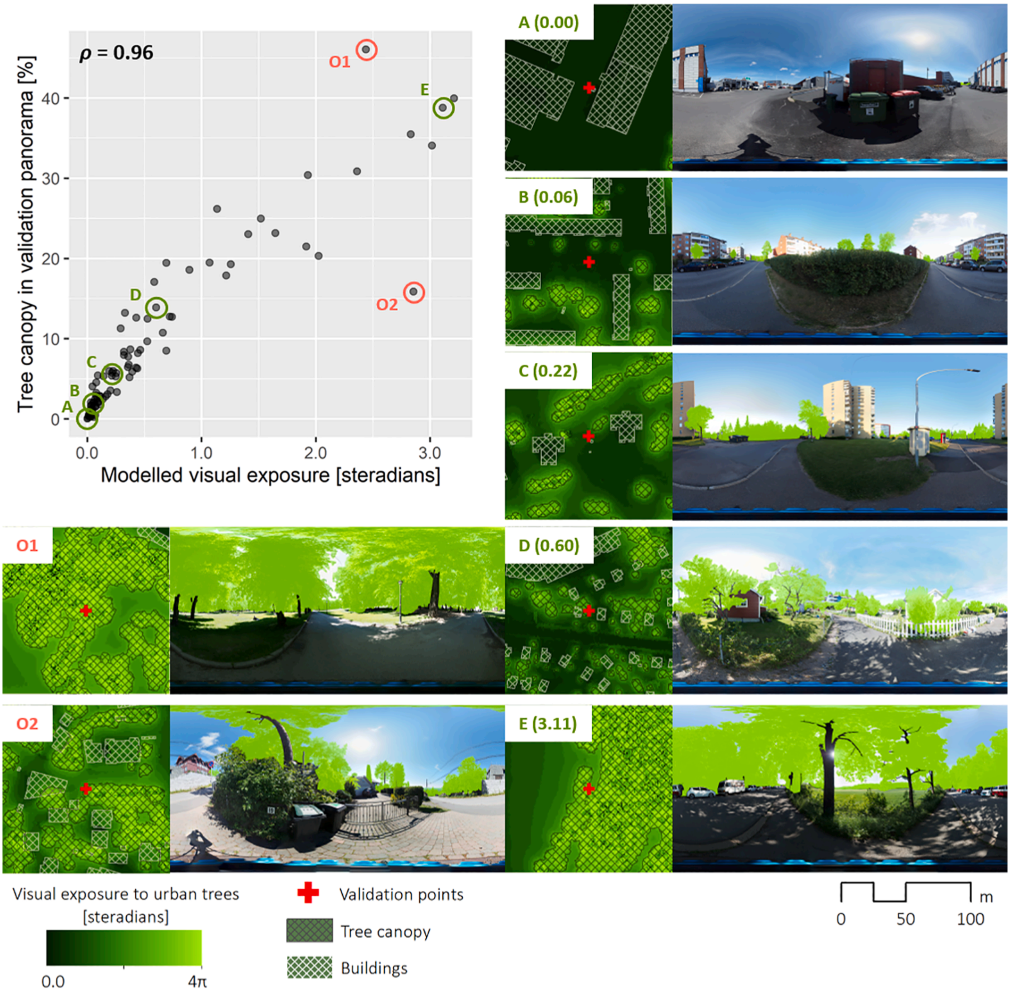

Fig. 4. Values of visual exposure to urban trees modelled with *r.viewshed.exposure* at validation points (solid angle function, 200 m exposure range), plotted against tree canopy percentage, and value range of modelling results. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

to lower the threshold for usage and with several user-specified settings to increase its flexibility, which is especially valuable for research. At the same time, the method was extensively assessed on the case of urban trees, which makes its applicability in practice easier. Furthermore, the general usability of the method is ensured by its high computational efficiency. In the following, we discuss this in more detail.

4.1. Method implementation in GRASS GIS

The method was implemented as a tool called *r.viewshed.exposure* in GRASS GIS. This lowers the technical demands on the users and enables direct integration of the method in the users' GIS workflows. Furthermore, user-specified settings like viewshed parametrisation function, exposure range, sampling density and observer height increase the method's flexibility and thereby enable adjusting it to specific needs of various application purposes. This flexibility also facilitates systematic validation and assessment of the method in various contexts and thus contributes to building knowledge about the visual effects of urban greenery. The integration of the method in open-source GIS ensures that the method can be improved beyond the current state, for instance by implementing new viewshed parametrisation functions.

4.2. Method assessment

The method was empirically assessed to see how its settings influence the performance in terms of accuracy and processing time. The findings provide important insight for application purposes where a minor accuracy loss might be acceptable in return for shorter processing time – for instance for planning purposes on city scale, where the processing extent is often large but computational resources may be limited. Furthermore, the findings about individual settings provide information about the "default values" to use in practical applications.

