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Current and potential urban canopy cover: a comparative study
across 10 European cities using i-tree canopy

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Abstract

This thesis work is a comparative study on current and potential canopy cover among 10 European cities utilizing i-tree Canopy. The measurement of tree canopy cover in urban areas is a convenient and cost-effective way to assess the extent of greenery. This metric not only reveals the amount of coverage within a specific area, but also offers valuable information about the potential benefits that an urban forest can provide to improve the quality of life of cities and its residents. A random selection was done to choose the cities according to the following parameters: not more than one city per European country, inhabitants ranging between 100,000 to 400,000 per urban core, and a balanced dispersal of cities across the European continent. i-Tree Canopy enables random point sampling and was used to determine whether a point is a tree, non-tree, or a potential tree cover. The software yielded value estimates for canopy ecosystem services such as carbon, air pollution, and hydrological benefits. The obtained canopy cover classes were then tested for relationships with socio-economic and geographic variables, revealing correlations with population density, latitude, and standard deviation in altitude.

List of abbreviations

AIC	Akaike information criterion
CATB	Cover Assessment and Tree Benefits
CCA	Canopy Cover over the Artificial areas
CCC	Canopy Cover over the Core
CLMS	Copernicus Land Monitoring Service
CRS	Coordinate Reference System
CSV	Comma-Separated Values
DTM	Digital Terrain Model
EAA	European Environment Agency
EC	European Commission
EDS	Ecosystem Disservices
ESRI	Environmental System Research Institute
FAO	Food and Agriculture Organization
FUA	Functional Urban Area
GI	Green Infrastructure
GIS	Geographic Information System
HRL TCD	High Resolution Layer Tree Cover Density
KML	Keyhole Markup Language
LAI	Leaf Area Index
LC/LU	Land Cover/Land Use
MMW	Minimum Mapping Width
NBS	Nature-Based Solutions
NO	Non-Tree
NUTS	Nomenclature of Territorial Units for Statistics
OECD	Organization for Economic Cooperation and Development
PCC	Potential Canopy Cover over the Artificial areas
PTC	Potential Tree Cover
SDG	Sustainable Development Goals
SE	Standard Error
T	Tree
UA	Urban Atlas
UC	Urban Core
UCC	Urban canopy cover
UF	Urban Forest
USDA	United States Department of Agriculture
VHR	Very high resolution
VOC	Volatile organic compounds
WTP	Willingness to pay

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1. Introduction

1.1. Urgent Action for Sustainable Cities: Why and How?

Planning environmentally conscious cities has become imperative, particularly considering that 5 billion people are expected to live in urban areas by the year 2050 (European Commission, 2023). Despite covering less than 3% of the Earth's surface, cities host more than half of the world's population (Aronson et al., 2014), and that is associated with rapid demographic shifts and environmental changes (Tian et al., 2018). In fact, global human activity has already been proven to be the dominant cause of most present-day environmental changes (Lewis & Maslin, 2015), which has also led to the suggestion of a new geological period, i.e., the Anthropocene epoch that is characterised by the impact humanity has on planet Earth (Waters et al., 2016). In addition to that, socio-ecological problems like the rapid declines in biodiversity and the surge of pandemics (e.g. COVID-19), along with human disputes on resources, only to name a few, enabled humans to cross most planetary boundaries (Beery et al., 2023). Urbanization worsens the already intense consequences of human activities, which emit anthropogenic heat, carbon dioxide, and particulate matter, thus resulting in poor city air quality and high air temperatures, especially when rural vegetation is absent (Doick et al., 2017; Vaz Monteiro et al., 2017). In the upcoming years, these urban environmental issues, such as the urban heat island effect and air pollution, will most likely be intensified by climate change (Lanza & Stone, 2016).

In response to climate change, it is widely advocated to remedy urban areas with green infrastructure (GI) due to the benefits it provides via nature-based solutions (NBS) (Davies et al., 2017; Dige, 2015). As opposed to grey infrastructure, GI is an intricately designed network of natural and semi-natural areas combined with other environmental elements and planned to provide an array of ecosystem services, including improved air quality, water purification, flood protection, recreational spaces, and climate mitigation and adaptation (Dige, 2015; EPA, 2024). GI elements can be introduced into communities at diverse scales. At the urban scale, an example could be a set of trees along a busy street. On the neighbourhood scale, GI could be a planted rain garden near a residential housing unit.

Protecting a natural area could be a GI feature at the landscape scale, while at the watershed scale, it would be the protection of a riparian ecosystem (EPA, 2024). As defined by the European Commission (EC), Nature-Based Solutions (NBS) are nature-inspired and cost-effective solutions that make cities more resilient by delivering ecological, social, and economic benefits. Particularly, planting trees has become a standard and economic GI tool in mitigating a city's environmental issues (Norton et al., 2015), thus enhancing urban areas' adaptability and sustainability amidst the rapid climate changes (Espeland & Kettenring, 2018).

1.2. Urban Forests as Nature-Based Solutions

When found in an urban and peri-urban setting, single trees, clusters of trees, and woodlands are referred to as Urban Forests (UFs) (FAO, 2017). UFs are studied and managed by urban forestry, a sub-discipline of forestry. Due to historical reasons (see Konijnendijk et al., 2006), the UF definition differs slightly from continent to continent, although the overall goals are roughly the same. For example, the Society of American Foresters defines it as the combination of art, science, and technology in managing an urban ecosystem and its surroundings, namely its trees and forest resources, to deliver the physiological, sociological, economic, and aesthetic benefits to its communities. The British National Urban Forestry Unit collectively describes UFs as all trees and woods in an urban setting, including "parks, private gardens, streets, around factories, offices, hospitals and schools, on wasteland and in existing woodlands." Therefore, various definitions exist to suit each country's specific city needs and greening goals (Tyrväinen et al., 2005).

Amidst the surge in urban population and the acute climate crisis, the urban forest, a subset of NBS, will have more opportunities to deliver ecosystem services to respond to pressing biodiversity and societal needs (De Vreese, 2018; Endreny, 2018). As there is growing importance to increase the greenery in cities, urban forest types vary from city parks and urban forests (of size greater than 0.5 ha) to pocket parks, public/private spaces with trees, riverain corridors, rooftops and green walls, and plant nurseries (Endreny, 2018). The Food and Agricultural Organisation (FAO) (2016) identified that five types of UFs contribute to the advancement of nine UN Sustainable Development Goals (SDGs), which are numbers 1,2,3,6,7,8,11,13, and 15. For each SDG, that is done by:

- #1 No poverty: the creation of jobs, the cost reduction of urban infrastructure, and the enhancement of local green economy;
- #2 Zero hunger: the supply of economical wood fuel, purified water and enriched soil, thus contributing to sustainable agricultural production;
- #3 Good health and well-being: the creation of outdoor recreational and relaxing spaces fostering the prevention and remediation of chronic diseases and care for mental health;
- #6 Clean water and sanitation: the regulation of urban hydrological cycles by capturing water, reducing flood and erosion hazards, and purifying water;
- #7 Affordable and clean energy: the production of renewable energy by sustainably managed UFs that can be an asset, especially for low-income urban communities;
- #8 Decent work and economic growth: the provision of housing materials, the generation of employment opportunities, the creation of an appealing setting for both tourism and business and by saving costs related to energy and human health maintenance;
- #11 Sustainable cities and communities: the shift towards environmentally and socio-economic resilient cities by climate change and natural hazards mitigation, energy cost and malnutrition reduction, and ecosystem services and public welfare provision;
- #13 Climate action: the sequestration of carbon, the aid in energy saving, the reduction of the urban heat island effect, and the mitigation of extreme events;
- #15 Life on land: the enhancement of biodiversity, the restoration of land, and the amelioration of soil quality.

The points above emphasize trees' ecological, social, and economic benefits in an urban ecosystem. Moreover, twenty-four years ago, Nowak & Dwyer (2000) studied the effects of urban trees on air quality and found that a mature tree could store as much as 10 tonnes of carbon. Nevertheless, this is possible depending on a series of considerations, like the health of the urban tree, its foliage type and duration, its leaf area index (LAI), surrounding soil moisture availability, pollution levels, and climatology. Urban trees can lower ground surface temperature by up to 15 degrees Celsius. However, the extent of cooling depends on the ground surface and tree characteristics, such as size, density, and typology (Owour et al., 2022).

As for human health and well-being, they are positively affected by UFs, directly and indirectly (Donovan, 2017). The FAO (2016) suggests the possibility that UFs have

contributed to the 16th SDG goal of “peace, just and strong institutions” by acting as a melting pot where city dwellers from different cultural and economic backgrounds meet. Therefore, UFs provide urban communities with common outdoor places to meet, exercise, play, and socialize, promoting a strong sense of community while strengthening their connection to nature. Consequently, the UF builds mutual interest among citizens, especially in an urban place’s ecological and cultural heritage, thus promoting local stewardship, ownership, and responsibility (Owour et al., 2022). Moreover, Owuor et al. (2022) state that exposing youngsters to nature has been proven to foster cognitive development and ecological literacy, with the latter remaining and growing with them as they age. Early exposure to nature can help prevent “nature deficit disorder,” a term coined by Richard Louv in 2005. This disorder refers to the negative consequences that children can experience when they are disconnected from nature, including weakened senses and a higher likelihood of emotional and physical illnesses. On the sensory level, urban trees also play a role in visually softening cityscapes (Davies et al., 2017) and increasing human attraction to some areas from an olfactive point of view due to pleasant fragrances by volatile organic compounds (VOCs) (X. Song & Wu, 2022). Human contact in the form of inhalation, touch, or ingestion of the microbiota of a healthy woodland can aid in the protection against autoimmune diseases and allergies, as VOCs have been proven to boost relaxation and the immune system (Owour et al., 2022). Other examples of UF factors improving human psychology were studied in Beijing, China, by Kong et al. (2022), who found that some types of urban parks (e.g. multifunctional, cultural, and ecologic) and their specific landscape attributes (e.g. area of the park and the area ratio of water bodies) evoke positive emotions in city dwellers and park visitors.

As for the economic benefits of UFs, they can be understood by assigning a monetary value to the ecosystem goods and services they deliver. This allows for the incorporation of ecological and biodiversity benefits such as carbon sequestration, stormwater runoff reductions, and energy savings into other economic assessments (X. P. Song et al., 2018). Thus, with the monetary value and the nature of trees, urban forests are resources that can be considered long-term investments (Owour et al., 2022). An exemplary case study has been conducted by Soares et al. (2011) on 40,000 street trees in Lisbon. The authors showed that these trees provide ecosystem services, which sum up to 8.4 million Euros/year, while maintaining them costs 1.9 million Euros/year. This means every citizen of Lisbon receives

4.5 Euros/year in the form of ecosystem services. Despite receiving 4.5 Euros/year, the citizens could first see the maintenance costs as high. However, it has been shown by Tavárez & Elbakidze (2021) that direct community involvement in the management of an UF increases the residents' willingness to pay (WTP) for its preservation. Consequently, considering citizens as key stakeholders in UF management and maintenance creates a sense of stewardship, which is of major importance to both the success and cost reduction of UFs.

Furthermore, another integral part of UF management is the communication between urban foresters and decision-making entities (X. P. Song et al., 2018). UF are thus urban and peri-urban socio-ecological interventions, integrating nature's processes and human management to greatly contribute to sustainable urban development (De Vreese, 2018).

However, an urban forest's benefits can, in particular cases, be a matter of perspective. Urban forests can be seen as disadvantages as property prices around urban green areas are known to increase and lead to green gentrification, with a good example represented by the high Line area in New York City (Jo Black & Richards, 2020). Disadvantages linked to UFs are known as ecosystem disservices (EDS) (Lyytimäki, 2017), and further include associated health issues (e.g. pollen allergies, injuries from falling branches, etc.), infrastructure damage (e.g. caused by roots), financial costs, public space safety concerns, and need to be considered and mitigated in the planning and decision phases of UFs (Owour et al., 2022).

To plan new and monitor existing UFs efficiently, urban canopy cover assessment has been proven to be the most common used and cost-effective tool to study urban trees and build their inventory for further action.

1.3. Urban Canopy Cover Assessment

The urban tree cover assessment was launched in 2006 by the U.S. Forest Service that wanted to evaluate the distribution and extent of tree canopy in Baltimore, Maryland (PLANIT Geo, 2022). As defined by Grove et al. (2006), urban canopy cover (UCC) refers to the city's ground-sheltering layer of foliage, branches, and stems of trees, as viewed from an aerial perspective. Being an index of two-dimensional nature, UCC is a land-cover class that conveys the coverage of trees over a studied urban area, regardless of the tree understory's land-cover classes (Korhonen et al., 2006). Within urban settlements, both publicly and privately owned trees constitute the UCC, especially since private lands hold a large

percentage of UCC in continents like North America and Europe (Nowak & Greenfield, 2012; FAO, 2018). UCC is generally estimated as the percentage of an area covered by tree canopies, which is a simple yet crucial metric in quantifying the extent of an UF (Richardson & Moskal, 2014). Moreover, UCC showed to be an informative tool for management decisions and policy analyses, with its estimation aiding municipalities in setting canopy cover targets, which are needed to achieve sustainable cities (Ucar et al., 2016; USDA, 2019b). In addition to that, the amount of tree canopy cover in an ideally thriving UF is closely tied to the provision of ecosystem services (Nowak & Greenfield, 2012). Thus, UCC and the quantification of its ecosystem services can be robust tools to push city officials to plant more urban trees. In fact, the UCC assessment is a useful tool aiding urban foresters in reaching new canopy cover targets to make cities more liveable, such as the 3-30-300 rule for urban forestry, proposed by Konijnendijk (2022). This rule suggests that 3 trees should be visible from every home, school, and work place, every neighbourhood should have a minimum UCC of 30%, and a citizen should not live more than 300 m away from an urban green space. Such guidelines can be achieved by utilizing the tool of UCC assessment.

UCC assessment can be field-based or non-field based. Field-based assessments characterize the forest from the ground. As for the non-field-based approaches, they use aerial or satellite imagery such as: LiDAR mapping, high-resolution imagery and land classification, spectral imagery, and aerial photography interpretation to remotely assess UCC (USDA, 2019b, 2019a).

1.4. Study Objectives

This thesis aims to use the i-Tree Canopy software, which is based on aerial photography interpretation, to assess and compare the current and potential urban canopy covers of ten European cities in different countries. The following will be specifically studied:

- 1) the existing canopy cover of the city's municipality;
- 2) the existing canopy cover of the municipality's artificial areas class;
- 3) the additional potential canopy cover that could be planted in the municipality's artificial areas.

Furthermore, the relationships among these three covers will be tested, along with the socio-economic and geographic variables influencing them. In addition to that, the i-Tree

Canopy estimations of the ecosystem services provided by the covers will be reported in amounts and monetary values and compared across the ten cities. This will be done in the aim to sensitize relevant stakeholders, namely decision and policymakers to better plan, implement, and manage urban forests via urban canopy cover.

2. Methods

2.1. Study sites

As study sites, ten European cities were chosen. Europe shows a megatrend towards denser populated cities, as by the year 2050, 84% of the population is projected to be living in cities (UN DESA, 2019). The selection of cities for this urban canopy cover (UCC) comparative study was random with the following guiding parameters: not more than one city per European country, urban core inhabitants ranging from 100,000 to 400,000, and a balanced dispersal across the European continent. The selected cities are Bergen (Norway), Debrecen (Hungary), Granada (Spain), Graz (Austria), Grenoble (France), Liège (Belgium), Messina (Italy), Northampton (United Kingdom), Olsztyn (Poland), and Tampere (Finland).

Figure 1 presents the distribution of the selected cities, along with their urban core population density (of reference year 2015, see section 2.2.4) and climate type according to the Köppen-Geiger Climate Classification. The base map shows Europe's biogeographical regions, as mapped by the European Environment Agency (EEA) in 2016, which is an indicator of the regions' biota (flora and fauna) systematics composition, climatic changes, continental movements, and the subsequent climatic and physical alterations that act as barriers to migration (The Encyclopedia of Ecology & Environment Management, 1998).

Figure 1 shows that the five cities with high population densities, starting with the highest, are Granada, Northampton, Liège, Graz, and Olsztyn. The rest follow this order: Grenoble, Messina, Debrecen, Bergen, and Tampere. As for the Köppen-Geiger Climate Classification, it represents Northampton, Liège, and Grenoble under *cfb*, which represents "temperate, no dry seasons, and warm summers." Graz, Debrecen, and Olsztyn are classified as *dfb*, that represents "cold, no dry seasons, and warm summers." As for Messina and Granada, they fall under the *csa* classification, noted by "temperate, dry and hot summers." Bergen and Tampere are classified as *dfc*, indicating "cold, no dry seasons, and cold summers." When it comes to their biogeographical regions, the cities are diversely characterized. Northampton and Bergen are within the Atlantic biogeographic region, while Liège, Graz, and Olsztyn are within the Continental region. Messina and Granada cover the Mediterranean, Tampere the Boreal, Debrecen the Pannonian, and Grenoble the Alpine.

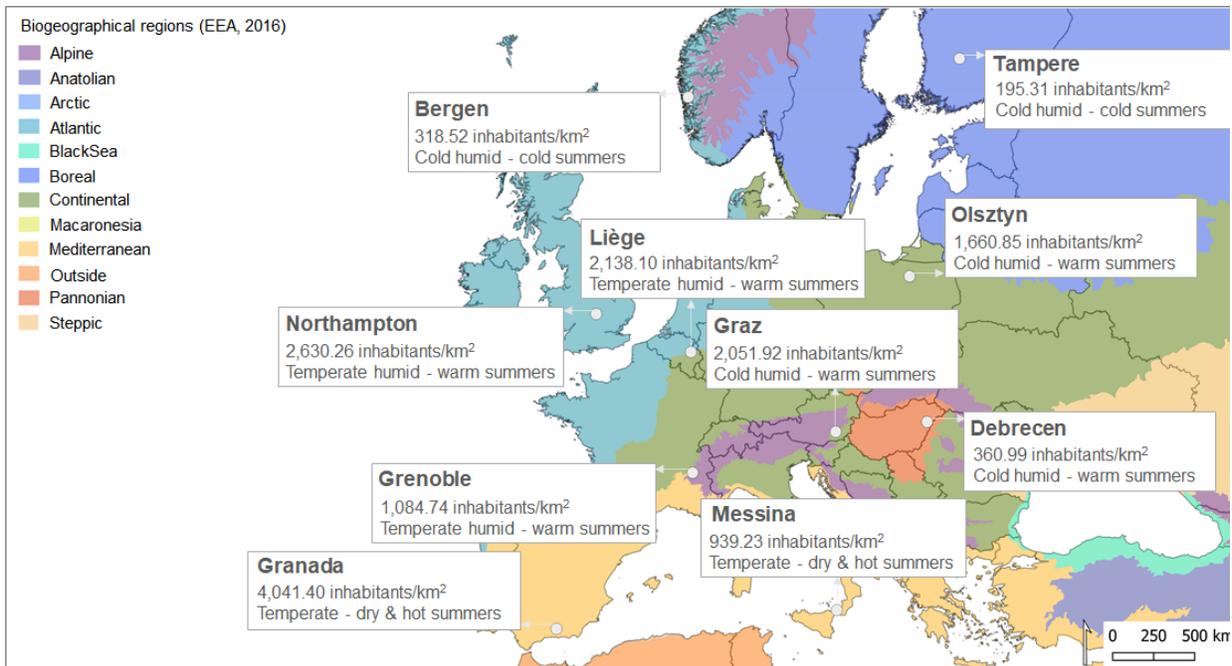


Figure 1 The selected cities and their distribution within the European Biogeographical Regions as mapped by the EEA (2016), along with their urban core population density and Köppen-Geiger Climate Classification.

Cities Overview

Bergen (longitude 5.30° E, latitude 60.364° N) is the second largest city in Norway and the capital of Norway's Vestland county. The city is located on the southwestern Norwegian coast, where fjords and mountains surround it, and offers a variety of parks for its inhabitants. Mentionable parks include the largest urban park, Nygårdspark (172,896 m²), Muséhagen, Byparken, and Norndesparken (www.studybergen.com). Forests can be found in the City Mountains of Bergen. In contrast to popular belief, these mountains do not host mainly native trees (the Scots Pine is the only native species). Moreover, the city's mountain forests were carefully planned in the past; they hosted a variety of tree species from North America and central Europe due to large-scale reforestation projects in the 19th century (partner.sciencenorway.no). In 2016, the city council of Bergen published its green strategy, which consists of various climate and energy actions (Grønn Strategi). With its ambitious goals, Bergen became the only European city invited to join the European Climate Forum (www.sustaineurope.com).

Debrecen (longitude 21.62° E, latitude 47.530° N) is the second largest city of Hungary and is situated in the Northern Great Plain region. The city is said to host the most beautiful forest in the country: the Great Forest, or Nagyerdő in Hungarian, being the lungs of Debrecen (www.debrecen.hu). Generally, Debrecen is one of Hungary's greenest cities, with 34% of its administrative area covered by forests. Despite that, the government of Debrecen still has ongoing projects to increase the city's greenery. For example, as part of the Debrecen2030 programme, urban afforestation efforts are planned to plant 2,000 trees, 30,000 m² of green space, and the planting of more than 24,000 forestry saplings to reduce dust and noise pollution (www.debrecen.hu), mainly from its Western intensive agricultural production area (Molnár et al., 2020).

Graz (longitude 15.43° E, latitude 47.076° N) is one of the largest cities of Austria and the capital of Styria, known as the "Green Heart of Austria" due to its mountains and forests. Graz is divided into 17 districts, with the Mur River splitting the city into two parts. Even though the city's green areas account for 68%, most of these do not represent street-level greening, as they are part of a forested zone on the outskirts of Graz. In 2018, the city of Graz started developing its climate action plan, but the fully formulated strategy was drafted four years later (Vuckovic et al., 2023). In its strategy, the city emphasizes preserving its green ecosystems to minimize city pollution and improve rainwater management through green infrastructure, namely street trees, vertical gardens, and green roofs, due to urban space constraints.

Granada (longitude -3.601° W, latitude 37.186° N) in Andalusia, Spain, is surrounded by the Sierra Nevada Mountain range, with the city overlooking the plains. Granada itself is mainly flat in its centre but has three hills, one of which hosts the famous Alhambra. The hills are separated by the Darro valley, created by the Darro River flowing through the city and ending in the Genil River. The city of Granada hosts green spaces covering an area of more than 1000 m², offering 4.74 m² of green space per person, as summarized by Cariñanos et al. (2016). In 2013, these green spaces contained over 39,000 trees, with *Platanus × hispanica* being the most common species, leading to a ratio of 160 trees per 1,000 residents, a value higher than the European average (Cariñanos et al., 2016). A noteworthy green initiative of Granada is the Granada Reforestation project, which aims to reduce air pollution by establishing a green belt of forests around the city (www.plant-for-the-planet.org).

Grenoble (longitude 5.725° E, latitude 45.148° N), the winner of the European Green Capital in 2022, lies right in front of the Alps in the south-eastern region Auvergne-Rhône-Alpes in France. With 35 parks and gardens the city offers a variety of green spaces (www.grenoble-tourisme.com). Despite being so close to the French Alps, Grenoble is relatively flat, as it is located on the alluvial planes of the two rivers Isère and Drac cross-cutting the city. The surrounding area of Grenoble and part of its area itself however are steep mountain ridges covered with forests.

Liege (longitude 5.572° E, latitude 50.635° N) is in the Wallonia region of Belgium, where it lies at the bottom of a relatively steep part of the Meuse valley (Beaumont et al., 2022). The city covers 69 km² of which the greenest parts can be found on the slopes and plateaus (Beaumont et al., 2022). To address its air pollution, noise pollution, and urban heat island effects, the city introduced the greening plan “Plan Canopée”, which aims to increase the urban canopy cover (Beaumont et al., 2022).

Messina (longitude 15.554° E, latitude 38.191° N) is located at the very north-eastern part of Sicily, lies at sea level on and at the lower slopes of the Peloritani Mountains. Unfortunately, Messina is not the first Italian city that comes to mind regarding green cities. In an environmental ranking of 100 Italian cities, Messina ranks on the 96th place (www.letteraemme.it). However, with the ForestaME project, Messina has an ambitious project which aims to improve this situation. By planting trees and improving drainage systems, the ForestaME tries to reduce CO₂ emissions and the urban heat island as well as possible floods, and by that improving the overall quality of living for its inhabitants (www.livesicilia.it).

Northampton (longitude -0.897° E, latitude 52.241° N) is one of the largest towns in England and is located in Northamptonshire at the Nene River. The city can be described as a relatively green city; however, trees are rather sparse since most of the city’s greenery consists of multi-functional parks and golf courses that do not have canopy cover. As can be seen in the “Northampton Green Infrastructure Plan”¹ which was provided by a group of consultants from Fiona Fyfe Associates, country scape, and the University of Northampton for the

¹ <https://www.fionafyfe.co.uk/2016/northampton-green-infrastructure-plan/>

Northampton borough counsel, the importance of improving and maintaining Northampton's green spaces is strongly recognised.

Olsztyn (longitude 20.478° E, latitude 53.782°N) the city of lakes and forests, lies surrounded by forests at the Łyna river in the North-East of Poland and is the capital of the Warmian-Masurian Voivodeship. The city is very green as twenty percent of the suburban city are covered with forests and as lakes, rivers and nature reserves can be found (www.staypoland.com).

Tampere (longitude 23.787° E, latitude 61.629° N) lies between the Näsijärvi and Pyhäjärvi lakes in the Pirkanmaa region in Western Finland. The city hosts a variety of parks, including the Hatanpää arboretum, and has forests close by (www.visittampere.fi). Like many other cities, Tampere aims to be CO₂-neutral by 2030. The Carbon Neutral Tampere 2030 Roadmap² roadmap was designed to achieve this goal, including a forest management plan of the 7,500 ha of city-owned forest with the overall goal of binding carbon.

Socio-economic data of the cities are presented in Table 1 where the data refers to the year 2015 for consistency across this study see (2.2.4).

Table 1 Socio-economic variables of the ten selected cities based on the year 2015.

City	Population FUA	Population UC	UC Population density (Inhabitants/km ²)	FUA GDP* [10 ⁶ €]	FUA GDPPC* [€]	Regional HH Income [10 ⁶ €]
Bergen	351358	148005	318.52	18595	51949	51615.60
Debrecen	322962	166657	360.99	5729	19050	7848.65
Granada	508590	355805	4041.40	13026	25795	92567.60
Graz	441137	261476	2051.92	28557	50197	29698
Grenoble	610376	338199	1084.74	24277	37750	148641.40
Liège	112939	381673	2138.10	23958	33903	22832.90
Messina	256489	198553	939.23	5737	23263	61078.50
Northampton	315375	212525	2630.26	17423	41341	92000
Olsztyn	219981	146686	1660.85	4940	21624	8433.35
Tampere	341850	134672	195.31	14899	38523	29295.13

*The GDP and GDP per capita (GDPPC) values are reported in 10⁶ € despite being reported in 10⁶ \$ on the OECD website. For comparison reasons to other socio-economic factors, the US-Dollar values were converted to Euro using the average USD-to-EUR exchange rate from 2015 of 0.9013 as reported by the European Central Bank

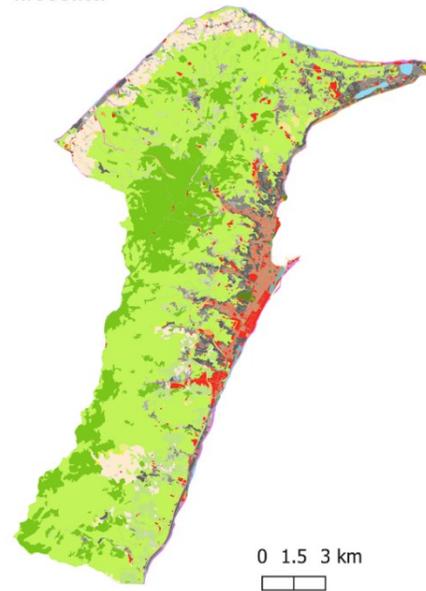
² <https://www.tampere.fi/en/nature-and-environment/climate-action-tampere>

Figure 2 and Figure 3 represent the land cover and land use (LC/LU) maps of the urban cores of the study sites based on the Urban Atlas for the reference year 2018.

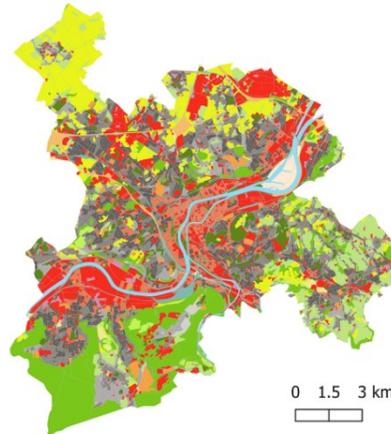
Urban Atlas Land Cover/Land Use (2018)

- Arable land (annual crops)
- Construction sites
- Continuous urban fabric (S.L. : > 80%)
- Discontinuous dense urban fabric (S.L. : 50% - 80%)
- Discontinuous low density urban fabric (S.L. : 10% - 30%)
- Discontinuous medium density urban fabric (S.L. : 30% - 50%)
- Discontinuous very low density urban fabric (S.L. : < 10%)
- Fast transit roads and associated land
- Forests
- Green urban areas
- Herbaceous vegetation associations (natural grassland, moors...)
- Industrial, commercial, public, military and private units
- Isolated structures
- Land without current use
- Mineral extraction and dump sites
- Open spaces with little or no vegetation (beaches, dunes, bare rocks, glaciers)
- Other roads and associated land
- Pastures
- Railways and associated land
- Sports and leisure facilities
- Water
- Wetlands
- No data

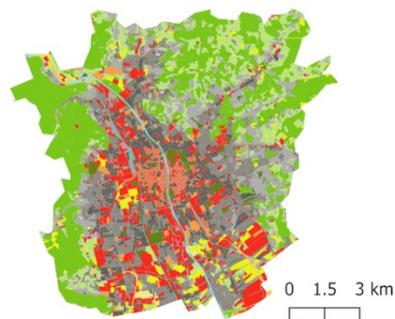
Messina



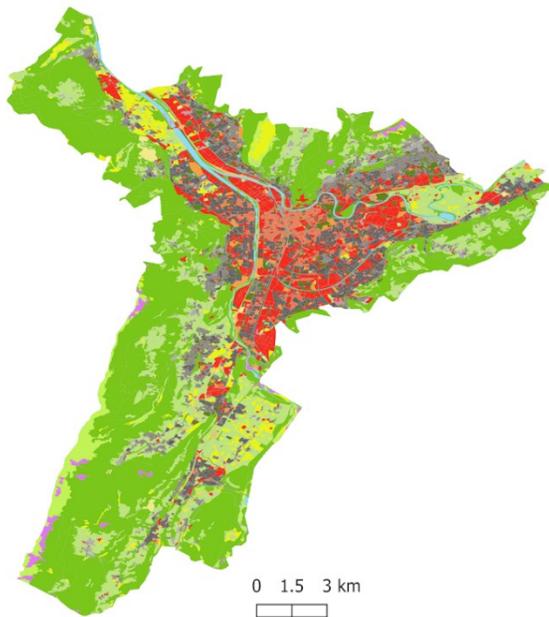
Liège



Graz



Grenoble



a)

Figure 2 Urban Atlas land cover and land use (2018) of the UC of the ten selected cities for 2018.

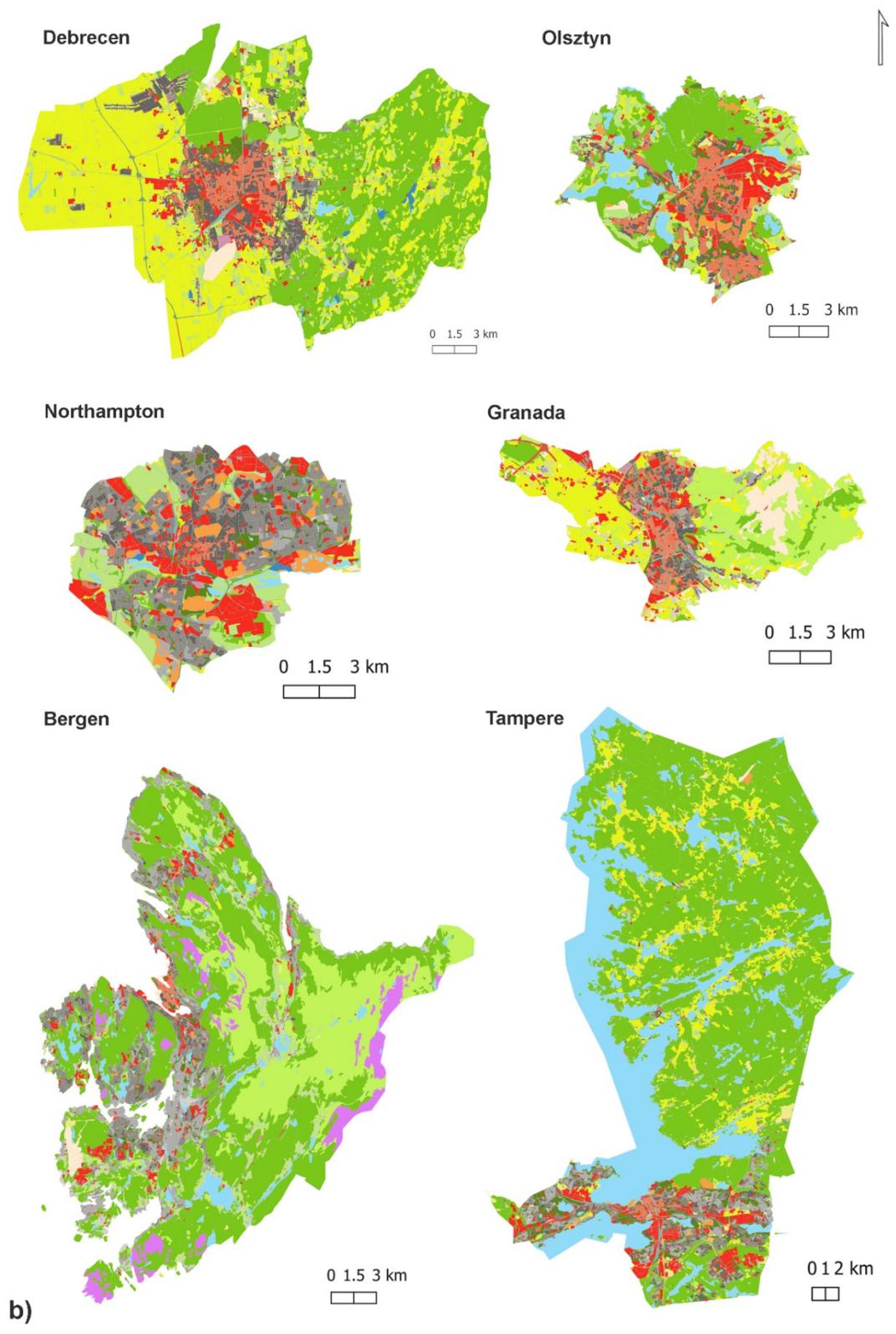


Figure 3 Urban Atlas land cover and land use (2018) of the UC of the ten selected cities.

2.2. Data Collection

2.2.1. Assessment of the tree canopy via i-Tree Canopy

To remotely estimate UCC, the chosen non-field method was random point sampling via i-Tree Canopy (<https://canopy.itreetools.org/>), which is one of the many tools that the i-Tree suite offers (<https://www.itreetools.org/tools>). i-Tree is a free-to-use, innovative, and peer-reviewed software enabling users to analyse and assess the benefits of urban and rural trees. It was developed by the USDA Forest Service and launched in 2006. Since then, i-Tree has been a public/private collaboration among a series of actors, which are listed on the i-Tree website. Its different applications have been improved for over 20 years. They are designed to aid in **tree planting** (i-Tree Planting, i-Tree Species, and MyTreeMap), **assessment of individual trees** (MyTree, i-Tree Design, i-Tree Eco), **core tree canopy area assessment** (OurTrees, i-Tree Landscape, and i-Tree Canopy), supplemental uses like **adding new tree species** (i-Tree Database), and **utilities, research, and collaborative efforts** (i-Tree Eco, MyTree data, HydroPlus, CoolAir, and more) (i-Tree, 2023).

i-Tree Canopy first requires its users to define a study area by drawing project area limits on Google Maps-based imagery, uploading an ESRI shapefile, or selecting geographic boundaries given by the software. It then offers the option to pick or personalize land cover classes, of which the cover labelled as “tree” will be assigned benefit valuations based on location, currency, and measurement unit fields chosen by the user. Once started, the software randomly generates a sample point within the selected boundaries and zooms into it while allowing further zooming in and out for a clearer view. The user would see imagery based on Google Maps aerial photography and a sample point marker in the form of a small yellow cross, which, from a dropdown list, will have to be labelled based on the pre-selected land cover classes. i-Tree Canopy recommends having a total of 500-1000 survey points, with more points making cover estimation more accurate. To calculate the tree cover percentage (p) and its standard error (SE), i-Tree Canopy uses the following equations (1) and (2):

$$p = n/N \quad (1)$$

$$SE = \sqrt{pq/N} \quad (2)$$

where N = number of sampled points, n = total number of points classified as tree, $q = 1 - p$

Once done with the point sampling, the user can generate a Cover Assessment and Tree Benefits (CATB) report, which represents the results of the cover class/land cover classification and the tree benefit estimates for carbon, air pollution, and hydrology (i-Tree Canopy, 2023). The points can be exported in the form of comma-separated values (CSV) files for a universal format that can be used in many programs, Keyhole Markup Language (KML), and the Zip-compressed KML known by KMZ, both viewable in geographic information systems (GIS) applications (e.g. Google Earth, ESRI ArcGIS, and QGIS).