The assessment showed that the values of visual exposure to urban trees modelled with the developed method are highly correlated to tree canopy percentage in street view panoramas. Thus, the developed method is a reliable alternative for quantifying visual exposure to urban

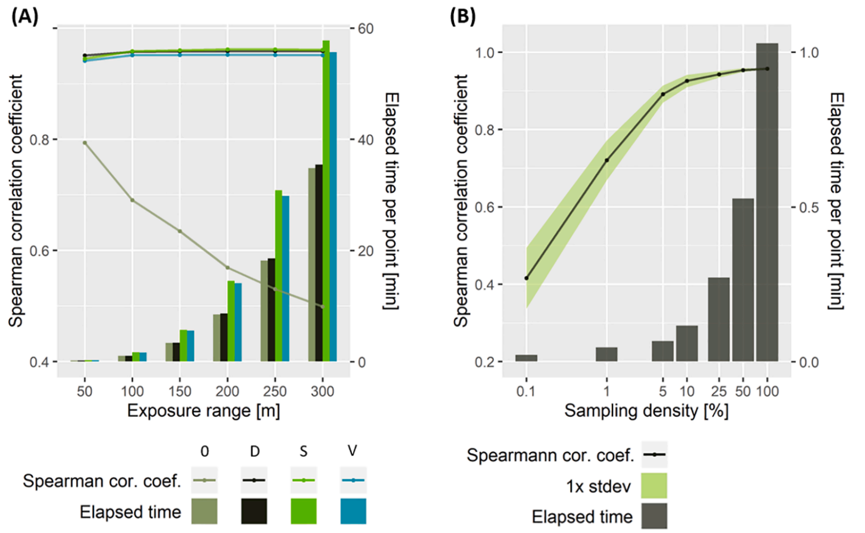

Fig. 5. (A) Effect of exposure range and viewshed parametrisation on method performance (100% sampling density). 0, D, S and V refer to no parametrisation, distance decay function, solid angle function and visual magnitude function, respectively. (B) Effect of sampling density on method performance (distance decay function, 100 m exposure range). X-axis is logarithmically scaled. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

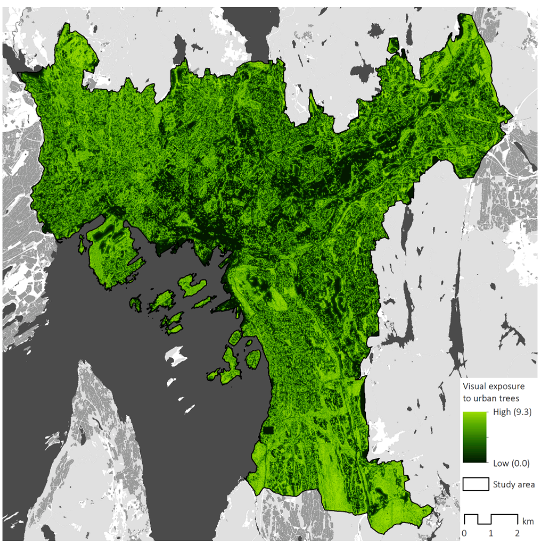

Fig. 6. Visual exposure to urban trees in Oslo (distance decay function, 100 m exposure range, 25% sampling density). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

trees. With a Spearman correlation coefficient of up to 0.96, the degree of correlation is significantly higher than the correlation reported for the method by Labib et al. (2021) (Pearson correlation coefficient 0.481). Apart from potential differences in viewshed computation and different correlation measures used, the lower correlation in Labib et al. (2021) may be attributed to different studied greenery types (all greenery vs only trees), lower input data resolution and different viewshed parametrisation function. The assessment further confirmed that the method is not suitable for modelling visual exposure under tree canopies. This is due to the 2.5D character of the DSM, where all surface locations have single elevation information. In turn, visual exposure values at tree locations represent the amount of tree canopy visible from the surface of the trees, not from under them. For the same technical reason, the method cannot model green visual exposure from vertical surfaces (e.g., from building facades to assess the exposure of building occupants). In further development, the method could therefore be adjusted to operate with 3D models (Bishop, 2003) or to minimise the effect of trees on view obstruction (Murgoitio et al., 2013).

In line with previous studies (Domingo-Santos, 2017; Groß, 1991; Ogburn, 2006), the assessment further underpinned the importance of parametrising the binary viewshed to better reflect visual significance of observed objects. All three parametrisation functions implemented in *r.viewshed.exposure* significantly improved the method's accuracy. Compared to the distance decay parametrisation function used in Labib et al. (2021), the functions in *r.viewshed.exposure* have significantly steeper slope. Given the high accuracy, we hypothesise that such steeper functions are more suitable for modelling visual exposure in urban areas. Further, we hypothesise that visual exposure to urban trees is mainly influenced by the distance between the observer and the observed object because including their relative slope and aspect did not significantly increase the accuracy. Larger exposure ranges did not increase accuracy but considerably increased processing time. Therefore, relatively short exposure ranges (100 m) might be sufficient for accurate and fast green visual exposure modelling in urban settings, where surrounding structures often limit visibility at relatively low distances. This is in accordance with studies of Łaszkiewicz and Sikorska (2020), R. Wang et al. (2019) and W. Wang et al. (2019). On the other hand, longer ranges are often used in regional or landscape scales (Brabyn, 2015; Fisher, 1994). In general, further research is needed to systematically check how the shape of viewshed parametrisation functions and exposure ranges affect the results.

Finally, the assessment underpinned the need for using high-resolution high-quality input spatial data because these influence the underlying viewshed analysis (Ervin and Steinitz, 2003). The visibility of greenery in urban areas is often affected by relatively small details in the physical urban structure, which are only represented in high-resolution surface models (e.g., individual trees, walls). The availability of high-quality input data might limit the application of the method, however, access to such data from laser scanning or Unmanned Aerial Vehicles increases due to technical development.

Photography-based methods to quantify green visual exposure (Helbich et al., 2019; W. Wang et al., 2019; Yang et al., 2009), here used to validate and assess the developed method, are based on the assumption that the amount of greenery measured from photographs reflects the amount of greenery observed by people. However, researchers disagree on the extent to which photographs really capture what people see (compare e.g., Aoki et al. (1985) and Falfán et al. (2018)), for instance due to observer characteristics (Falfán et al., 2018) or photograph distortion due to lens settings and panorama projections (Aoki et al., 1985; Zelnik-Manor et al., 2005). The values of visual exposure to urban greenery measured from photographs or modelled by *r.viewshed.exposure*, therefore, represent a measure of potentially visible greenery from human perspective (Falfán et al., 2018). An important next step would be to assess the correspondence between these objective modelled/measured values and subjective, self-reported perceived green visual exposure. Moreover, research suggests that quality of greenery also determines the benefits obtained (Reid et al., 2017). Therefore, the method could be further extended to enable weighting the individual viewsheds by quality of greenery, if such data are available for instance from remote sensing (Yan et al., 2018).

The findings regarding accuracy, viewshed parametrisation functions and exposure ranges are based on an assessment conducted across different urban form types in Oslo. However, the suitability of different combinations of the method's settings might vary with urban form types. For instance, while a short exposure range might provide sufficient accuracy in a dense urban centre, longer exposure ranges might perform better in low-density suburbs. This might be important information to consider in application purposes targeted at specific urban form type. Caution should also be paid when generalising the findings to study areas with significantly different urban morphology than Oslo. An important next step would therefore be to systematically assess the sensitivity of the method's setting to different urban form types and explore the method's performance in other study areas.

Similarly, caution needs to be paid when generalising the findings to other types of greenery than urban trees. Urban trees have a specific visual impact due to their vertical dimension, while other types of urban greenery (e.g. grass, low shrubs) are mostly horizontal, and their visual impact might be different. Future studies could therefore assess the developed method on other types of urban greenery.

Future work should also focus on clarifying the range of numerical values of green visual exposure resulting from the modelling. The range can vary significantly, depending on viewshed parametrisation function, exposure range, sampling density and resolution of the underlying spatial data. This also hinders further interpretation of the numerical values. Previous studies expressed the modelled green visual exposure values as a proportion of total viewshed comprising urban greenery (Labib et al., 2021; Łaszkiewicz & Sikorska, 2020), which is easy to interpret, or as absolute values (Domingo-Santos et al., 2011; Nutsford et al., 2015), as in this study, where interpretation is more challenging.

4.3. Computational efficiency

The method can be efficiently run on a personal computer or server, which is especially beneficial in daily planning practice and small-scale studies. Its ability to efficiently process large spatial extents at fine detail is likewise advantageous in large-scale studies. Compared to the method of Labib et al. (2021), *r.viewshed.exposure* is significantly faster. Direct comparison to the performance of the method by Labib et al. (2021) is not possible due to different hardware and input data used. The city-wide applications however give some general hints. The amount of data processed for Oslo is roughly twice the amount in Labib et al. (2021) (152 and 86 million pixels, respectively), while processing time is less than half (5.6 and 11.5 days, respectively). As a rough estimate, assuming that the computer used in this study computes at the same speed as reported by Labib et al. (2021) (0.8 s per viewshed), processing time for their method applied to the Oslo dataset would have been ~1680 h (or 70 days). Several factors contribute to computational efficiency of *r.viewshed.exposure*. First, the processing workflow reduces the number of viewshed operations by only processing green pixels. Areas with little greenery are therefore processed faster than equally large areas with high green coverage. Second, the assessment showed that computational time can be significantly reduced by decreasing exposure range and sampling density of the input map, with limited effect on the accuracy. Finally, the method is implemented using effective in-memory operations and process parallelisation. For very large rasters, memory consumption might become a bottleneck, but this can be addressed by processing data in chunks (tiled processing). GRASS GIS offers off-the-shelf solutions for that if necessary.