For this study, i-Tree Canopy was used to provide a point-based urban canopy cover assessment, which also includes a potential urban cover recommendation for the ten chosen cities. One-thousand points per city were sampled for high accuracy, while keeping the standard error (SE) of the cover below 2%. For each of the 10 chosen cities, three cover classes were input in i-Tree Canopy for assessment: Tree (T), Potential Canopy Cover (PTC), and Non-Tree (NT). Table 2 provides a description of these variables.

Table 2 Cover classes and their descriptions as input in i-Tree Canopy

Cover Class	Description
Tree (T)	A tree (excluding shrubs)
Potential Tree Cover (PTC)	An area without tree canopies, in which a tree could be planted. A buffer radius of roughly 2.5 m is considered: no built or artificial surfaces should be found. Areas that do not have this potential are sports grounds, buildings/other infrastructures, and small-scale agricultural lands, vineyards and plantations
Non-Tree (NT)	All other surfaces

Since this study is concerned with tree canopy cover rather than vegetation or total canopy cover, it was decided that all other vegetation covers would be labelled as NT. If the yellow cross falls on a garden hedge or low bush, the point will not be marked as a tree. If the cross falls on the ground in a tree’s shadow, it would not be considered a tree. As for trees, every street, ornamental, agricultural, or plantation tree would be marked as T. Scale and

context could be evaluated with the ability to zoom in and out when a point is generated, and this is helpful in determining whether a tree is not a shrub.

As for points that would be labelled as PTC, they would have to fall in a spot where there is no existing tree cover and no built or artificial surfaces surround it: a buffer of around 2.5 m is considered. Vegetation cover, however, is not included in this buffer. If a point falls on a sports field, building, or other artificial infrastructure, or in a small-scale agricultural field, vineyard and plantation, it would not be marked as PTC. The decision to exclude a point that would be eligible for being a PTC but that falls onto small-scale agricultural land is to avoid shifting the focus of the study and delving into land use conversion. Considerations of public and private ownership of the land on which points randomly fall have been excluded from this study. That is due to the introduced definition of an UF, which includes private trees, and since many assessments show that urban vegetation is mainly located on private property and that the opportunities to increase UCC are in private/residential areas (King et Locke, 2013).

To assign appropriate tree benefit valuations to tree cover in the software's allocated section, the United Kingdom and Sweden were selected as reference locations, with an emphasis on "urban" areas, not "rural." This choice is based on European country availability, as the software will retrieve benefit values from the selected locations to estimate tree benefits, and selecting European locations makes this data more accurate. Since i-Tree Canopy does not offer the possibility of selecting other European countries yet, selecting both the United Kingdom and Sweden instead of one would make the comparison less subjective.

2.2.2. Implication of boundary definition on potential canopy cover assessment

The study site city limits that had to be used in the i-Tree Canopy software for this urban cover assessment were defined differently for the existing canopy cover and the potential canopy cover. That is because deciding whether a point could be considered a PTC would need a thorough assessment of the ten cities' various land cover, land use, and forest management on top of the PTC description in Table 2. The following scenarios further explain the implication of boundary definition on the PTC. If a point falls in a forest or semi-natural area, as seen in Figure 4, the decision to label it as PTC or not would be a matter of forest

management: considering it a PTC could mean engaging in active reforestation efforts while dismissing it as a PTC could suggest waiting for the natural arrival of the forest over time, via forest regeneration. The latter is an essential global forest management tool, especially since its costs are significantly lower than those incurred by big-scale reforestation efforts (García et al., 2020; Bullock et al., 2011). However, one of the aims of this study is to suggest potential UCC. Thus, the forest management approach in favour of planting must be adopted in this case and carried out similarly among the ten chosen cities. However, the reasoning of the forest management decision would differ from city to city. For instance, in Mediterranean contexts, such as Messina and Granada, points within the city boundaries could be randomly generated in the Garrigues or Maquis scrublands. Specific to the Mediterranean, these vegetation types are characterized by sclerophyllous low and dense plant communities that develop on open land after human disturbances or fires (Guarino et al., 2020). It would not be sure why one would suggest a PTC in these scrublands since they are known for only having scattered trees and for being dominated by species that do not grow into tall trees, especially in the Maquis (EUNIS, 2019). An example of that is shown below in Figure 5.



Figure 4 Random point via i-Tree Canopy in a forest setting within Messina's city boundaries



Figure 5 Random point via i-Tree Canopy in a scrubland setting within Messina's city boundaries

Therefore, the solution was to exclude natural, agricultural, and aquatic areas from the study site coverage of the PCC assessment. This was done by considering the Urban Atlas (UA) as the tool to classify LC/LU, and it was decided to only work on the "artificial areas" class for more efficient point sampling. Consequently, for each city, two i-Tree Canopy sampling projects of different boundary definitions were carried out:

- 1) the Urban Core (UC) limits as sampling boundaries, in which the existing canopy cover would be assessed;
- 2) the artificial areas of the Urban Core as sampling boundaries, in which the existing and potential canopy covers would be assessed.

The Organisation for Economic Co-operation and Development (OECD) has defined the UC based on a people-based method. To locate the UC of local units, the detection of high-density cells within a population grid was done for cities with a minimum of 50,000 inhabitants. Next, the commuting zone (the city's labour market) was identified by looking at the population's commuting flows to surrounding local units of less population density. This is how the term Functional Urban Area (FUA) rose, defining the economic and functional boundaries of cities by considering its population's daily movements (Dijkstra et al., 2019).

The UA is a joint initiative under the EU Copernicus Programme and is a suite of products by the Copernicus Land Monitoring Service (CLMS). It is classified as an area of

priority monitoring, which provides detailed information on LC/LU of hot spot areas that the CLMS defines as susceptible to distinct environmental challenges (CLMS, 2023).

For this study, the Urban Atlas Land Cover/Land Use for the reference year 2018 was downloaded from the CLMS website (<https://land.copernicus.eu/en/products/urban-atlas/urban-atlas-2018>). In the EEA Geospatial Data Catalogue (<https://doi.org/10.2909/fb4dffa1-6ceb-4cc0-8372-1ed354c285e6>), the report of this dataset explains that it is characterized by high resolution LC/LU data for 788 FUAs of a minimum of 50,000 inhabitants. The LC/LU data was retrieved from semi-automatic Sentinel-2 time series classification, along with visual interpretation from Very High Resolution (VHR) satellite imagery (Copernicus et SIRS, 2020). This version v013 is vector-based data with a Minimum Mapping Width (MMW) of 10 m and with ETRS89-LAEA, EPSG:3035 as Coordinate Reference System (CRS). For each FUA, the dataset provides a ZIP folder including: (1) vector data in OGC GeoPackage SQLite format; (2) a high-resolution map and its legend as PDF; (3) the delivery report as PDF; (4) legend files in .lyr, .qml, and .sld; and (5) metadata as an .xml document (EEA Geospatial Data Catalogue, 2021).

To extract the “artificial areas” class from the UA LC/LU data for each city, the downloaded UA vector data was visualized via Quantum Geographic Information System (QGIS). Each city’s UA vector data was represented by 3 multi-polygons: FUA boundaries (UA2018_Boundary), UC boundaries (UA2018_UrbanCore), and FUA LC/LU data (UA2018). The following steps were taken:

1. The “select features using an expression” tool of the attribute table of the FUA LC/LU was used to select the UA LC/LU typology codes for artificial areas, as seen below:

11100 Continuous urban fabric (S.L.: >80%)	12210 Fast transit roads and associated land
11210 Discontinuous Dense Urban Fabric (S.L.: 50% - 80%)	12220 Other roads and associated land
11220 Discontinuous Medium Density Urban Fabric (S.L.: 30% - 50%)	12230 Railways and associated land
	12300 Port areas
	12400 Airports
	13100 Mineral extraction and dump sites

11230 Discontinuous Low-Density Urban Fabric (S.L.: 10% - 30%)	13300 Construction sites
11240 Discontinuous Very Low-Density Urban Fabric (S.L.: <10%)	13400 Land without current use
11300 Isolated Structures	14100 Green urban areas
	14200 Sports and leisure facilities

2. The selected features were then saved as an ESRI shapefile under the same CRS, and its geometry was given a spatial index (layer properties > source > geometry).
3. From the Processing Toolbox, the clip tool of the vector overlay was used to fit the artificial area selection (as input layer) into the UC boundaries of the city (as overlay layer).
4. The output generated in step 3 was then simplified using the dissolve tool of the vector geometry. That was done to simplify the representation of the new LC/LU shapefile, so that it is lighter to use in i-Tree Canopy. It was then saved as an ESRI shapefile under the same CRS.

For each city, the UC limits and the produced shapefile of the artificial areas of the UC were then loaded into i-Tree Canopy as the project boundaries. Figure 6 and Figure 7 show the difference in project boundaries between the UC shapefile and the UC's artificial areas shapefile, as seen in i-Tree Canopy.

The cover classes assessed within each of these boundaries are summarized in Table 3

Table 3 The assessed cover classes within the two project boundaries: UC and UC AA

	UC	UC AA*
T	CCC	CCA
PTC		PCC
NT		

*Artificial Areas

2.2.3. Estimating the tree benefits of the canopy cover classes

In the final CATB report of i-Tree Canopy, the estimated amounts and monetary values are summarized in a carbon benefits table, an air pollution benefits table, and a hydrological benefits table, respectively. Each of these tables reports amounts (in t or Megaliters Ml) and their connected monetary value (in €). The estimated amounts are calculated by using a carbon rate (t/km²/yr) and CO₂ equivalent rate (t/km²), air pollution removal rate (t/km²/yr), and hydrological tree effects (Ml/km/yr), respectively, and multiplying them with the area covered by tree canopies (km²). Subsequently, the monetary value reported for each benefit is calculated by multiplying the obtained benefit amount (in t or Ml) by its specific monetary value conversion rate given in €/t, €/t/yr, and €/Ml/yr, respectively.

The rates for carbon, CO₂ equivalent, air pollution and hydrological tree effects are represented below in Table 4.

The reports generated at the end of the two sampling projects gave the tree benefit estimates for the canopy cover over the core (CCC) and the canopy cover over the artificial areas (CCA). To calculate the estimated tree benefit amounts and monetary values of the potential canopy cover over the artificial area (PCC), the same conversion rates were used.

Table 4 i-Tree Canopy’s rates for carbon, CO₂ equivalent, air pollution and hydrological tree effects

Tree Benefit Estimates: Carbon		
	Sequestered [t/km ² /yr]	Value [€/t/yr]
C	306	191.37
CO ₂ equiv	1122	52.19
	Stored [t/km ²]	Value [€/t]
C	7685	191.37
CO ₂ equiv	28178	52.19
Tree Benefit Estimates: Air Pollution		
	Removal Rate [t/km ² /yr]	Value [€/t/yr]
CO	0.114	1048.56
NO ₂	2.616	165.4
O ₃	11.647	252.08
SO ₂	0.942	60
PM _{2.5}	1.625	7035.24
PM ₁₀ *	3.309	4834.2
Tree Benefit Estimates: Hydrological		
	Tree Effect [Ml/km ² /yr]	Value [€/Ml/yr]
AVRO	62.728	1773.24
E	355.28	N/A
I	356.346	N/A
T	240.445	N/A
PE	754.281	N/A
PET	581.273	N/A

With C: Carbon, CO₂equiv: Carbon Dioxide equivalent, CO: Carbon Monoxide, NO₂: Nitrogen Dioxide, O₃: Ozone, SO₂: Sulphur Dioxide, PM_{2.5}: Particulate Matter<2.5 microns, PM₁₀*: Particulate Matter> 2.5 microns and <10 microns, AVRO: avoided runoff, E: Evaporation, I: Interception, T: Transpiration, PE: Potential Evaporation, PET: Potential Evapotranspiration

While comparing the CATB reports among the cities, it was observed that the conversion rate of the monetary values was different based on the date of generation of the report. Consequently, the report for each project per city was re-generated on the 29th of December 2023 in order to have tree benefit estimates based on unified and updated monetary values.

It was also noted that for some of the cities, the software generated the tree benefit estimate amounts in different units (kilotons, tons, kilograms, or grams), most likely

depending on what would be more visually appealing based on the size of the amount. To make the cover classes data comparable, the units were standardized to tons.

2.2.4. Socio-economic and geographic data

The following socio-economic and geographic data were collected and adapted from the same data sources when possible to maintain consistency. From the OECD Regional Statistics Data (<https://www.oecd.org/regional/regional-statistics/>), the “Cities in the world” data visualization tool was accessed to get the FUA and UC population data. The year 2015 was chosen as the reference year, as more recent population data from the OECD could not be found for all cities. Moreover, the OECD’s definitions for the UC and the FUA were adopted in this study, so the adoption of different sources for the cities would make them less comparable. As for the GDP and GDP per capita, they were retrieved for each FUA for the year 2015 from the OECD’s Statistical Database (https://stats.oecd.org/Index.aspx?datasetcode=FUA_CITY). The household income balance for 2015 regional data was found based on the Nomenclature of Territorial Units for Statistics (NUTS) 2 classification. The NUTS is a framework used to divide the European Union and the United Kingdom’s economic territory and the NUTS 2 was chosen as it represents medium territorial units (Eurostat). The median household income for 015 was found on the national level on the GlobalData platform³.

For area precision and unity among the cities, the areas (km²) of each UC and its artificial areas were extracted from the UA vector data via QGIS. To do that, the Field Calculator was used to update the existing area field of the UC boundary and to create the area field of the artificial areas of the UC. The population density of the UC (reference year 2015) was then calculated. As for the cities’ latitudes (deg), they were extracted from the centroid that was produced via QGIS for each UC boundary. The altitude (m) of the cities was considered for both the UC and the artificial areas of the UC. The chosen parameters for altitude were the minimum, mean, maximum, and standard deviation, which were generated in QGIS using each city’s Digital Terrain Model (DTM) and using the Raster Layer Statistics tool. The DTMs were retrieved from OpenTopography (<https://opentopography.org/>), a platform aiming to facilitate online access to high resolution topographic maps and

³ <https://www.globaldata.com/data-insights/listing/search/?q%5b%5d=macroeconomic&exactWord=3>

resources. The chosen dataset was the “Digital Terrain Model for Continental Europe”, released in 2022. It has a raster resolution of 30 m and CRS in ETRS89-extended, LAEA Europe [EPSG: 3035] (horizontal) and EGM2008 [EPSG: 3855] (vertical). With the platform’s square selection option, each city’s approximate DTM was selected and downloaded to be input into QGIS with its corresponding UC boundary and UC artificial areas shapefiles. Since the DTMs surpassed the boundaries of two UC shapefiles, the raster DTM was clipped to fit the vector UC boundaries by using the “clip raster by mask layer” raster extraction tool. This yielded the elevation data for the UC and for the artificial areas of the UC. Using the raster layer statistics tool, the minimum, mean, maximum, and standard deviation were obtained from each elevation layer, and are represented in Table 5.

Table 5 Geographical data of the ten selected cities reporting the latitude, the minimum, maximum, mean and standard deviation (σ) values for the altitude in meters as well as the corresponding areas of both the urban cores and the artificial areas of the urban cores in km².

City	Altitudes of the urban cores						Altitudes of the urban cores’ artificial areas				
	lat	min	max	mean	σ	area	min	max	Mean	σ	area
	[°]	[m]	[m]	[m]	[m]	[km ²]	[m]	[m]	[m]	[m]	[km ²]
Bergen	60.364	-1.70	966.09	204.71	186.72	464.67	-0.89	550.40	61.25	46.79	111.52
Debrecen	47.530	98.40	157.19	120.65	9.17	461.67	99.9	153.3	119.60	7.68	91.00
Granada	37.186	575.29	1164.30	778.41	153.16	88.04	581.20	1153.90	691.62	70.42	27.70
Graz	47.076	327.20	746.29	416.18	78.03	127.43	328.89	746.20	376.11	40.03	74.98
Grenoble	45.148	187.19	2154.39	524.98	368.39	311.78	192.19	1556.90	264.7	111.64	107.18
Liège	50.635	50.70	323.10	148.44	59.93	178.51	50.70	279.79	137.23	59.76	114.58
Messina	38.191	-0.69	1113.80	280.25	223.62	211.40	-0.20	1113.8	110.88	125.05	65.90
Northampton	52.241	45.09	136	81.31	19.17	80.80	47.7	136	83.75	18.59	62.51
Olsztyn	53.782	85.19	156.39	121.98	12.57	88.32	89	152.5	125.75	11.69	37.49
Tampere	61.629	75.69	204.80	116.76	20.55	689.53	76	186.50	110.15	17.54	108.23

2.3. Data Analysis

To compare data among the ten chosen cities, histograms were chosen to represent the three assessed canopy covers and their benefit estimates.

Statistical analyses

With R Statistical Software (version 4.3.2), a correlation analysis with the Pearson method was carried out among the three canopy covers calculated by i-Tree Canopy: CCC,

CCA, and PCC. To explore the role of the geographic and socio-economic variables in defining current and potential canopy cover, these variables were modelled by using multiple linear regression in R. Explanatory variables were tested for correlation to avoid multicollinearity in the models. Spearman's rank correlation coefficient was used as data for different possible explanatory variables was not normally distributed. The function "core.test" was used to assess significant correlations ($p < 0.05$).

A forward selection procedure was applied by using the function "step" in R with model selection based on AIC. Model residuals were tested for normality with the Shapiro-Wilk test ($p < 0.05$ indicating not normal distribution) and homoscedasticity was tested with the Breusch-Pagan test through the "ncvTest" function of the "car" package (Fox & Weisberg, 2018). For this reason, both dependent and explanatory variables were log-transformed in the second model referred to the canopy cover over artificial surface.

3. Results

3.1. Canopy cover assessment across the cities

3.1.1. Comparison of canopy cover classes

Figure 8 shows the histograms of the three cover types assessed for each city, displayed in descending order of the CCC. The city that resulted in the highest CCC is Tampere, with a cover of $50.75 \pm 1.58\%$. Grenoble is the second highest, with $48.35 \pm 1.58\%$. From Bergen on, the CCC gradually decreases to a value of $45.70 \pm 1.58\%$ and $40.30 \pm 1.55\%$ for Olsztyn. Subsequently, Debrecen's coverage drops to $35.30 \pm 1.51\%$, closely followed by Graz with $34.43 \pm 1.50\%$ and Messina with $33.53 \pm 1.49\%$. Liège, Northampton, and Granada constitute the lowest covers among the studied cities, with a CCC of $27.50 \pm 1.41\%$, $21.36 \pm 1.29\%$, and $19.68 \pm 1.26\%$ respectively.

As for the CCA, it resulted in the same descending order as the CCC for the first three cities: Tampere with $36.70 \pm 1.52\%$, Grenoble with $24.50 \pm 1.36\%$, and Bergen with $22.60 \pm 1.32\%$. Northampton ranks fourth with $19.90 \pm 1.26\%$, and Olsztyn closely follows with $19.40 \pm 1.25\%$. Liège showed a CCA of $17.50 \pm 1.20\%$, Messina of $16.70 \pm 1.18\%$, Debrecen of $15.00 \pm 1.13\%$, Graz of $14.09 \pm 1.10\%$ and Granada, ranking last with $11.50 \pm 1.01\%$.

The city showing the highest PCC value is Graz, with $15.88 \pm 1.16\%$. It is closely followed by Debrecen, with a PCC of $15.40 \pm 1.14\%$. The rest of the cities are ordered as follows: Liège with $14.60 \pm 1.12\%$, Tampere with $13.90 \pm 1.09\%$, Olsztyn with $13.30 \pm 1.07\%$, Bergen with $12.40 \pm 1.04\%$, Northampton with $11.50 \pm 1.01\%$, Grenoble and Messina both with $10.50 \pm 0.97\%$ and Granada, still ranking last with $10.30 \pm 0.96\%$.

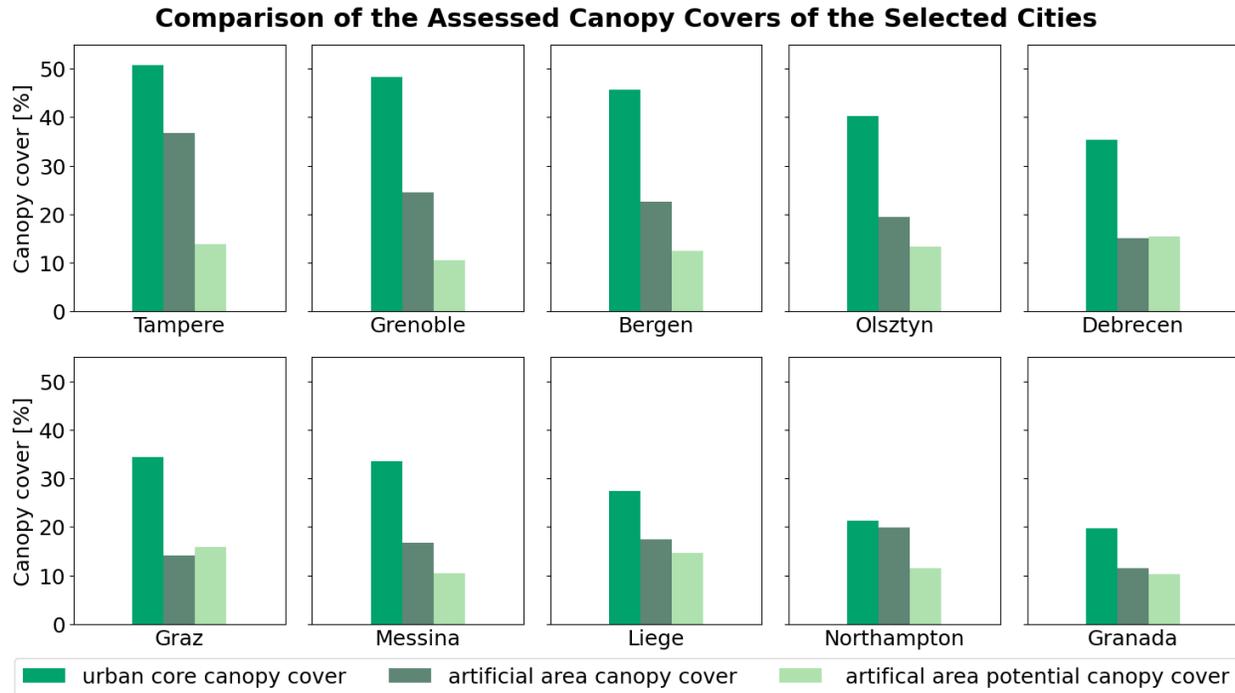


Figure 8 Comparison of the assessed canopy covers of the selected cities, ordered by decreasing urban core canopy cover in percent.

Consequently, to show each city's potential to increase canopy cover targets, the CCA and PCC were summed, resulting in the following total potential canopy cover values in decreasing order: Tampere (50.6%), Grenoble and Bergen (35%), Olsztyn (32.7%), Liège (32.1%), Northampton (31.4%), Debrecen (30.4%), Graz (29.97%), Messina (27.2%), and Granada (21.8%).

Table 6 shows a comparison between the obtained CCC values for this study's cities and a city tree cover study by the EEA for the year 2018. As reported in the difference column, the data for Debrecen, Graz, Northampton, and Olsztyn are very similar with small differences of up to +4.63%. However, the remaining six cities have rather large differences ranging from -10.5% for Grenoble up to +17.72% for Granada.

Table 6 Comparison of urban canopy cover values in percent between this study and published data by the European Environment Agency.

City	Core Canopy Cover [%]		Difference (EEA - this study)
	This study	EEA	
Bergen	45.70	59.21	+13.51
Debrecen	35.30	39.93	+4.63
Granada	19.68	37.4	+17.72
Graz	34.43	37.98	+3.55
Grenoble	48.35	37.85	-10.5
Liège	27.50	35.2	+7.7
Messina	33.53	43.28	+9.75
Northampton	21.36	18.31	-3.05
Olsztyn	40.30	44.2	+3.9
Tampere	50.75	60.33	+9.58

3.1.2. Canopy cover correlations

The CCC was strongly correlated to the CCA (correlation: 0.73 and p-value= 0.01554; Figure 9). Interestingly, no correlation was observed between the canopy cover variables and the PCC.

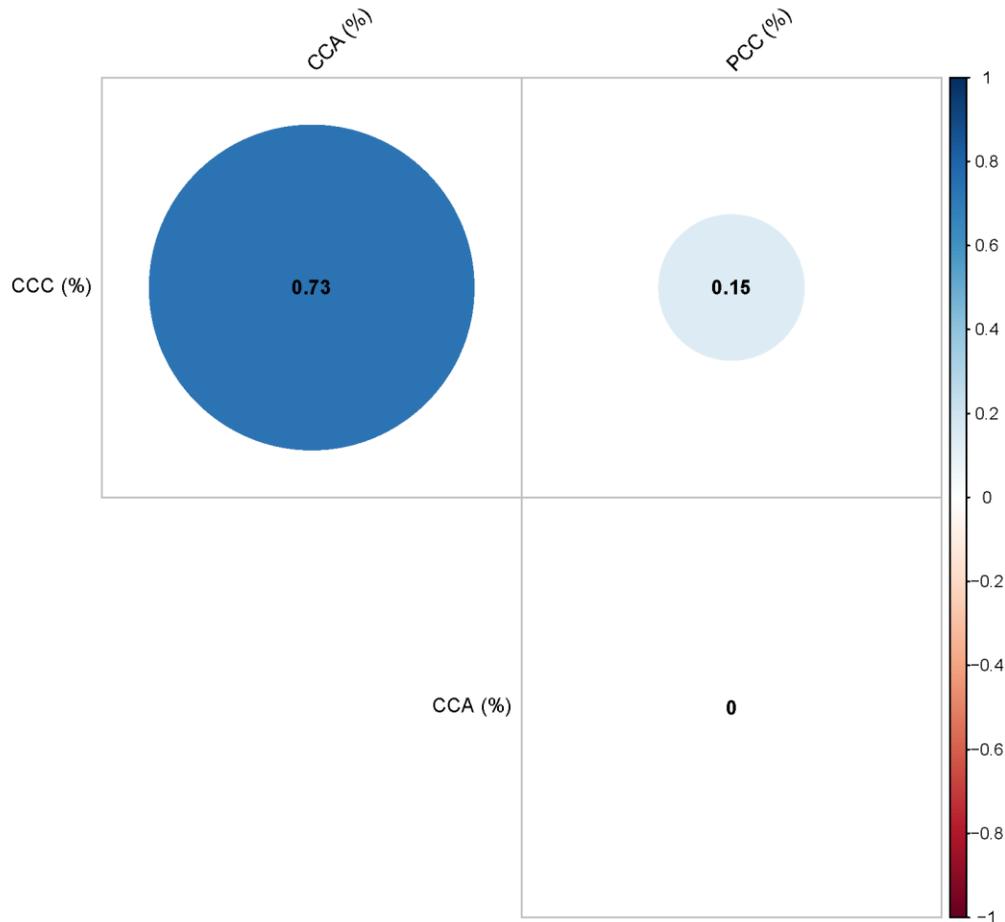


Figure 9 The strong correlation between the CCC and the CCA.

3.2. Benefit Estimates Comparisons of the Assessed Canopy Covers

The results of the i-Tree Canopy tree benefit estimations and their standard errors are presented in the Appendix.

The histograms in Figure 10–Figure 14 represent the main ecosystem services annually delivered by each of the three assessed canopy covers in tonnes (t) or megaliters (ML) with their respective monetary value in Euros. The only exception is stored carbon, which is not reported as an annual rate.

Tree Benefit Estimates: Sequestered Carbon

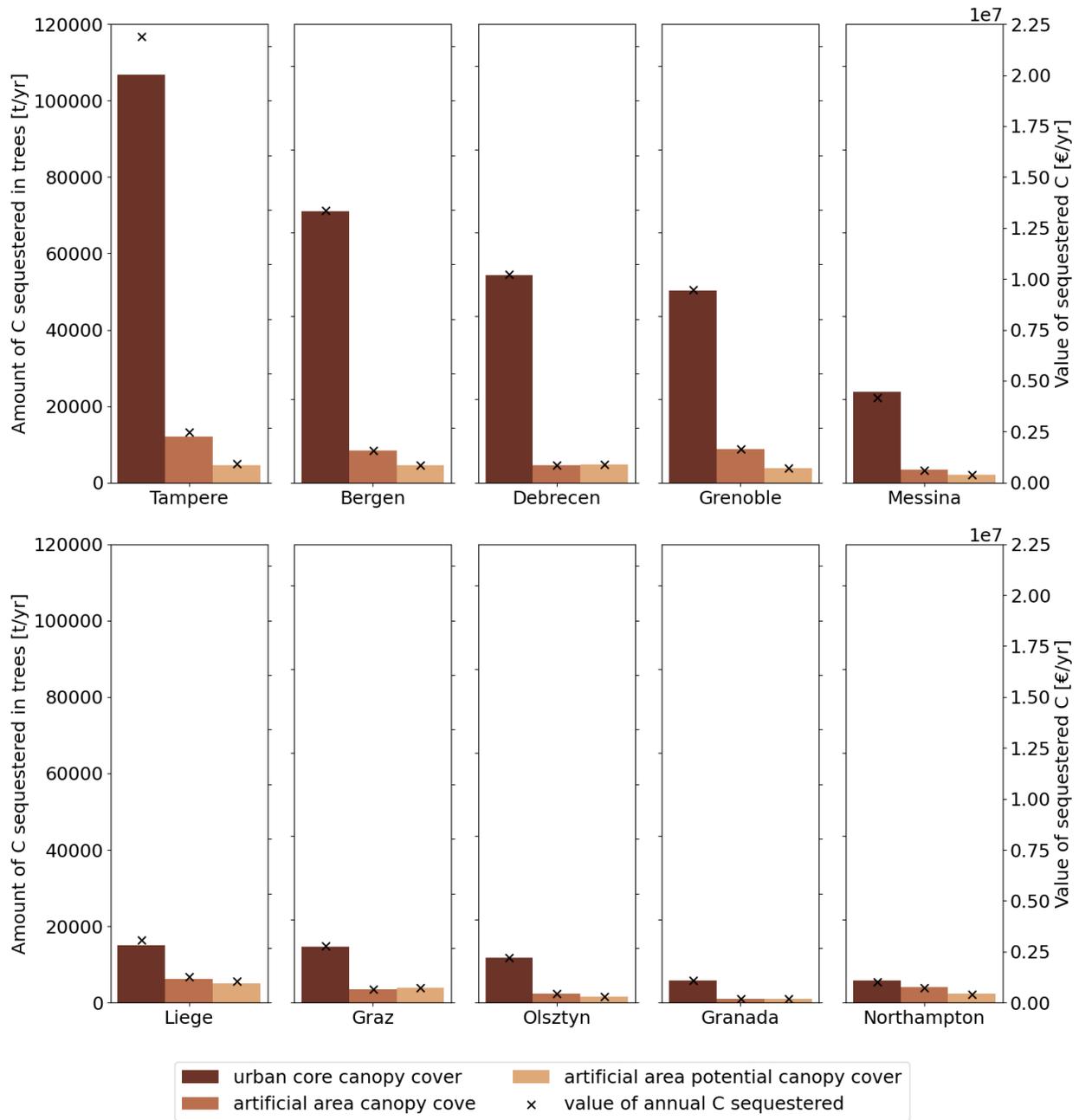


Figure 10 The annual carbon sequestration estimates of the three assessed canopy covers in amounts and monetary values

Tree Benefit Estimates: Stored Carbon

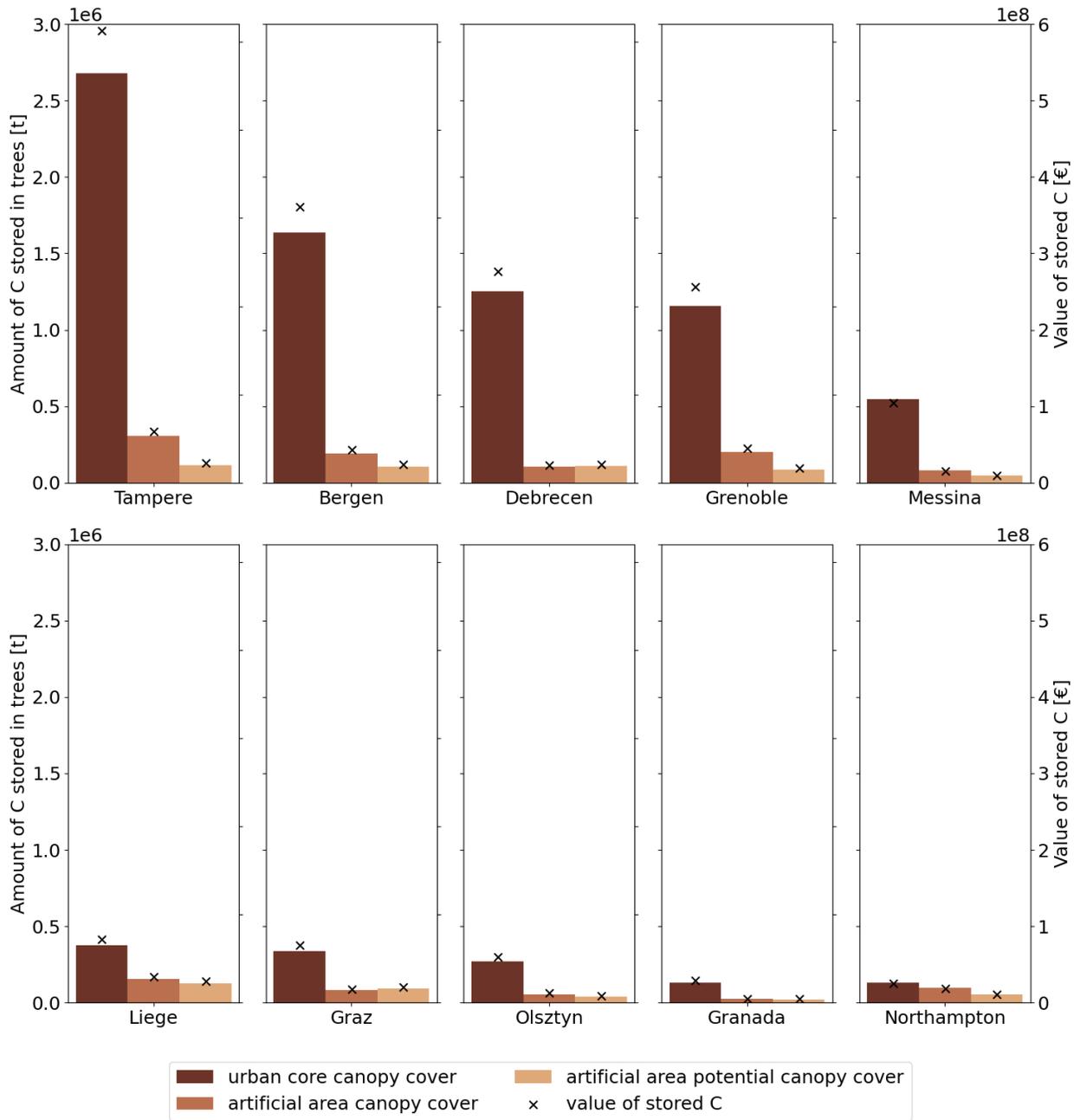


Figure 11 The carbon storage estimates of the three assessed canopy covers in amounts and monetary values

Tree Benefit Estimates: Total Air Pollution

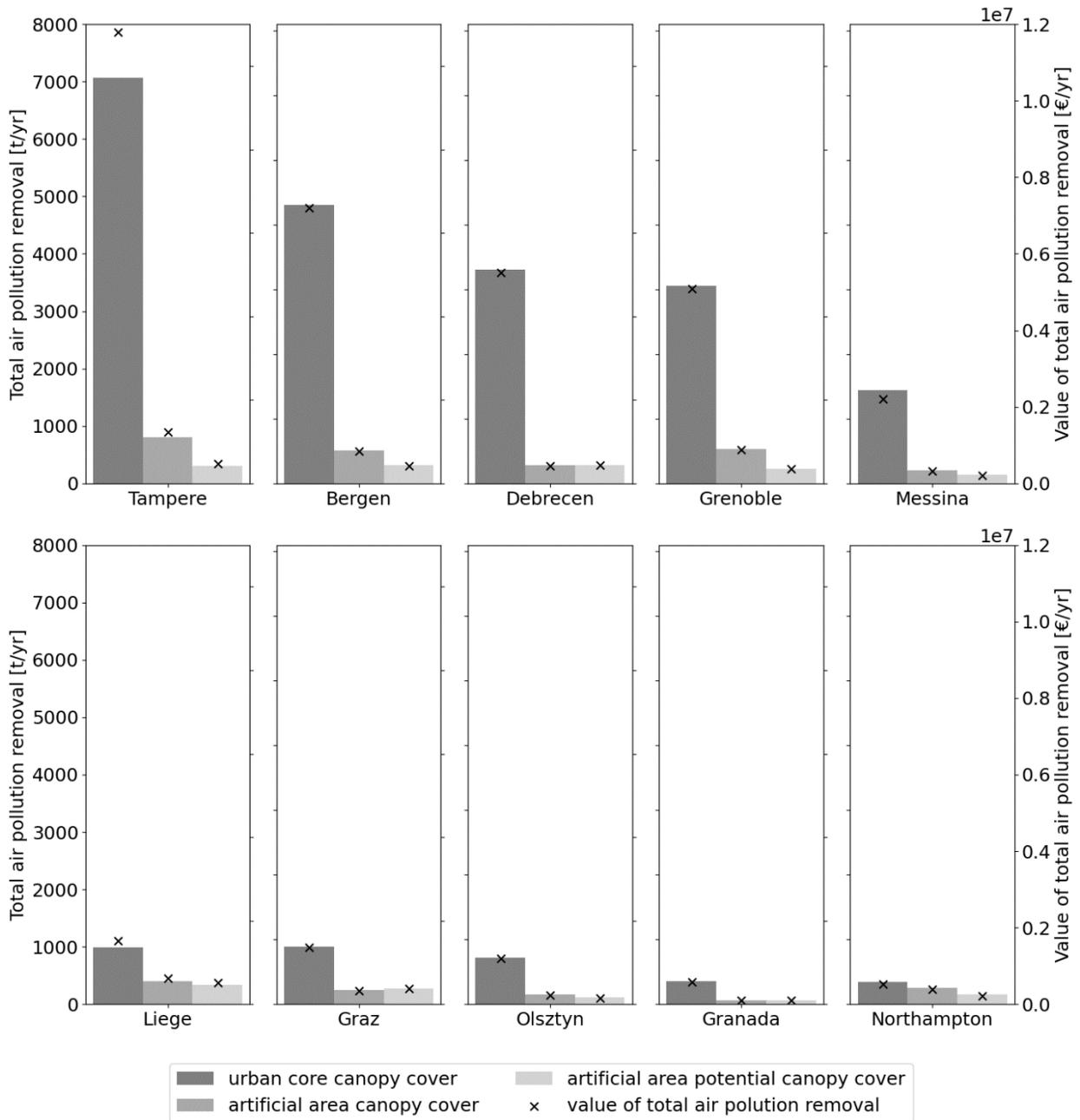


Figure 12 The annual total air pollution estimates of the three assessed canopy covers in amounts and monetary values

The total air pollution is the sum of Carbon Monoxide (CO), Nitrogen Dioxide (NO₂), Ozone (O₃), Sulphur Dioxide (SO₂), Particulate Matter less than 2.5 microns (PM_{2.5}) and Particulate Matter greater than 2.5 microns and less than 10 microns (PM₁₀*).