4.4. Relevance for urban planning and research applications

The method developed in this paper is relevant for numerous urban planning and policy applications. First, urban foresters can use the green visual exposure map for awareness-raising amongst the public. Second, the method provides useful input into urban ecosystem accounting, as it enables documenting and reporting on the temporal changes of green visual exposure, for example following tree planting programs. The results of green visual exposure modelling can also be aggregated and used in comparisons of neighborhoods or cities. Third, in strategic tree planting, the visual exposure maps can be used to identify areas with low green exposure, i.e. possible locations where tree planting will have the greatest effect in terms of increasing green visual exposure. Strategic tree planting is especially important in the light of ongoing densification, where space for establishing large green areas is often limited and where planting single trees can represent an efficient way of increasing the overall green views. Fourth, by manipulating the input data, the method is applicable in scenario modelling and impact assessment. Manipulating the input tree canopy map (adding or removing trees) enables planners to compare different tree planting or felling scenarios and select those which result in the largest increase or smallest decrease in green visual exposure, respectively. Manipulating the input DSM on the other hand facilitates assessing the effect of planned construction projects on green visual exposure in the surroundings. Finally, thanks to the method's flexibility, application in areas beyond the scope of urban planning is also possible, for instance in landscape aesthetic and architectural studies (e.g. modelling exposure to landmarks or buildings) (Dramstad et al., 2006) or in visual impact assessment (e.g. modelling the visual impact of quarries or power plants).

The method developed in this paper further has the potential to further advance our knowledge on the relationship between green visual exposure and obtained benefits by providing reliable estimates of the amount of green visual exposure from human perspective. The continuous representation of the result can be combined e.g. with information on people's daily movements in exposure studies to gain a more in-depth and detailed insight into green exposure of individual participants. In environmental psychology studies, the method can easily be adjusted to reflect e.g., studied exposure range or dose–response curves. Further, the method complements research on olfactory and auditive sensory mapping (McLean, 2019).

5. Conclusion

The method developed in this paper underpins findings of earlier studies showing that geospatial modelling with viewshed analysis can be a reliable and highly accurate means of quantifying visual exposure to urban greenery from human perspective. For the specific case of urban trees, the method achieves increased accuracy compared to previous studies. Systematic assessment of the method's settings based on validation data shows that it is essential for the accuracy of the results to parametrise the viewshed analysis according to the variable visual significance of observed greenery. It also identifies reasonable default settings and illustrates how those influence the trade-off between accuracy and processing time, providing important insight for application purposes where a minor accuracy loss might be acceptable in return for shorter processing time. Furthermore, the implementation of the method significantly improves its computational performance to a degree that makes it usable at city-wide scale with high-resolution data on commodity hardware. The tool developed in this study represents a major technical step forward as it makes the method available as a practical and flexible tool for a broad range of research and practical applications. While developing the method and the tool, an R-package with a similar functionality has been made available, which further underpins the relevance of the method (Brinkmann & Labib, 2021). Therewith, the method contributes to the emerging number of quantitative methods that enable easier modelling of cultural ecosystem services that otherwise often are challenging to include in ecosystem accounting or landscape management.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2022.104395.

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Paper III

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Paper IV

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

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Tree inventory

ABSTRACT

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

1. Introduction

More than half of the world's population lives in cities. The proportion is predicted to rise to 68 % by 2050 globally and from 75 % in 2020 to nearly 84 % in 2050 in Europe (UN, 2018), leading to increased demand for living space. This results in the conversion of natural vegetation cover to artificial surfaces and soil sealing (European Environment Agency (EEA, 2006). Urban green infrastructure comprising all types of vegetation provides ecosystem services (ES) to urban populations (European Commission, 2013; Gomez-Baggethun and Barton, 2013). Urban forests and individual trees are the major components of urban green infrastructure, delivering provisioning, cultural and regulating services (Mullaney et al., 2015; Nesbitt et al., 2017; Nowak et al., 2008; Song et al., 2018) with social, economic, health and visual aesthetic benefits to humans (Roy et al., 2012). For example, the health benefits of trees and forests in the coterminous US were valued at 1.5–13 billion USD, mostly occurring in urban areas (Nowak et al., 2014).

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

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

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

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

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

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

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

These advances suggest a greater role of remote sensing in automated surveying of individual tree structural attributes and species for i-Tree Eco. Furthermore, attributes of tree's spatial context, i.e. expressing the relationship between a tree and its surrounding structures and phenomena (buildings, other trees, land use), can more rapidly, consistently and at low cost be estimated using geospatial analysis methods from digital terrain models, cadastral maps or land use maps. To our knowledge, these new approaches are scarcely used in i-Tree Eco studies. Zhao et al. (2018) used geospatial technologies to create an urban tree inventory in Nantong City, China. They employed mobile TLS to automatically detect location, height, crown width and stem diameter of individual street trees for evaluation of carbon sequestration and PM2.5 removal. We found only two studies exploring the integration of spatial data with existing municipal tree inventories for calculating missing tree attributes; both use spatial data to estimate attributes of spatial context. Scholz et al. (2018) used a high-resolution digital surface model to estimate trees' crown light exposure (for estimation of carbon sequestration) in Duisburg, Germany. Similarly, at University of Pennsylvania, US, Bassett (2015) measured trees' distance and direction to buildings (for estimation of building energy savings by temperature regulation due to trees) in GIS; buildings were represented by their footprints in a cadastre map.