Tree Benefit Estimates: Air Pollution (PM2.5)

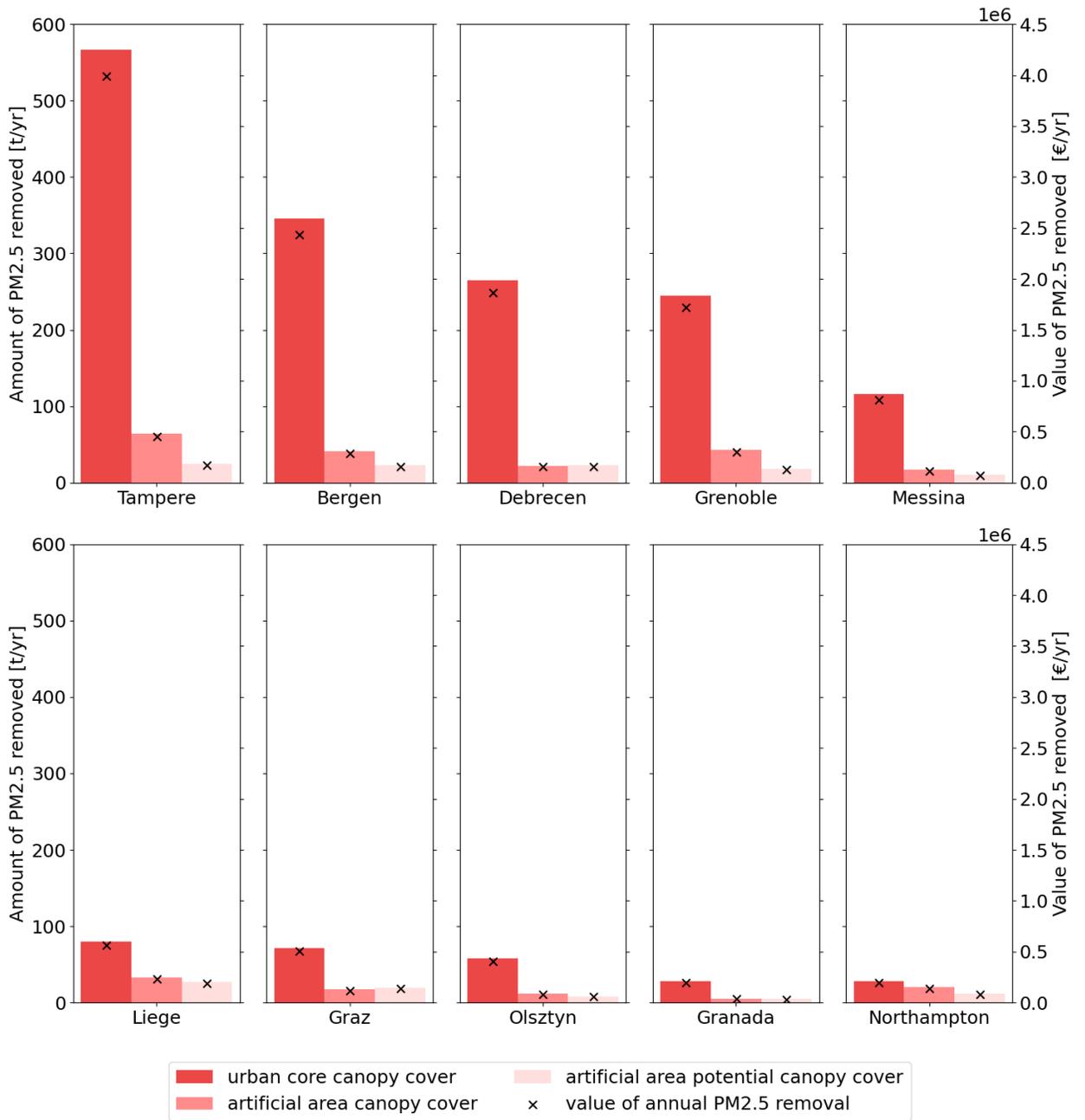


Figure 13 The annual particulate matter (< 2.5 microns) estimates of the three assessed canopy covers in amounts and monetary values

Tree Benefit Estimates: Hydrological (AVRO)

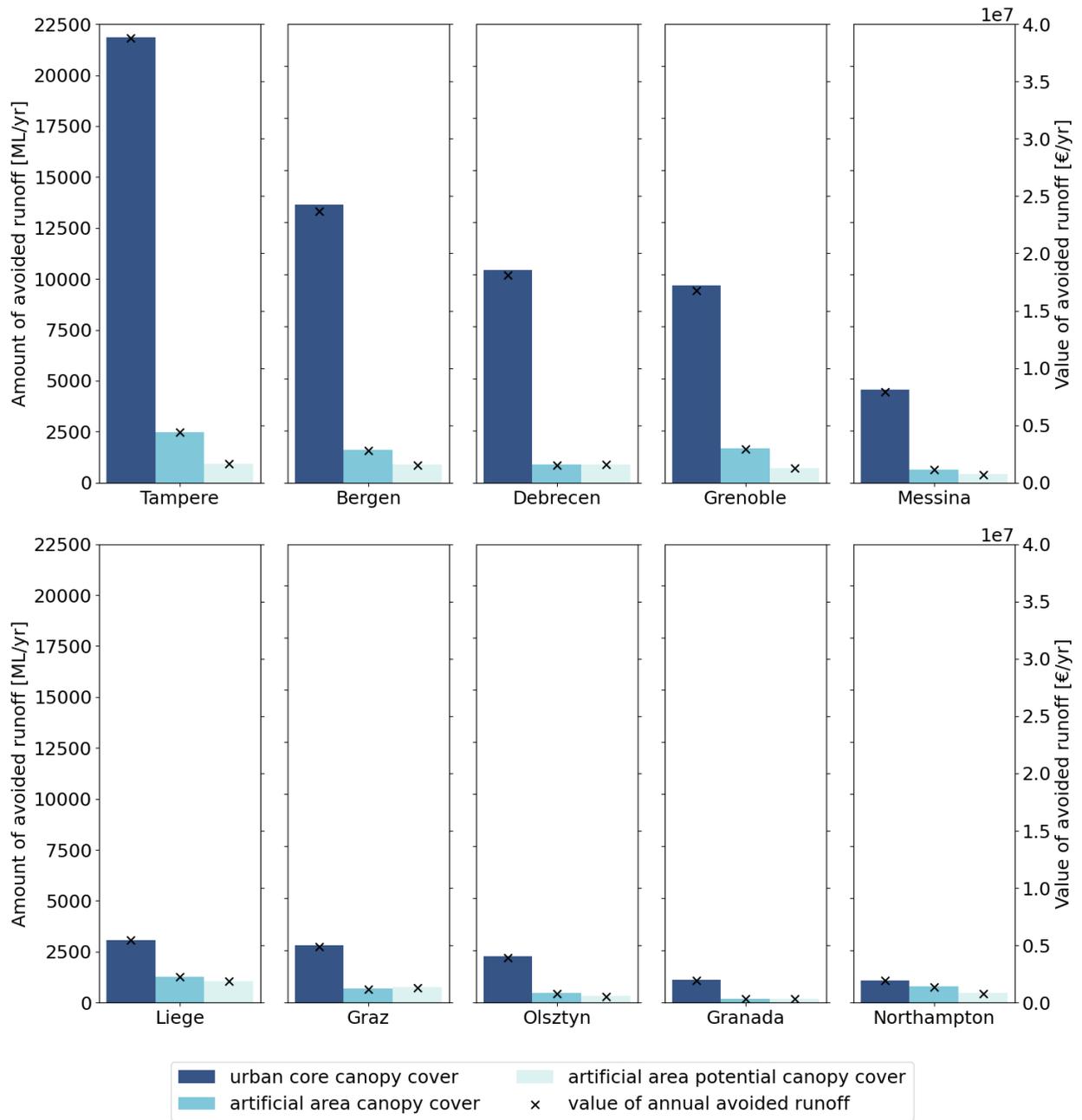


Figure 14 The annual avoided runoff estimates of the three assessed canopy covers in amounts and monetary values

To make the ecosystem services more comparable, their values in Euros were divided by the urban core area (m²) of the CCC and by the artificial area (m²) of both the PCC and CCA, see Figures 15 – 18 for their stored carbon and total ecosystem services benefits.

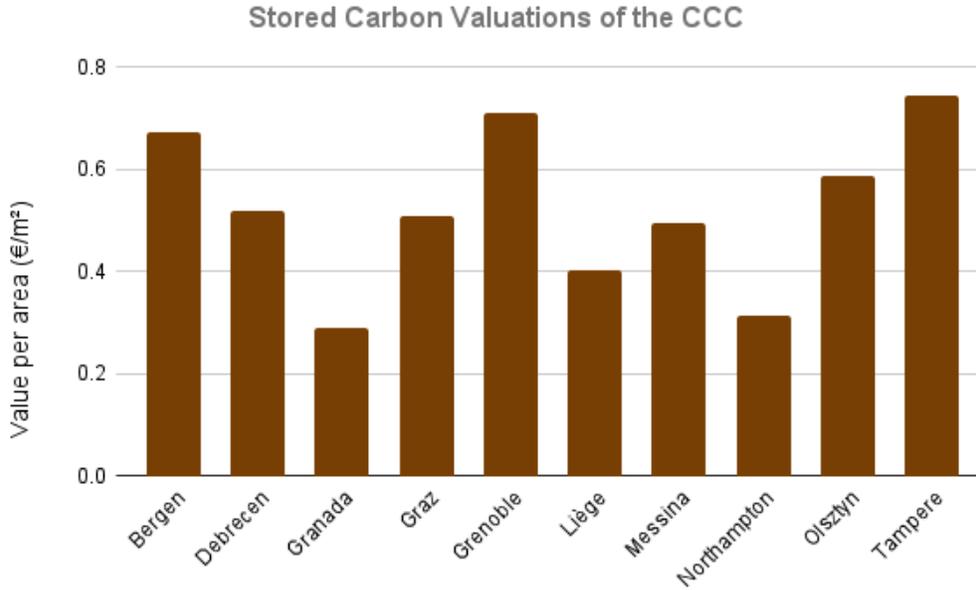


Figure 15 The stored carbon valuations of the CCC per area (€/m²).

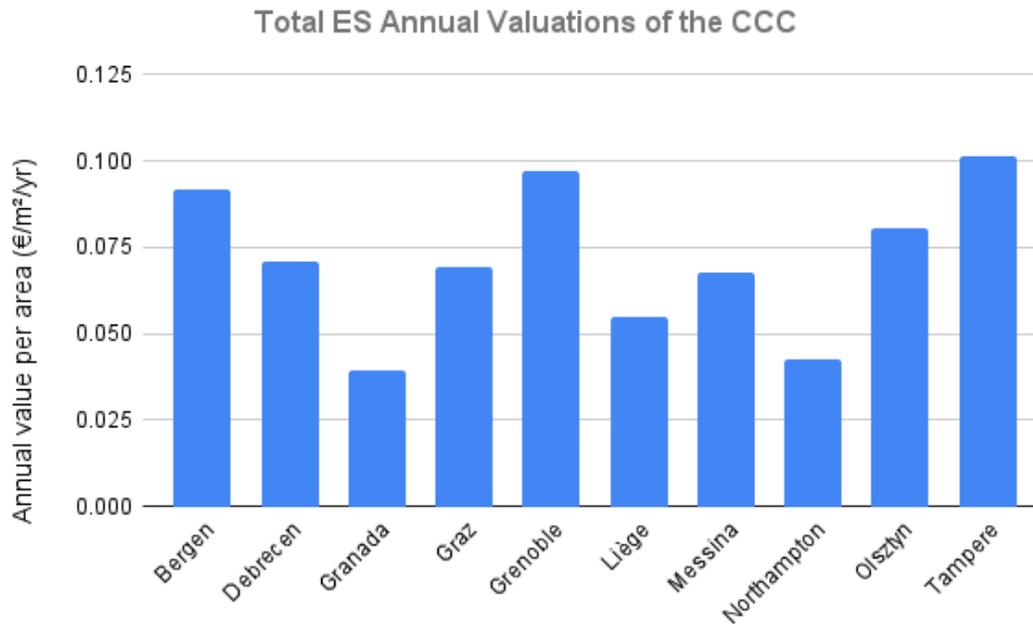


Figure 16 The total ecosystem services annual valuations of the CCC per area (€/m²/yr).

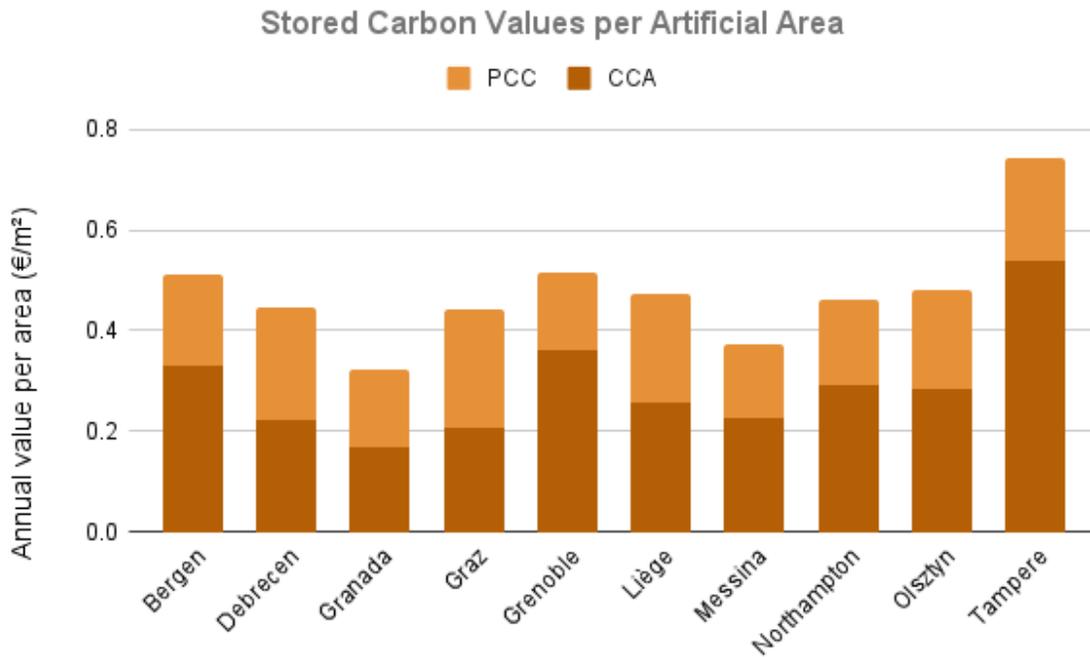


Figure 17 The stored carbon valuations of the PCC and the CCA per area (€/m²).

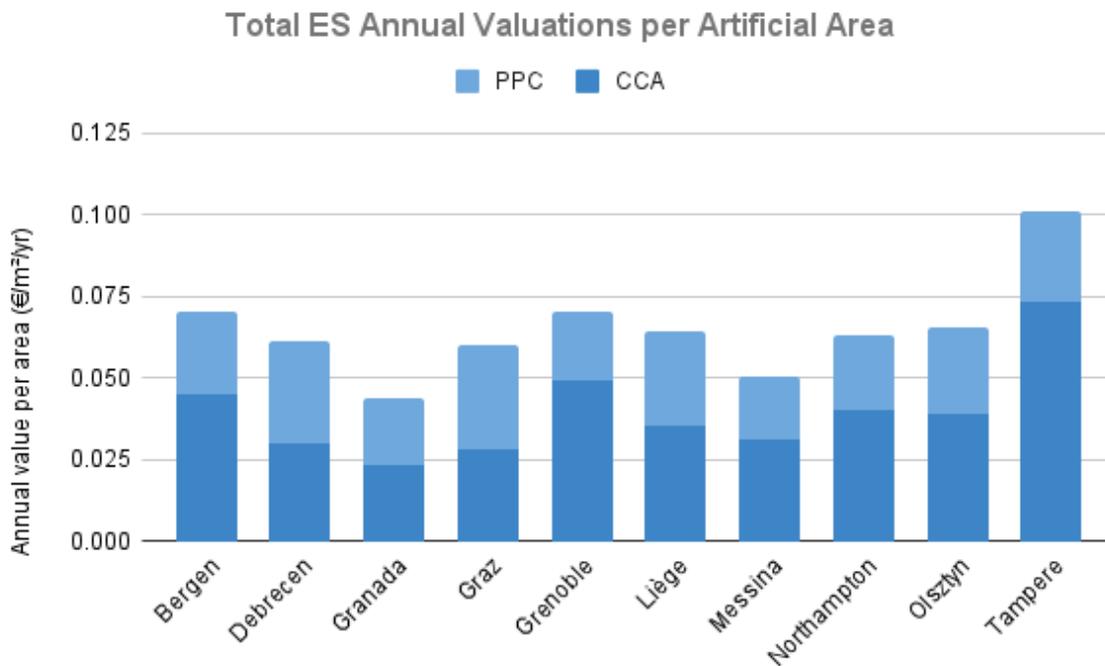


Figure 18 The total ecosystem services annual valuations of the PCC and the CCA per area (€/m²/yr).

Histograms showing the remaining ecosystem services are presented in the the Appendix as Figures A1 – A4.

3.3. Assessed canopy covers and their socio-economic and geographic relationships

Three models were maintained; one for each dependent variable. Two multiple linear regressions significantly described variation in canopy cover and canopy cover over artificial surface, whereas one multiple linear model only marginally significantly described variation in potential additional canopy area over artificial surface (Table 7). Population density was a significant variable in the model regarding in canopy cover. Latitude was a significant variable in the model regarding in canopy cover over artificial surface. Altitude standard deviation was a significant variable in the model describing variation in potential additional canopy area over artificial surface.

Table 7 Best multiple regression models explaining variation for the three dependent variables.

	Regression coefficient	Standard error	t-value	p-value	R² adjusted	AIC
<i>(i) Canopy cover</i>				0.008199**	0.6741	38.75427
Intercept	70.57					
Population density	-0.006524	0.001771	-3.683	0.00783**		
Population	-0.0001225	0.00008896	-1.377	0.21088		
<i>(ii) Canopy cover over artificial surface</i>				0.03668**	0.5	-26.97716
Intercept	-4.31882					
Latitude	1.75665	0.53881	3.260	0.0139*		
Altitude standard deviation	0.11926	0.09529	1.252	0.2509		
<i>(iii) Potential additional canopy area over artificial surface</i>				0.06949	0.5015	10.75008
Intercept	19.84105					
Altitude standard deviation	-0.05494	0.01873	-2.934	0.02615*		
Artificial area	0.04708	0.02199	2.140	0.07610		
Latitude	-0.16174	0.10957	-1.476	0.19036		

Hereafter, the plots representing the relationships of the explanatory variables with the three dependent variables that were identified as significant in the three multiple linear models. Figure 19 shows that canopy cover (CCC) decreases with increasing population density.

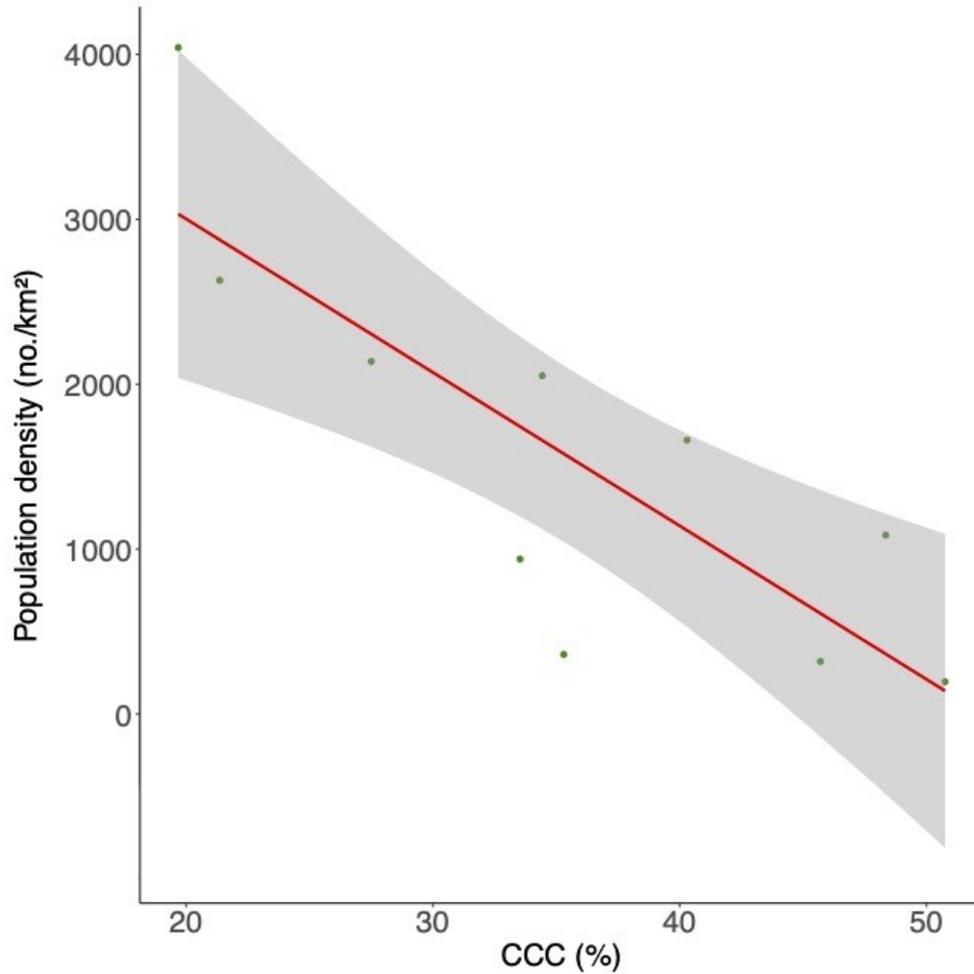


Figure 19 Representation of a linear relationship between canopy cover (CCC) and population density.

Figure 20 shows that canopy cover over artificial surface increases with increasing latitude.

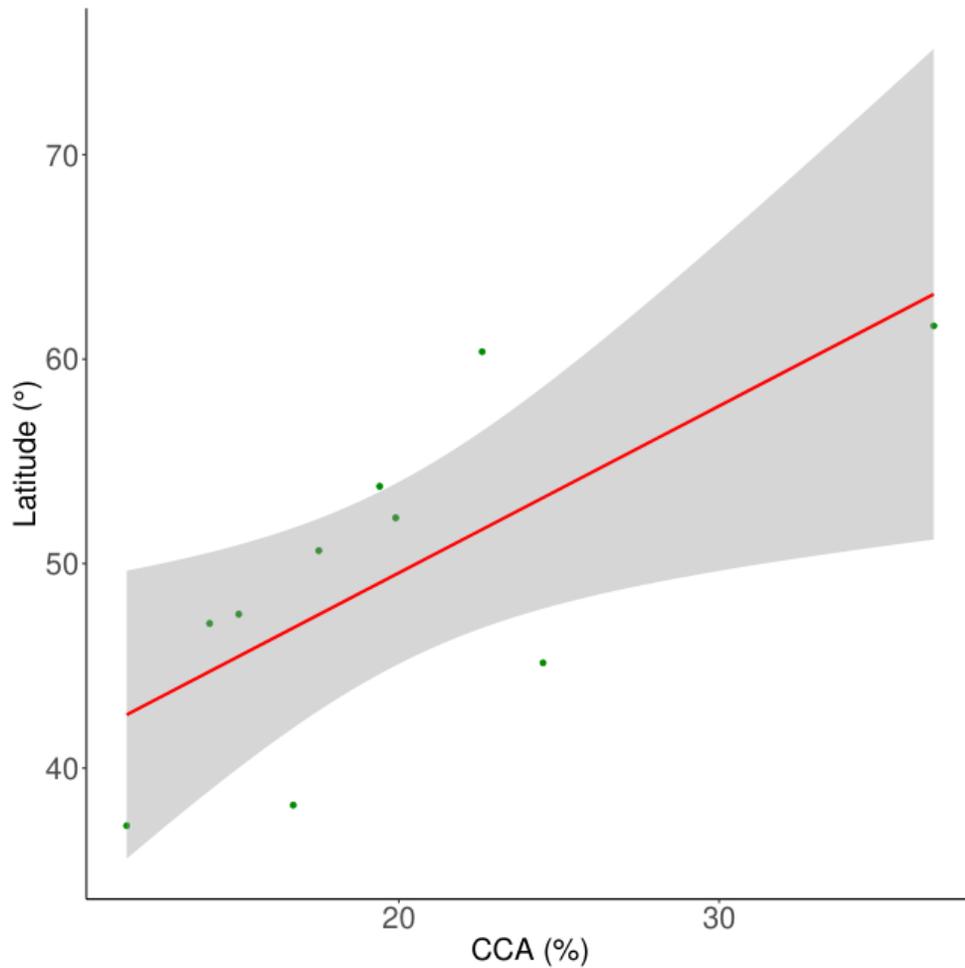


Figure 20 Representation of a linear relationship between canopy cover over artificial area (CCA) and latitude.

Interestingly, potential canopy cover increases with decreasing altitude standard deviation, as seen in Figure 21. This indicates that heterogeneity in terms of altitude implies a reduction in potential canopy cover. In fact, a higher standard deviation indicates that pixel values in the altitude raster layer are more spread out from the altitude mean. This suggests greater heterogeneity in altitudinal data.

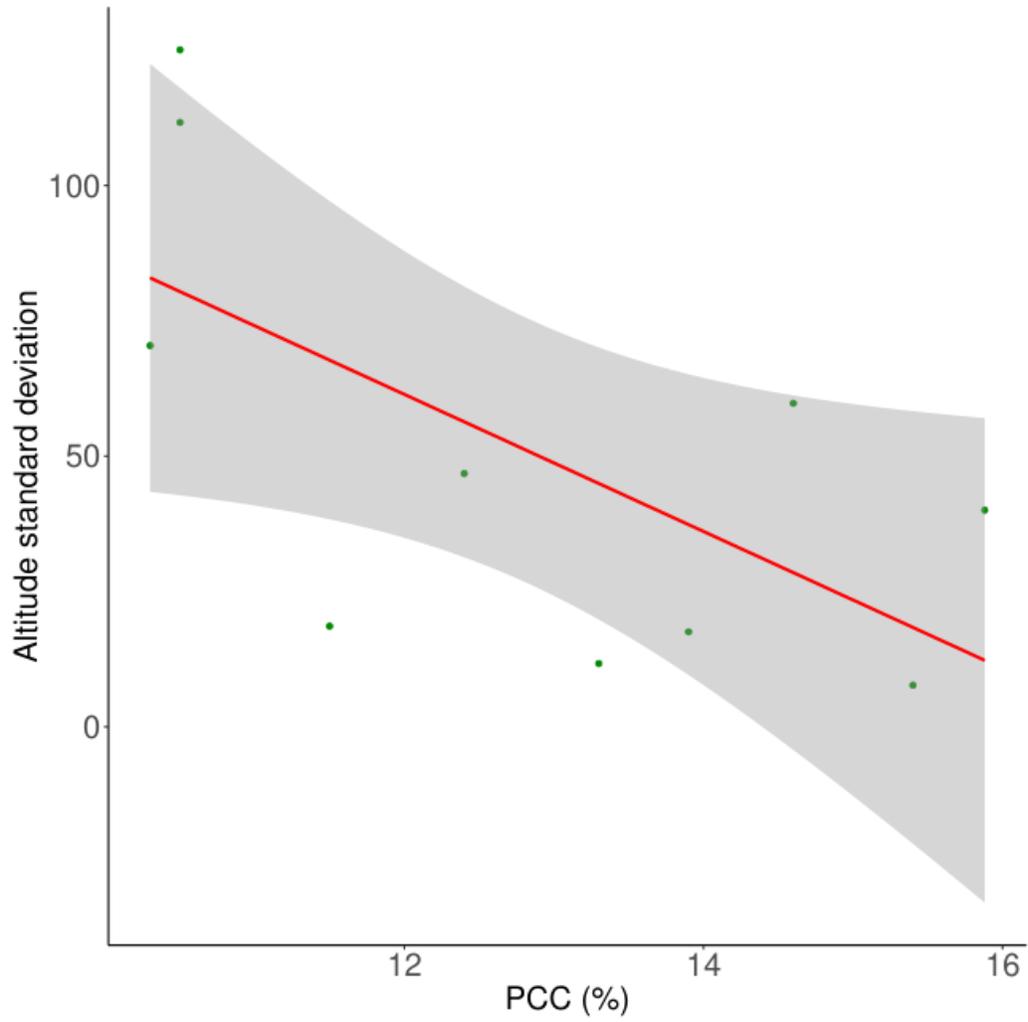


Figure 21 Representation of a linear relationship between potential additional canopy cover over artificial area (PCC) and altitude standard deviation.

4. Discussion

Variability of the assessed covers

The variability in the existing cover classes across the cities was expected due to the cities' geographical distribution. Factors such as latitude, population density, geomorphological features thus influence canopy cover. As for the potential canopy cover across cities, its low variability across the study sites could be justified by the LC/LU of the cities, with fewer potential to plant trees in densely built urban areas. The findings of this study showed a negative statistical relationship between the PCC and the standard deviation in altitude.

Tampere, Grenoble, and Bergen ranked as the top three for both the CCC and the CCA assessments, confirming the correlation found between these two covers. Across the three studied cover types, Tampere and Olsztyn were always among the top five cities with the highest cover percentage. Reasons for that proved to be the low population density and high latitude for high CCC and CCA values, respectively, and the low standard deviation altitude for a higher PCC. Intuitively, one would expect that if the canopy cover of a city is low, the potential to plant more trees should be high. This study has shown that it is not the case. The absence of a correlation between existing canopy covers and the PCC can be explained by the variability in available spaces for tree planting that may depend on several factors, such as existing land covers and urban planning. Instead, the correlation between the CCC and the CCA was expected. While estimating the CCC does not allow the estimation of the PCC, summing the CCA and the PCC could potentially increase the CCC.

The difference in the reported urban tree cover values between the EEA and this study could be due to the adopted methods. The EEA's study relies on combined data from three CLMS products with 2018 as the reference year: High-Resolution Layer Tree Cover Density (HRL, TCD), the UA LU/LC, and the UA Street Tree layer. In contrast, this study utilizes random point sampling. While the EEA's reference data have an MMW of 10 m, the assessment of points done throughout this study delivers a higher precision in detecting canopy cover in urban settings. Another point worth considering is that the HRL TCD, for example, includes and excludes certain elements from the tree covered area with 10 m imagery. In such case, it is likely the method does not depict single small trees.

Setting tree canopy cover targets

When it comes to what the ideal city canopy cover goal is, it has been suggested that there's no "one size fits all" recommendation. While the European Commission's Nature Restoration Law⁴ indicates that European cities need a minimum of 10% UCC, other studies have indicated the importance of setting an UCC target of minimum 30% on the neighbourhood scale to maximize the benefits provided by urban trees for healthier and more liveable cities (e.g. Konijnendijk, 2022). For instance, Ziter et al. (2019) found that a UCC of 40% is necessary to considerably decreased the air temperature by day at the scale of a 60-90m urban block. By summing the sampled cities' CCA and PCC, this study shows the potential additional canopy cover that can be reached within a city's artificial areas, thus contributing in developing cooler and more resilient cities to meet EU nature and biodiversity policies such as the 2030 Biodiversity Strategy⁵, and its proposed Urban Green Plans.

Considering for example, a UCC target of 30% and the total cover that could be achieved in this study's cities, Granada and Messina unfortunately still do not reach that target. However, Graz, Debrecen, Northampton, Liege, Olsztyn, and Bergen could reach a 30% canopy cover and even more. In this aspect, Tampere represents the most successful city having already a CCA of more than 30% and a great potential to reach a total of 50% canopy cover. Moreover, with these total canopy cover values that can be reached, seven out of ten of the assessed cities could significantly progress in urban forestry and greening. This could be scaled down and replicated on the urban neighbourhood level, thus moving towards the neighbourhood canopy cover target set by the 3-30-300 rule, for instance.

It is yet essential to highlight that setting general targets for UCC may be too ambitious; instead, it is advisable to establish targets that are site and context-specific (Borelli et al., 2023). This comparative study has shown the variability in existing and potential canopy cover, which in turn, are connected to a certain degree, to population density, latitude and variability in altitude. Furthermore, each city will need canopy cover targets not only adapted to its environmental, economic, and social contexts, but also to its planning and political contexts. These factors are especially important, as target setting has

⁴ https://environment.ec.europa.eu/topics/nature-and-biodiversity/nature-restoration-law_en

⁵ https://ec.europa.eu/commission/presscorner/detail/en/fs_20_906

been focused on increasing canopy cover, but not enough on how to achieve that. (Walters & Sinnett, 2021).

Furthermore, canopy cover assessment alone is not enough to tackle all components of UFs, mainly because it just measures trees and does not differentiate between species or evaluate tree density which represent crucial parameters in the evaluation of a healthy forest (Conway & Bourne, 2013) and how to further improve it.

Factors influencing canopy cover

The results of this study confirmed to a certain degree that population presence can have a negative impact on urban tree cover. Indeed, if space is used for housing and artificial infrastructures, less would be available for trees (Grove et al., 2014). Therefore, cities with higher population densities would be expected to have a greater pressure on land availability, thus resulting in less available area for tree cover.

For instance, this can be seen in the example of Granada, which has a high population density among the sampled cities and a high LC/LU of (i) industrial, commercial, public, military and private units, (ii) continuous urban fabric, and (iii) discontinuous dense urban fabric with respect to its area. These reasons justify Granada's CCC being the lowest among the ten sampled cities. The counterexample of this relationship can be seen in Tampere. Here, the population density is relatively low, and the LC/LU map shows a low distribution of the aforementioned LC/LU classes (i) – (iii) in relation to its area. These findings align with Vuckovic et al. (2023), who further discussed that high fragmentation in city tree clusters is evident in central densely built urban fabric, such as Graz.

However, when focusing on the CCA, the relationship between population density and urban tree canopy was not evident. Instead, latitude explains variations in canopy cover over artificial surfaces. This can be explained by different reasons. One could be related to the different history of urban silviculture and greenery between south, central and northern Europe, and better management of urban cover. Another reason could be the climate at continental scale and at the urban scale. For a wide range of tree species, the Mediterranean climate can be considered less suitable compared to higher European latitudes. This could be stressed by the higher temperatures that are usually related to artificial surfaces in cities. There is thus the urgency to act, especially in cities like Messina and Granada, which are

vulnerable to desertification (Benassi et al., 2020; Delgado-Capel et al., 2023) and need to take immediate action to decrease their residents' vulnerability to urban heat waves.

Within cities, altitudinal heterogeneity has a relationship with potential additional tree cover. This may be related to the fact that cities with more variable altitudes had already a relatively high canopy cover and, therefore, flat areas have less space available for planting trees. In such cities, innovative solutions (e.g. green roofs) are needed to account to urban space and population density constraints.