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

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

2. Methods

2.1. Study area and used software

The study area is the city of Oslo built zone regulated for urban development, where the analysed tree inventory is located. Oslo built zone covers 147 km^2, of which 47 % was covered by vegetation in 2017, 27 % of which was regulated green space (Agency for Planning and Building Services (PBE, 2018a). The population was 640 902 in 2015, which is the reference year in this study (Statistics Norway (SSB, 2019).

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

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

2.2. Input data

2.2.1. Municipal tree dataset

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

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

2.2.2. ALS tree dataset

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

2.2.3. Auxiliary spatial datasets

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

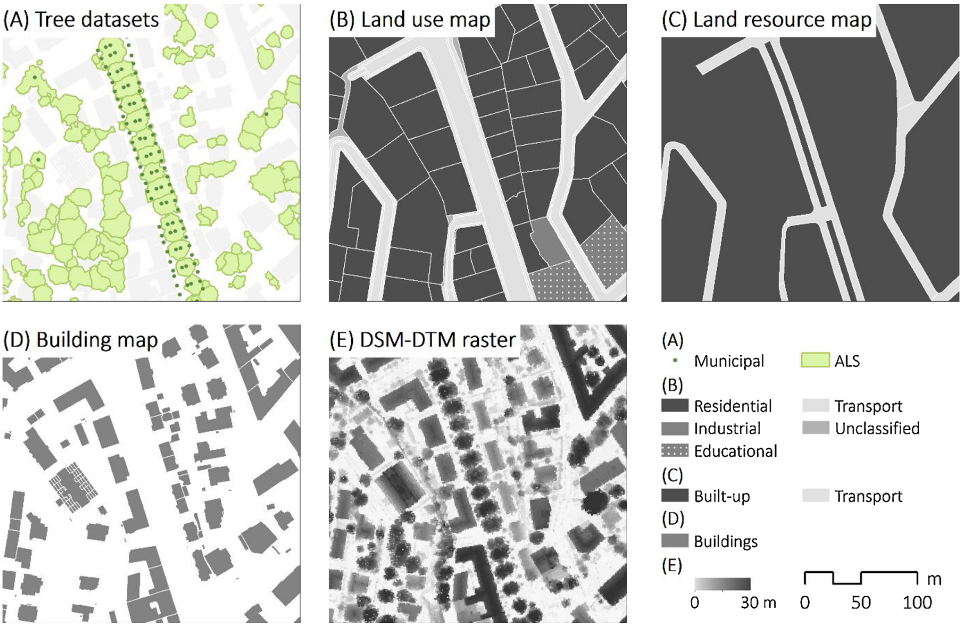

Fig. 1. Used spatial datasets.

2.2.4. Location information

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

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

Air pollution in Oslo varies significantly, depending mainly on distance from a pollution source (Schneider et al., 2017). To account for heterogeneity in air pollution levels and thus enable more precise estimation of air pollution removal by trees, we replaced the stored air pollution data by air pollution levels spatially disaggregated to three zones, defined by limits for daily, winter and annual means of NO2 and PM10 (NILU and MET, 2015). In 2015, there were 12 stations monitoring hourly air pollution levels in Oslo (Norwegian Institute for Air Research (NILU, 2015). Levels of PM2.5 and NO2 in each zone were represented as medians of levels recorded by monitoring stations within each zone. Levels of CO, O3 and SO2 were recorded by one station only and were considered constant across all three zones.

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

2.3. Methodology workflow

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

2.4. Step 1: associating stem points with crown geometry

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

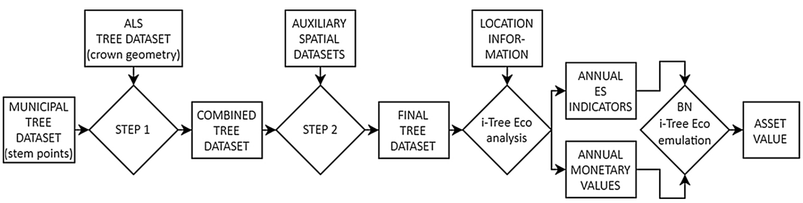

Fig. 2. Methodology workflow of i-Tree Eco implementation in Oslo.

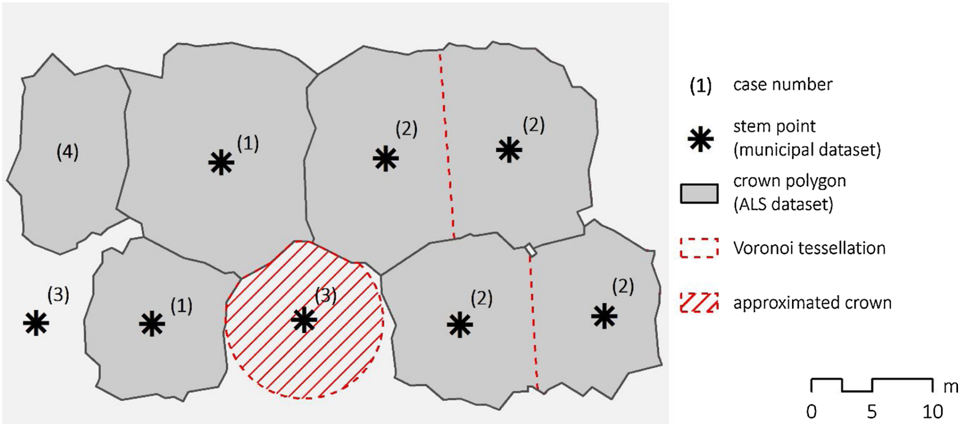

Fig. 3. Four cases of geometrical relationship between stem points (municipal dataset) and crown polygons (ALS dataset).

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

2.5. Step 2: integrating auxiliary spatial datasets

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

2.5.1. Species

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

2.5.2. Stem diameter at breast height (DBH)

In manual surveys, DBH is measured at 1.37 m above the ground. If DBH is not recorded, it can be either predicted from other structural attributes using allometric equations (Jucker et al., 2017), measured directly from TLS imagery (Cabo et al., 2018; Moskal and Zheng, 2011) or predicted indirectly from metrics calculated from ALS imagery (Tanhuanpää et al., 2014). To calculate DBH of municipal trees whose stem diameter or circumference was not recorded, we predicted DBH from derived total tree height (H) using an allometric equation suggested by Jucker et al. (2017) (69 % of records in the municipal dataset; see Supplementary Material for further details on model fitting).

2.5.3. Crown width (CD)

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

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

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

2.5.5. Height to crown base (HCB)

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

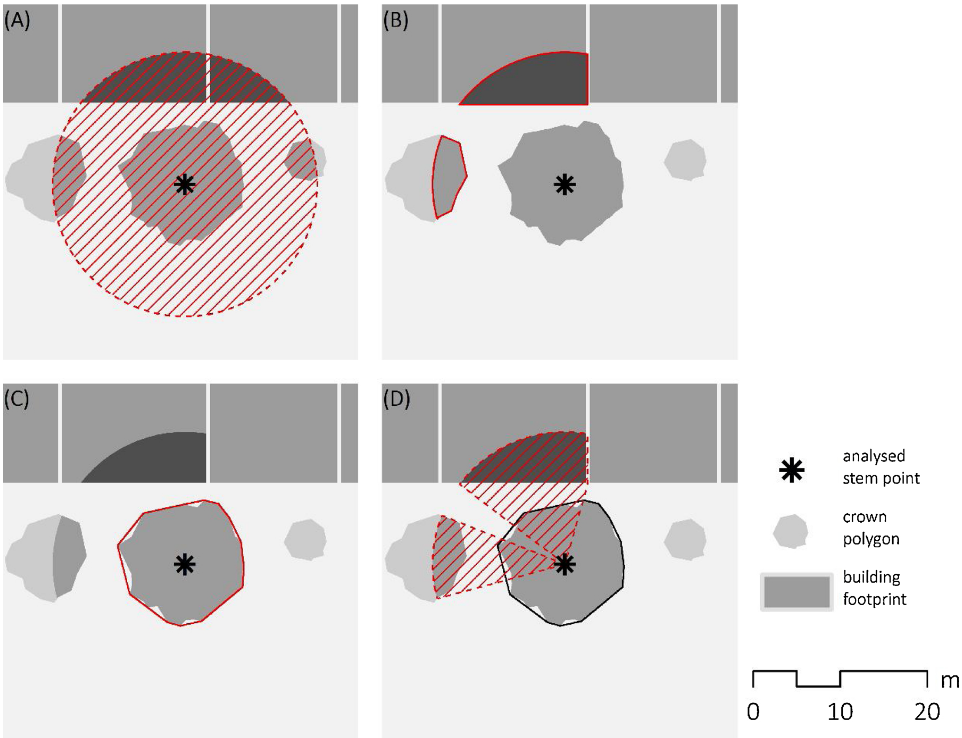

Fig. 4. Modelling crown light exposure. (A) a buffer of radius equal to the crown diameter and objects within this buffer, (B) selected objects taller than the analysed tree, (C) convex hull of the analysed tree crown, (D) tangents between stem point and edges of extracted objects define parts of crown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

allometric equations.