Our results confirm that UCC assessment is a useful first step in urban forestry planning, but becomes more powerful when combined with data such as population density, latitude, LC/LU maps, geographic, socio-economic, and environmental variables, as mentioned by the USDA (2019). That is especially true when comparing the assessed canopy covers in percent. For example, 50.75% and 48.45% CCC in the cases of Tampere and Grenoble do not reflect the impact of that cover on the population and city area. Plotting them against the population density variables puts the data into scale for more effective comparison. Such information is needed to better plan, design, and manage adaptive and resilient UFs.

UF stakeholders and Ecosystem Services

The findings of this study show that the monetary values of the ecosystem services provided by the three assessed covers increase with canopy cover. These values can be used to inform citizens how increasing urban forests can help them save on costs related to climate and health mitigation. Consequentially, a shift towards novel economic models through the valuation of UF ecosystem services opens up funding prospects for urban forestry, which however requires the society to acknowledge the importance of biodiversity and invest in it (Palahí et al., 2020; Borelli et al., 2023). In fact, there are models that are emerging to better design and plan green infrastructures, such as the Nature-Based Solutions Business Model Canvas⁶, which can be used to frame the UF stakeholders and how the UF valuation of ecosystem services can be pivotal in the early-stage design of UFs.

⁶ <https://connectingnature.eu/nature-based-solutions-business-model-canvas>

Additionally, many studies show that urban vegetation is mostly located on private property and that much of the opportunities for further increases in tree canopy are also on private residential sites (King et Locke, 2013). This highlights the role of the community in achieving a higher urban canopy cover. Furthermore, incentives can be given by municipalities or governments to encourage citizens in planting more trees on their properties.

Limitations

Some limitations within this study should be recognized. The reference year adopted for the socio-economic variables could significantly differ from the actual population data, and not reflect recent population density.

The accuracy in estimating UCC using i-Tree Canopy depends upon the user's interpretation of the aerial images and detection of UCC at each generated point. This accuracy is prone to decrease depending on the satellite image's resolution and the presence of shadows. An over estimation of UCC can happen due to trees being confused with shrubs or even tall grasses (Parmehr et al., 2016). The latter could be the cause of an under-estimation of tree cover as well. While assessing the canopy covers in this study, the quality of the aerial imagery could have been a limiting factor, as in the case of Debrecen, the image quality was poor. During the CCC sampling, it was sometimes challenging to distinguish between trees and medium shrubs, particularly in Bergen and Tampere.

As for the locations that i-Tree Canopy uses to estimate tree benefits, they are a limiting factor for this study, since the United Kingdom and Sweden were the only European countries that were available as reference locations. This selection does not fully account to this study's Northern-Southern region gradient when it comes to climate and tree growth rates, for instance. Additionally, the monetary values that i-Tree Canopy uses in the conversion rates to estimate tree benefits are constantly updated. This value change can affect comparative area studies if their CATB reports are exported in different timeframes. Furthermore, i-Tree Canopy's estimation method does not take into account the species, size, or age of trees, and thus affects the accuracy of the benefit amounts and values.

5. Conclusion

This comparative study across ten European cities showed the variability of tree cover for relatively small urban areas. This study enabled to assess canopy cover at different urban scales (city and artificial cover) as well as the potential tree cover achievable. By using the online tool i-Tree canopy, it was possible to provide a rough estimation of ecosystems services for the studied cities. Finally, a first analysis provided interesting results of factors influencing current and potential tree cover. It is worth noticing that: (i) the higher the population density, the lower the canopy cover over the urban core, (ii) the higher the latitude, the higher the canopy cover over artificial surface, and (iii) the higher the standard deviation in altitude, the lower the potential canopy cover over the artificial surface. Evidently, there are other factors that might influence these three cover classes, such as the climate, biogeographical regions, LC/LU, and UF management and governance, which require further studies.

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Appendix

Table A1 Tree Benefit Estimates report as created by i-Tree Canopy for the CCC.

	Bergen	Debrece n	Granad a	Graz	Grenoble	Liege	Messina	Northhampt on	Olsztyn	Tampere
seq_CA	65130	49850	5300	13510	46130	15000	21750	5260	10820	106700
seq_CA_e	2240	2130	340	590	1510	770	970	320	420	3320
seq_CO2_eq	238790	182780	19440	49550	169140	55010	79770	19290	39670	391240
seq_CO2_eq_e	8230	7830	1240	2160	5530	2820	3550	1170	1530	12180
seq_CA_val	12462787	9539627	1014347	2586116	8827580	2870977	4163119	1006951	2070608	20418955
seq_CA_val_e	429593	408410	64769	112582	288368	147412	185162	61042	79695	635782
sto_CA	1635550	1251930	133120	339390	1158480	376770	546350	132150	271740	2679670
sto_CA_e	56380	53600	8500	14770	37840	19350	24300	8010	10460	83440
sto_CO2_eq	5997010	4590410	488100	1244420	4247780	1381500	2003270	484540	996360	9825470
sto_CO2_eq_e	206720	196520	31170	54170	138760	70930	89100	29370	38350	305930
sto_CA_val	312987334	239575823	25474055	64947071	221693649	72101008	104551534	25288326	52000741	512796585
sto_CA_val_e	10788687	10256703	1626582	2827361	7242005	3702065	4650119	1533001	2001447	15966866
CO_am	24.29	18.59	1.98	5.04	17.2	5.59	8.11	1.96	4.03	39.79
CO_am_e	0.84	0.8	0.13	0.22	0.56	0.29	0.36	0.12	0.16	1.24
CO_am_val	25465	19492	2073	5284	18038	5866	8507	2058	4231	41722
CO_am_val_e	878	835	132	230	589	301	378	125	163	1299
NO2_am	556.86	426.25	45.32	115.55	394.43	128.28	186.02	44.99	92.52	912.35
NO2_am_e	19.19	18.25	2.89	5.03	12.88	6.59	8.27	2.73	3.56	28.41
NO2_val	92107	70503	7497	19113	65241	21218	30768	7442	15303	150908
NO2_val_e	3175	3018	479	832	2131	1089	1368	451	589	4699
O3_am	2478.86	1897.44	201.75	514.38	1755.82	571.04	828.05	200.28	411.85	4061.35
O3_am_e	85.45	81.23	12.88	22.39	57.36	29.32	36.83	12.14	15.85	126.46
O3_val	624866	478303	50858	129664	442602	143947	208733	50487	103817	1023777
O3_val_e	21539	20477	3247	5645	14458	7391	9284	3061	3996	31877
SO2_am	200.58	153.54	16.33	41.62	142.08	46.21	67	16.21	33.33	328.63
SO2_am_e	6.91	6.57	1.04	1.81	4.64	2.37	2.98	0.98	1.28	10.23
SO2_val	12035	9213	980	2497	8525	2773	4020	972	2000	19719
SO2_val_e	415	394	63	109	278	142	179	59	77	614
PM2.5_am	345.9	264.77	28.15	71.78	245.01	79.68	115.55	27.95	57.47	566.73
PM2.5_am_e	11.92	11.34	1.8	3.12	8	4.09	5.14	1.69	2.21	17.65
PM2.5_val	2433521	1862736	198064	504973	1723699	560596	812903	196620	404313	3987066
PM2.5_val_e	83884	79747	12647	21983	56308	28784	36155	11919	15562	124145
PM10_am	704.31	539.11	57.32	146.15	498.87	162.25	235.27	56.91	117.02	1,153.94
PM10_am_e	24.28	23.08	3.66	6.36	16.3	8.33	10.46	3.45	4.5	35.93

	Bergen	Debrece n	Granad a	Graz	Grenoble	Liege	Messina	Northampt on	Olsztyn	Tampere
PM10_val	3404781	2606186	277115	706516	2411658	784339	1137347	275095	565681	5578373
PM10_val_e	117363	111576	17695	30757	78781	40272	50586	16676	21772	173693
AP_totam	4310.81	3299.70	350.86	894.52	3053.41	993.05	1440.00	348.30	716.21	7062.80
AP_totam_e	148.59	141.27	22.4	38.94	99.74	50.99	64.05	21.11	27.57	219.91
AP_totval	6592776	5046434	536586	136804 7	4669763	151873 8	2202277	532674	109534 5	1080156 5
AP_totval_e	227253	216048	34262	59556	152546	77980	97950	32291	42159	336327
AVRO_am	13350.37	10219.03	1086.59	2770.30	9456.27	3075.44	4459.61	1078.67	2218.07	21873.17
AVRO_am_e	460.19	437.5	69.38	120.6	308.91	157.91	198.35	65.39	85.37	681.06
AVRO_val	2367346 7	1812083 0	192678 5	491241 1	1676827 4	545351 4	7907979	1912737	393318 7	3878646 7
AVRO_val_e	816025	775788	123030	213853	547765	280014	351722	115952	151384	1207688
E_am	75613.88	57878.56	6154.22	15690.4 1	53558.45	17418.7 1	25258.36	6109.35	12562.7 4	123885.3 3
E_am_e	2606.41	2477.89	392.96	683.06	1749.58	894.37	1123.41	370.35	483.53	3857.40
E_val	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
E_val_e	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
I_am	75840.80	58052.26	6172.69	15737.5 0	53719.18	17470.9 9	25334.16	6127.68	12600.4 4	124257.1 1
I_am_e	2614.24	2485.33	394.14	685.11	1754.83	897.06	1126.78	371.47	484.98	3868.97
I_val	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
I_val_e	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
T_am	51173.70	39170.85	4165.03	10618.9 0	36247.10	11788.5 8	17094.27	4134.66	8502.17	83842.69
T_am_e	1763.96	1676.98	265.95	462.28	1184.07	605.29	760.30	250.65	327.24	2610.60
T_val	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
T_val_e	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
PE_am	160532.7 7	122879.6 4	13065.7 7	33311.6 8	113707.7 8	36980.9 7	53625.00	12970.51	26671.4 4	263015.9 3
PE_am_e	5533.57	5260.71	834.28	1450.17	3714.46	1898.81	2385.07	786.28	1026.55	8189.49
PE_val	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
PE_val_e	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
PET_am	123711.7 8	94695.05	10068.9 1	25671.0 6	87626.92	28498.7 4	41325.18	9995.50	20553.8 8	202688.6 5
PET_am_e	4264.35	4054.08	642.92	1117.55	2862.48	1463.28	1838.01	605.94	791.09	6311.08
PET_val	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
PET_val_e	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

Table A2 Tree Benefit Estimates report as created by i-Tree Canopy for the CCA.

	Bergen	Debrece n	Granad a	Graz	Grenobl e	Liege	Messina	Northampto n	Olsztyn	Tamper e
seq_CA	7690	4170	976.86	3230	8040	6130	3120	3800	2220	12110
seq_CA_e	450	310	85.7	250	450	420	220	240	140	500
seq_CO2_eq	28180	15310	3581.83	11840	29460	22470	11460	13930	8150	44410
seq_CO2_eq_e	1650	1150	314.22	920	1640	1540	810	880	530	1840
seq_CA_val	1470947	798908	186938	618173	1537685	1172702	597975	727248	425114	2317526
seq_CA_val_e	86082	60140	16399	48254	85361	80518	42233	46139	27401	96248
sto_CA	193040	104840	24532.68	81130	201800	153900	78480	95440	55790	304140
sto_CA_e	11300	7890	2152.13	6330	11200	10570	5540	6060	3600	12630
sto_CO2_eq	707810	384430	89953.18	297460	739920	564300	287740	349950	204560	1115180
sto_CO2_eq_e	41420	28940	7891.13	23220	41080	38740	20320	22200	13190	46310
sto_CA_val	36941002	20063570	4694704	15524638	38617052	29450940	15017398	18263926	10676219	58201775
sto_CA_val_e	2161847	1510331	411842	1211837	2143727	2022121	1060618	1158734	688152	2417158
CO_am	2.87	1.56	0.36	1.2	3	2.29	1.17	1.42	0.83	4.52
CO_am_e	0.17	0.12	0.03	0.09	0.17	0.16	0.08	0.09	0.05	0.19
CO_am_val	3006	1632	382	1263	3142	2396	1222	1486	869	4735
CO_am_val_e	176	123	34	99	174	165	86	94	56	197
NO2_am	65.72	35.7	8.35	27.62	68.71	52.4	26.72	32.49	18.99	103.55
NO2_am_e	3.85	2.69	0.73	2.16	3.81	3.6	1.89	2.06	1.22	4.3
NO2_val	10871	5904	1382	4569	11364	8667	4419	5375	3142	17128
NO2_val_e	636	444	121	357	631	595	312	341	203	711
O3_am	292.57	158.9	37.18	122.96	305.85	233.25	118.94	144.65	84.556	460.96
O3_am_e	17.12	11.96	3.26	9.6	16.98	16.02	8.4	9.18	5.450	19.14
O3_val	73751	40056	9373	30994	77097	58798	29982	36463	21315	116197
O3_val_e	4316	3015	822	2419	4280	4037	2117	2313	1374	4826
SO2_am	23.67	12.86	3.01	9.95	24.75	18.87	9.62	11.7	6.84	37.30
SO2_am_e	1.39	0.97	0.26	0.78	1.37	1.3	0.68	0.74	0.44	1.55
SO2_val	1421	772	181	597	1485	1132	577	702	411	2238
SO2_val_e	83	58	16	47	82	78	41	45	26	93
PM2.5_am	40.83	22.17	5.19	17.16	42.68	32.55	16.6	20.18	11.80	64.32
PM2.5_am_e	2.39	1.67	0.46	1.34	2.37	2.23	1.17	1.28	0.76	2.67
PM2.5_val	287222	155997	36502	120706	300253	228985	116762	142005	83009	452527
PM2.5_val_e	16809	11743	3202	9422	16668	15722	8246	9009	5350	18794
PM10_am	83.13	45.15	10.56	34.93	86.9	66.27	33.79	41.1	24.02	130.97
PM10_am_e	4.86	3.4	0.93	2.73	4.82	4.55	2.39	2.61	1.55	5.44
PM10_val	401857	218258	51071	168882	420089	320377	163364	198681	116139	633138
PM10_val_e	23517	16430	4480	13183	23320	21997	11538	12605	7486	26295
AP_totam	508.79	276.34	64.66	213.82	531.88	405.63	206.84	251.55	147.04	801.62

	Bergen	Debrece n	Granad a	Graz	Grenobl e	Liege	Messina	Northampto n	Olsztyn	Tamper e
AP_totam_e	29.78	20.8	5.67	16.69	29.53	27.85	14.61	15.96	9.48	33.29
AP_totval	778127	422620	98889	327012	813431	620356	316327	384712	224884	1225964
AP_totval_e	45537	31814	8675	25526	45156	42594	22341	24408	14495	50915
AVRO_am	1575.71	855.80	200.25	662.20	1647.20	1256.22	640.56	779.04	455.39	2482.58
AVRO_am_e	92.21	64.42	17.57	51.69	91.44	86.25	45.24	49.43	29.35	103.1
AVRO_val	2794112	1517551	355094	1174239	2920883	2227585	1135873	1381431	807519	4402216
AVRO_val_e	163516	114237	31151	91660	162145	152947	80222	87643	52050	182827
E_am	8924.49	4847.11	1134.18	3750.56	9329.40	7114.98	3628.02	4412.34	2579.24	14060.83
E_am_e	522.28	364.88	99.5	292.76	517.90	488.52	256.23	279.94	166.25	583.96
E_val	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
E_val_e	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
I_am	8,951.27	4,861.66	1,137.59	3,761.82	9,357.40	7,136.34	3,638.91	4,425.58	2,586.98	14,103.03
I_am_e	523.84	365.97	99.79	293.64	519.45	489.99	257	280.78	166.75	585.71
I_val	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
I_val_e	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
T_am	6,039.89	3,280.41	767.59	2,538.29	6,313.92	4,815.25	2,455.36	2,986.17	1,745.57	9,516.04
T_am_e	353.46	246.94	67.34	198.14	350.5	330.62	173.41	189.45	112.51	395.21
T_val	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
T_val_e	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
PE_am	18947.22	10290.71	2407.94	7962.66	19806.88	15105.53	7702.50	9367.66	5475.89	29851.98
PE_am_e	1108.82	774.66	211.24	621.56	1099.53	1037.16	544	594.32	352.96	1239.77
PE_val	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
PE_val_e	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
PET_am	14601.35	7930.35	1855.63	6136.29	15263.83	11640.82	5935.80	7219.02	4219.90	23004.91
PET_am_e	854.49	596.98	162.79	478.99	847.33	799.27	419.22	458	272	955.41
PET_val	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
PET_val_e	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

Table A3 Tree Benefit Estimates report as created by i-Tree Canopy for the PTC.

	Bergen	Debrece n	Granada	Graz	Grenoble	Liege	Messina	Northam pton	Olsztyn	Tampere
seq_CA	4216.68	4287.06	875.16	3641.40	3442.50	5113.26	1964.52	2197.08	1523.88	4586.94
seq_CA_e	354.96	318.24	82.62	266.22	318.24	391.68	180.54	192.78	122.40	361.08
seq_CO2_ eq	15461.16	15719.22	3208.92	13351.80	12622.50	18748.62	7203.24	8055.96	5587.56	16818.78
seq_CO2_ eq_e	1301.52	1166.88	302.94	976.14	1166.88	1436.16	661.98	706.86	448.80	1323.96
seq_CA_val	806924.9	820393.2	167474.99	696836.51	658774.01	978499.00	375940.37	420444.21	291617.30	877779.77
seq_CA_val_e	67926.92	60900.00	15810.58	50945.19	60900.00	74953.84	34549.04	36891.34	23423.08	69098.07
sto_CA	105899.30	107666.85	21979.10	91451.50	86456.25	128416.35	49337.70	55178.30	38271.30	115198.15
sto_CA_e	8914.60	7992.40	2074.95	6685.95	7992.40	9836.80	4534.15	4841.55	3074.00	9068.30
sto_CO2_e q	388292.84	394773.78	80589.08	335318.20	317002.50	470854.38	180902.76	202318.04	140326.44	422388.22
sto_CO2_e q_e	32686.48	29305.12	7608.06	24514.86	29305.12	36067.84	16625.02	17752.14	11271.20	33250.04
sto_CA_val	20265419.54	20603666.75	4206030.47	17500616.30	16544700.28	24574394.82	9441508.96	10559195.38	7323787.32	22044893.97
sto_CA_val_e	1705942.43	1529465.63	397072.81	1279456.82	1529465.63	1882419.23	867677.61	926503.22	588256.01	1735355.23
CO_am	1.57	1.60	0.33	1.36	1.28	1.90	0.73	0.82	0.57	1.71
CO_am_e	0.13	0.12	0.03	0.10	0.12	0.15	0.07	0.07	0.05	0.13
CO_am_val	1647.20	1674.70	341.87	1422.48	1344.78	1997.44	767.42	858.27	595.29	1791.84
CO_am_val_e	138.66	124.32	32.27	104.00	124.32	153.01	70.53	75.31	47.81	141.05
NO2_am	36.05	36.65	7.48	31.13	29.43	43.71	16.79	18.78	13.03	39.21
NO2_am_e	3.03	2.72	0.71	2.28	2.72	3.35	1.54	1.65	1.05	3.09
NO2_val	5962.42	6061.94	1237.48	5148.97	4867.72	7230.19	2777.85	3106.69	2154.78	6485.97
NO2_val_e	501.92	449.99	116.83	376.44	449.99	553.84	255.28	272.59	173.07	510.57
O3_am	160.50	163.17	33.31	138.60	131.03	194.62	74.77	83.63	58.00	174.59
O3_am_e	13.51	12.11	3.14	10.13	12.11	14.91	6.87	7.34	4.66	13.74
O3_val	40457.75	41133.02	8396.89	34938.11	33029.73	49060.15	18848.96	21080.31	14621.16	44010.28
O3_val_e	3405.73	3053.41	792.71	2554.30	3053.41	3758.05	1732.23	1849.66	1174.39	3464.45
SO2_am	12.98	13.20	2.69	11.21	10.60	15.74	6.05	6.76	4.69	14.12
SO2_am_e	1.09	0.98	0.25	0.82	0.98	1.21	0.56	0.59	0.38	1.11
SO2_val	778.85	791.85	161.65	672.59	635.85	944.45	362.86	405.81	281.47	847.23
SO2_val_e	65.56	58.78	15.26	49.17	58.78	72.35	33.35	35.61	22.61	66.69
PM2.5_am	22.39	22.77	4.65	19.34	18.28	27.15	10.43	11.67	8.09	24.36
PM2.5_am_e	1.89	1.69	0.44	1.41	1.69	2.08	0.96	1.02	0.65	1.92
PM2.5_val	157536.61	160166.03	32696.28	136043.95	128612.98	191033.15	73395.14	82083.66	56932.68	171369.65
PM2.5_val_e	13261.43	11889.56	3086.71	9946.07	11889.56	14633.30	6745.04	7202.33	4572.91	13490.07
PM10_am	45.60	46.36	9.46	39.38	37.23	55.29	21.24	23.76	16.48	49.60
PM10_am_e	3.84	3.44	0.89	2.88	3.44	4.24	1.95	2.08	1.32	3.90
PM10_val	220429.95	224109.11	45749.61	190356.78	179959.14	267299.31	102696.68	114853.92	79661.91	239785.55

	Bergen	Debrece n	Granada	Graz	Grenoble	Liege	Messina	Northam pton	Olsztyn	Tampere
PM10_val_e	18555.79	16636.22	4319.02	13916.84	16636.22	20475.35	9437.86	10077.71	6398.55	18875.71
AP_totam	279.09	283.74	57.92	241.01	227.85	338.43	130.02	145.42	100.86	303.59
AP_totam_e	23.49	21.06	5.47	17.62	21.06	25.92	11.95	12.76	8.10	23.90
AP_totval	426812.77	433936.64	88583.78	368582.87	348450.20	517564.69	198848.91	222388.66	154247.29	464290.53
AP_totval_e	35929.09	32212.28	8362.80	26946.82	32212.28	39645.89	18274.28	19513.21	12389.34	36548.55
AVRO_am	864.39	878.82	179.40	746.46	705.69	1048.18	402.71	450.39	312.39	940.29
AVRO_am_e	72.76	65.24	16.94	54.57	65.24	80.29	37.01	39.52	25.09	74.02
AVRO_val	1532774.19	1558357.50	318122.94	1323658.40	1251357.74	1858683.36	714108.15	798644.31	553934.36	1667364.66
AVRO_val_e	129028.89	115681.07	30032.59	96771.66	115681.07	142376.70	65626.76	70076.03	44492.72	131253.52
E_am	4895.76	4977.47	1016.10	4227.83	3996.90	5936.73	2280.90	2550.91	1769.29	5325.65
E_am_e	412.12	369.49	95.93	309.09	369.49	454.76	209.62	223.83	142.11	419.23
E_val	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
E_val_e	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
I_am	4910.45	4992.41	1019.15	4240.52	4008.89	5954.54	2287.74	2558.56	1774.60	5341.63
I_am_e	413.36	370.60	96.21	310.02	370.60	456.12	210.24	224.50	142.54	420.49
I_val	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
I_val_e	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
T_am	3313.33	3368.63	687.67	2861.30	2705.01	4017.84	1543.66	1726.40	1197.42	3604.27
T_am_e	278.92	250.06	64.92	209.19	250.06	307.77	141.86	151.48	96.18	283.73
T_val	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
T_val_e	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
PE_am	10393.99	10567.48	2157.24	8975.94	8485.66	12604.04	4842.48	5415.74	3756.32	11306.67
PE_am_e	874.97	784.45	203.66	656.22	784.45	965.48	445.03	475.20	301.71	890.05
PE_val	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
PE_val_e	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
PET_am	8009.94	8143.63	1662.44	6917.15	6539.32	9713.07	3731.77	4173.54	2894.74	8713.28
PET_am_e	674.28	604.52	156.94	505.71	604.52	744.03	342.95	366.20	232.51	685.90
PET_val	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
PET_val_e	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

Table A4 Legend for the abbreviations used in 0 – 0.

Abbreviation	Description
seq_CA	carbon sequestered annually in trees
seq_CA_e	carbon sequestered annually in trees - standard error
seq_CO2_eq	co2 equivalent sequestered annually in trees
seq_CO2_eq_e	co2 equivalent sequestered annually in trees - standard error
seq_CA_val	carbon and co2 annual sequestration value
seq_CA_val_e	carbon and co2 annual sequestration value - standard error
sto_CA	carbon stored in trees (not annual)
sto_CA_e	carbon stored in trees (not annual) - standard error
sto_CO2_eq	co2 equivalent stored in trees (not annual)
sto_CO2_eq_e	co2 equivalent stored in trees (not annual) - standard error
sto_CA_val	carbon storage in trees (not annual) value
sto_CA_val_e	carbon storage in trees (not annual) value - standard error
CO_am	carbon monoxide removed annually
CO_am_e	carbon monoxide removed annually - standard error
CO_am_val	value of carbon monoxide annual removal
CO_am_val_e	value of carbon monoxide annual removal - standard error
NO2_am	nitrogen dioxide removed annually
NO2_am_e	nitrogen dioxide removed annually - standard error
NO2_val	value of nitrogen dioxide annual removal
NO2_val_e	value of nitrogen dioxide annual removal - standard error
O3_am	ozone removed annually
O3_am_e	ozone removed annually - standard error
O3_val	value of ozone annual removal
O3_val_e	value of ozone annual removal - standard error
SO2_am	sulfur dioxide removed annually
SO2_am_e	sulfur dioxide removed annually - standard error
SO2_val	value of sulfur dioxide annual removal
SO2_val_e	value of sulfur dioxide annual removal - standard error
PM2.5_am	particulate matter <2.5 µm removed annually
PM2.5_am_e	particulate matter <2.5 µm removed annually - standard error
PM2.5_val	value of particulate matter <2.5 µm removed annually
PM2.5_val_e	value of particulate matter <2.5 µm removed annually - standard error
PM10_am	particulate matter >2.5 µm and <10 µm removed annually
PM10_am_e	particulate matter >2.5 µm and <10 µm removed annually - standard error
PM10_val	value of particulate matter >2.5 µm and <10 µm removed annually
PM10_val_e	value of particulate matter >2.5 µm and <10 µm removed annually - standard error
AP_totam	air pollution total amount
AP_totam_e	air pollution total amount - standard error
AP_totval	value of air pollution total amount

Abbreviation	Description
AP_totval_e	value of air pollution total amount - standard error
AVRO_am	avoided runoff amount
AVRO_am_e	avoided runoff amount - standard error
AVRO_val	value of avoided runoff
AVRO_val_e	value of avoided runoff amount - standard error
E_am	evaporation amount
E_am_e	evaporation amount - standard error
E_val	value of evaporation
E_val_e	value of evaporation - standard error
I_am	interception amount
I_am_e	interception amount - standard error
I_val	value of interception
I_val_e	value of interception - standard error
T_am	transpiration amount
T_am_e	transpiration amount - standard error
T_val	value of transpiration
T_val_e	value of transpiration - standard error
PE_am	potential evaporation amount
PE_am_e	potential evaporation amount - standard error
PE_val	value of potential evaporation
PE_val_e	value of potential evaporation - standard error
PET_am	potential evapotranspiration amount
PET_am_e	potential evapotranspiration amount - standard error
PET_val	value of potential evapotranspiration
PET_val_e	value of potential evapotranspiration- standard error

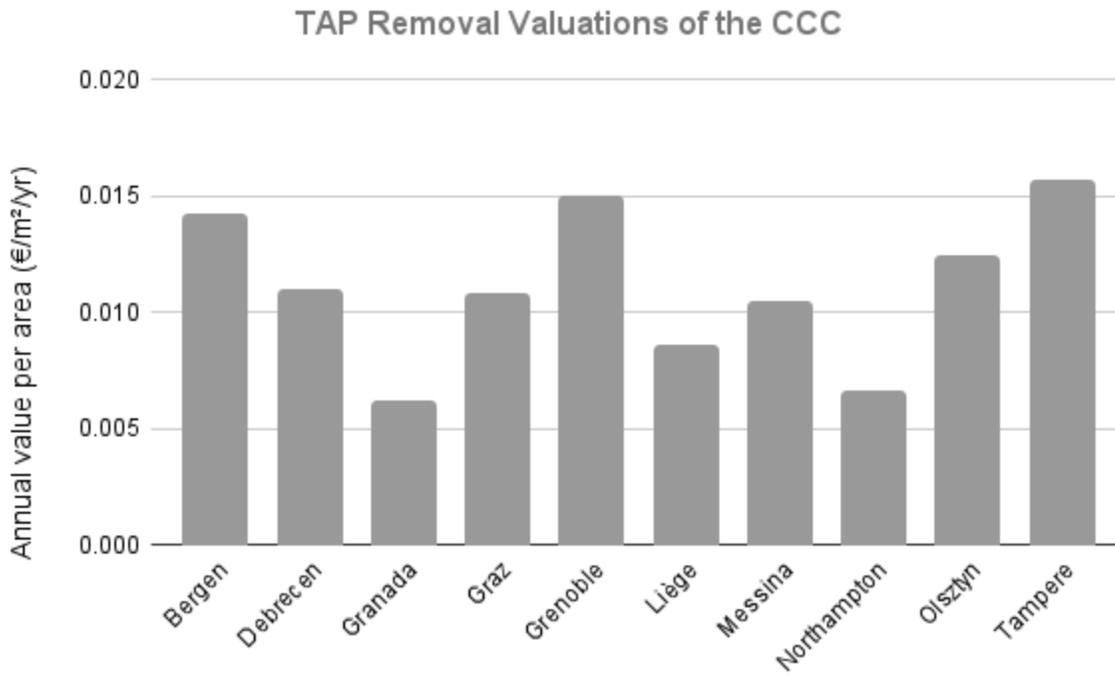


Figure A1 The total annual air pollution removal valuations of the CCC (€/m²/year)

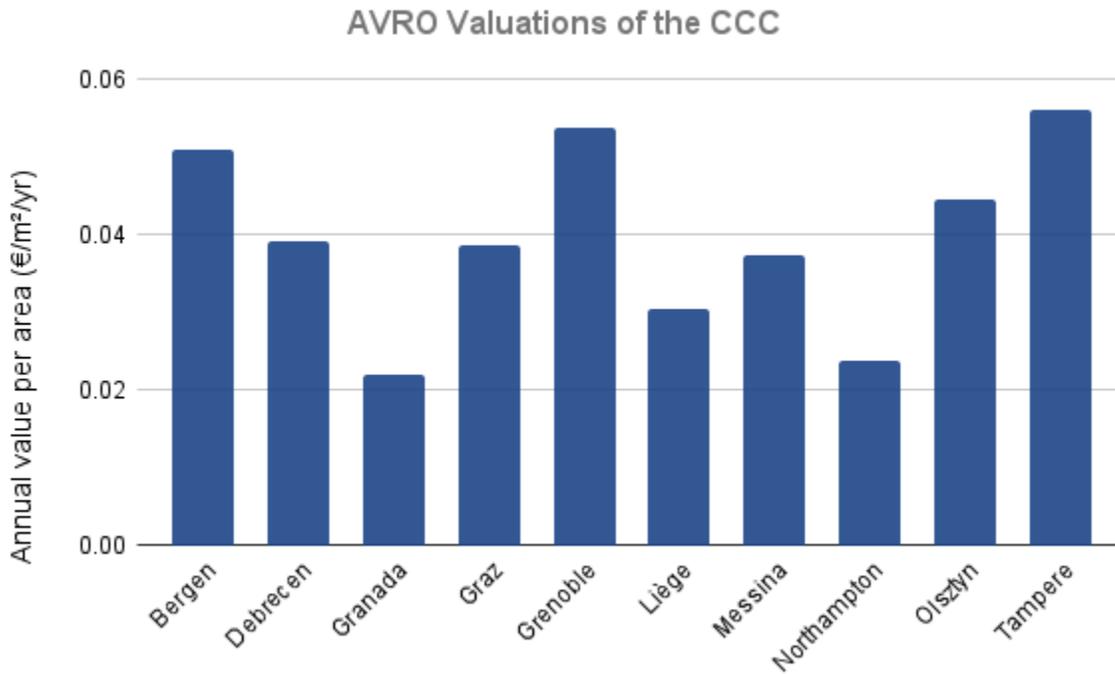


Figure A2 The annual avoided runoff valuations of the CCC (€/m²/year).

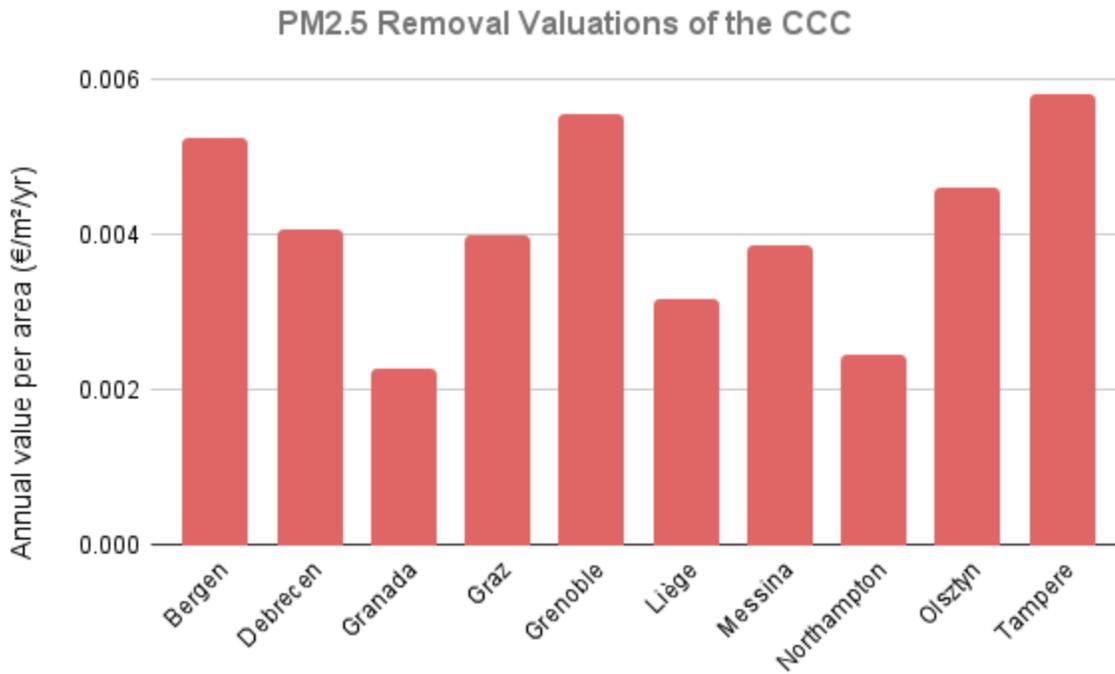


Figure A3 The annual removal of particulate matter <2.5 microns valuations of the CCC (€/m²/year).

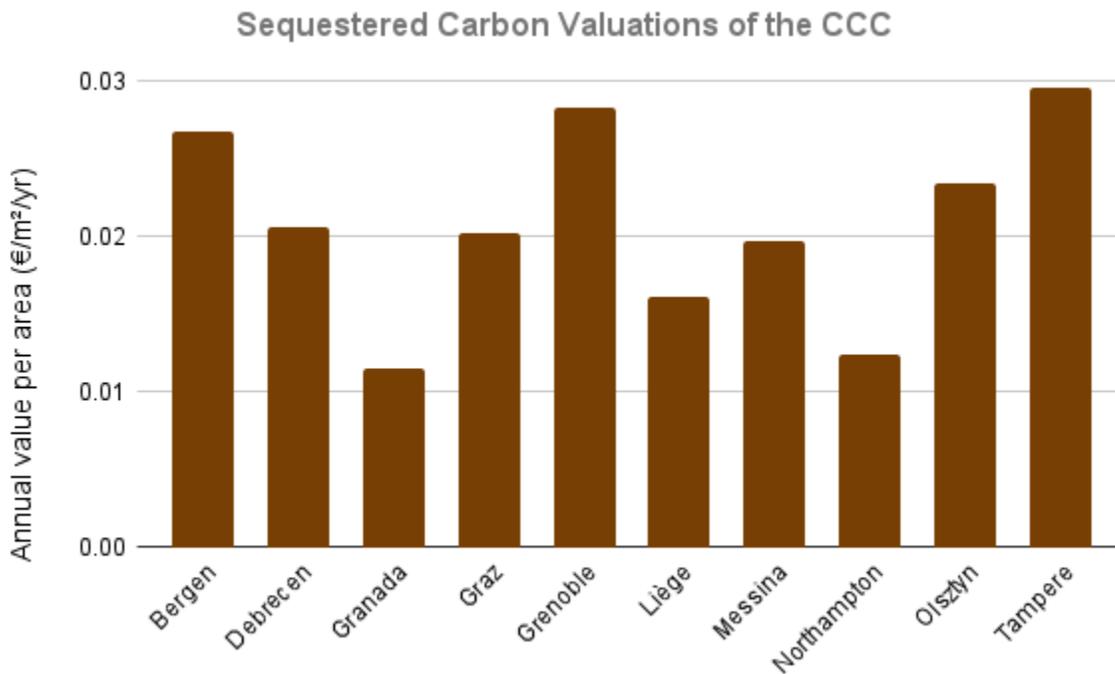


Figure A4 The annual carbon sequestration valuations of the CCC (€/m²/year).