2.5.6. Crown light exposure (CLE)

The i-Tree Eco Field Guide defines crown light exposure as "the number of sides of the tree's crown receiving light from above or the side" where obstructions for light are "any parts of an adjacent tree crown or building that are a) overtopping any part of that crown side, or b) within one average crown width away from the measured tree's stem and the object is at least as tall as the measured tree". CLE is expressed by a score from 0 (tree does not receive light from any side) to 5 (tree receives light from all directions and from above). Several geospatial analysis methods for deriving CLE have been developed. Scholz et al. (2018) estimate CLE by observing whether digital surface model pixels in four compass directions from the tree's centre are located higher (casting a shadow on the tree) or lower (permitting the sun to reach the tree) than the tree's height. Alternatively, Pace et al. (2018) estimate CLE from a competition index computed in the Single-tree-based stand simulator SILVA (Pretzsch et al., 2002) and using a fixed distance buffer to account for shading by buildings and other trees. We estimated CLE in a GIS processing routine as the percentage of crown perimeter exposed to open light (Fig. 4). Following the i-Tree Eco Field Guide, we first selected all adjacent buildings and tree crowns, i.e. all pixels from the DSM-DTM raster within a buffer around stem point with radius equal to CD (Fig. 4A). We then extracted all pixels with a value equal to or larger than recorded H (Fig. 4B). To minimize the effect of concavities in the crown perimeter, we approximated the crown geometry by its convex hull (Fig. 4C). Finally, we calculated the proportion of crown's perimeter receiving light by constructing tangents between stem point and edges of extracted objects (Fig. 4D). To match the calculated proportion to i-Tree Eco scores, we classified the proportion of crown's perimeter receiving light as follows: 0–12.5 %: CLE = 1, 12.6–37.5 %: CLE = 2, 37.6–62.5 %: CLE = 3, 62.6–87.5 %: CLE = 4, > 87.6 %: CLE = 5. Due to the origin of the ALS dataset, no overlaps exist between detected crowns and we assumed light from above for all trees, although in reality overlaps between crowns are common in dense tree stands.

2.5.7. Distance and direction to building (DB)

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

2.5.8. Land use (LU)

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

2.5.9. Percent crown missing (PCM)

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

2.6. i-Tree Eco analysis

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

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

2.7. i-Tree Eco emulation and model assessment

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

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

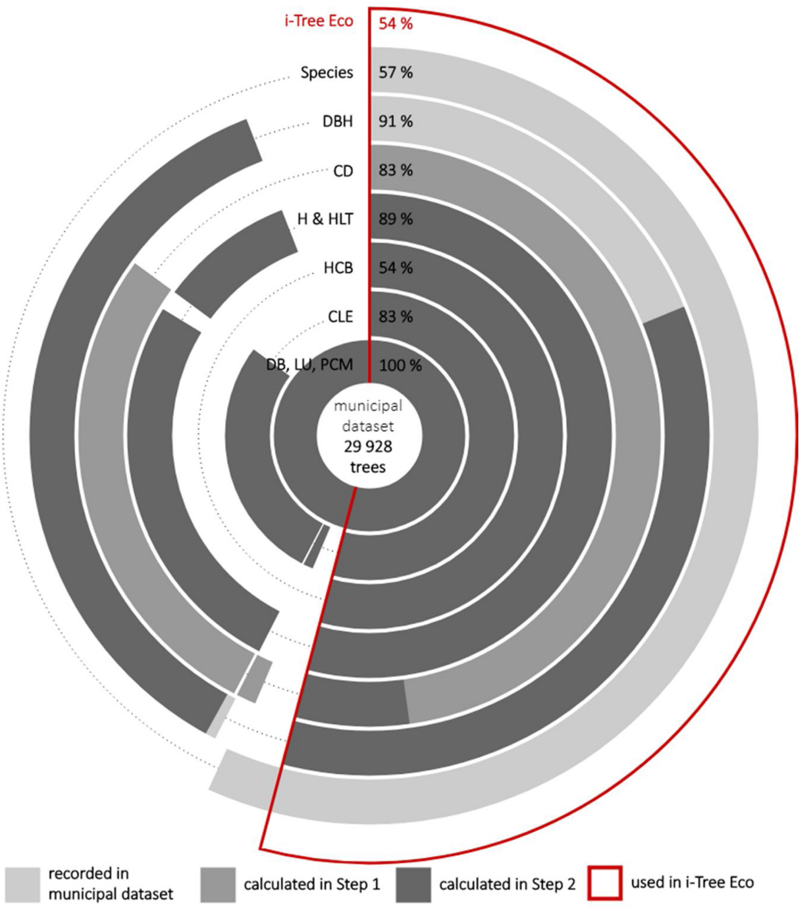

Fig. 5. Information gain from integrating municipal tree dataset with available spatial data. Each concentric circle symbolizes one attribute. Arc size is proportional to the percentage of trees with that attribute in the final dataset. Arc colour represents the origin of the attribute – the original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

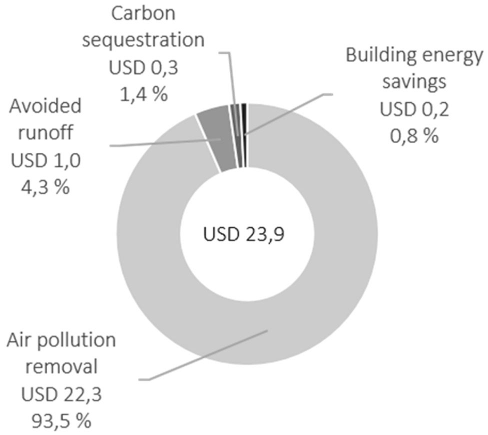

Fig. 6. Per-tree average annual monetary value distributed per ES indicator.

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

3. Results

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

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

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

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

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

3.2. Ecosystem services of individual municipal trees

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

3.3. Asset value of all municipal trees

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

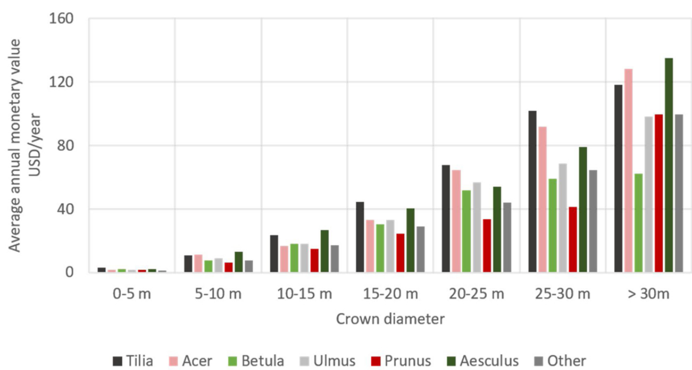

Fig. 7. Distribution of per-tree average annual monetary value for the most common genera and crown diameter classes.

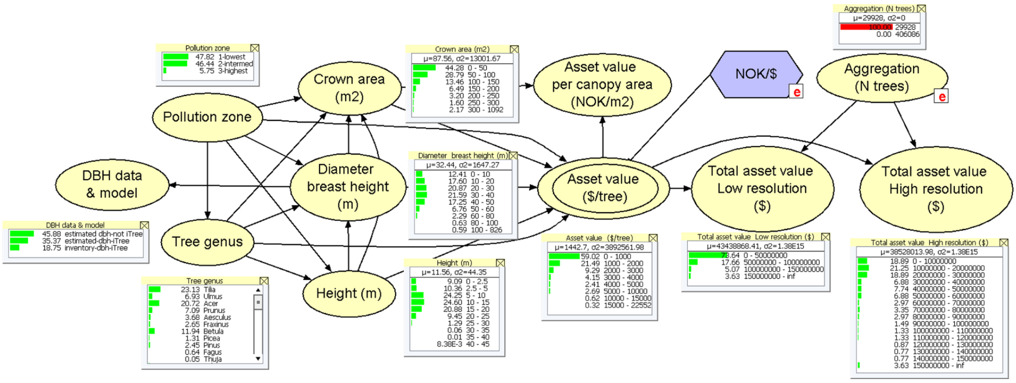

Fig. 8. A Bayesian network emulating tree asset value based on i-Tree Eco and a selection of attributes from the final dataset. Variable windows show probability distributions for categorical variables and continuous variables discretized into intervals. Mean (μ) and variance (σ^2) of continuous variables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

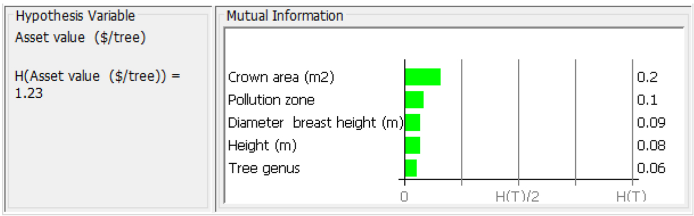

Fig. 9. Index of mutual information between asset value and tree attributes.

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

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

4. Discussion

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

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

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

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

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

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

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

models). This is reflected in the relatively low R^2 value of the respective prediction models used in this study (0.46 for CD, 0.51 for DBH). Accounting for these factors might lead to more reliable estimates (Vaz Monteiro et al., 2016). Similarly, the in-built i-Tree Eco allometric equations, used in this study to predict H and HCB, are fitted on datasets from numerous cities and might not be representative for the conditions of Oslo. Finally, our regression models lead to underestimation of CD and DBH, because these were estimated without applying a correction factor for logarithmic transformation bias. This underestimation means that the resulting ES indicators and associated monetary value are conservative for 77 % of trees suitable for the i-Tree Eco analysis. When using allometric equations, it is important to always apply a bias correction term when back-transforming prediction on a logarithmic scale to prediction on the original scale (Baskerville, 1972; Clifford et al., 2013; Smith, 1993). In a further use of the municipal tree dataset, this bias correction will be applied.

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

In addition to complementing manual field measurements, geospatial methods open possibilities for estimating tree attributes which are difficult to measure in the field, and thereby enable valuation of benefits which are unevenly distributed in space. Across urban areas, the supply of regulating ES such as air pollution removal by urban trees has been shown to vary and may be limited relative to total air pollution emissions of cities (Baró et al., 2015). Escobedo and Nowak (2009) documented the importance of micro-scale meteorological data for assessing air pollution removal by trees. Yet, the i-Tree Eco model does not enable spatial differentiation of air pollution levels and requires practitioners to assign average levels to all trees. In this study, we have demonstrated the importance of taking of air pollution into consideration. Air pollution removal constitutes the largest proportion (93.5 %) of the annual monetary value of an average tree. Air pollution level at tree location is one of the main determinants of trees' asset value.

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

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

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

5. Conclusions

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

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

CRediT authorship contribution statement

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

Declaration of Competing Interest

The authors report no declarations of interest.

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Appendix A. Supplementary data

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

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