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Tools and methods for monitoring the health of the urban greenery

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Check for updates

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Urban greenery supports cities in achieving Sustainable Development Goals, but it is increasingly affected by multiple stressors impacting its health. Owing to the high costs of greenery inspection and monitoring, local governments often lack adequate data to effectively manage their urban greenery and prevent damage. In this Review, we present an overview of technology-supported methods and tools to measure the health of urban greenery and discuss the space–time resolution trade-offs associated with the various methods presented. To inform researchers and policymakers in global cities, we highlight how high-resolution urban greenery health data can support in achieving Sustainable Development Goals at scale.

Urban greenery provides a wide range of ecosystem services such as air filtering[1], carbon sequestration[2], stormwater run-off[3] and lower local temperatures[4–6]. Urban greenery also acts as a barrier for traffic noise[7], may encourage physical activity[8], and provides spaces for physical and mental restitution[9]. It also helps to achieve the Sustainable Development Goals (SDGs) outlined by the United Nations Agenda 2030, including climate action (SDG 13), sustainable cities and communities (SDG 11), life on land (SDG 15), and good health and well-being for all at all ages (SDG 3).

Urban greenery encompasses greenery (trees, plants, flowers, shrubs, grass) on the ground and on buildings[4]. In this Review, we mainly focus on greenery on the ground, in particular trees[10], as they are the most widespread form of urban vegetation. Trees are characterized by a high heterogeneity across the urban landscape. They can be evergreen or deciduous, belong to different species and have different sizes. They can be found along streets, in parks, in wetlands, in unused land or in sites under construction. They can be tightly nested with grey (human-constructed) structures such as fences, light poles and façades in a green-to-grey continuum[11].

Our definition of greenery is limited compared with the broader concept of urban ecological infrastructure (UEI)[12], which encompasses ecological structures (ecosystem of species, soils, waterways and so on) and ecological functions (for example, life cycles and pollination). In addition, our definition covers only the green part of UEI and only greenery that is, to some extent, managed. It also omits bare soil and aquatic vegetation. Yet, we do not exclude that the methods discussed in this Review can be applied to forms of greenery other than urban managed trees, or provide information that is aggregated to an ecology level. We are aware that geographical and domain shifts play a key role in evaluating the methods reviewed. For instance, methods designed for US cities might not apply to European cities due to different species distribution. Similarly, methods designed for monitoring deciduous trees might not apply to evergreen trees. The aim of this Review is to give an overall picture of all the methods available.

Urban greenery is often affected by an ample amount of abiotic stressors, such as the urban heat island (UHI) effect and soil salinity, and biotic stressors, such as insects and bacteria attacks. The negative effect of these conditions is currently exacerbated owing to climate change[13,14]. As a result, the functionality, productivity and survival of urban greenery is of increasing concern. Trees with poor health cannot provide most of the beneficial ecosystem services[15] and thus, they are less effective in achieving the SDGs. For instance, trees with low transpiration rates do not cool the environment effectively and trees with low growth rates have a reduced shading effect.

Although frequent inspections can identify and rectify these stressors, inspection costs can make urban greenery a high-maintenance asset. Globally, the total cost of inspection, maintenance and settlement of tree damages is estimated to exceed US$2 trillion[16,17]. Maintaining large trees is particularly costly, yet large trees can provide up to eight times more ecosystem benefits compared with smaller ones[18].

The practice of measuring and monitoring urban trees began over a century ago[19]. Currently, a tree's health can be inspected by arborists

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with good-quality results, but usually at high costs[20]. This leads to an assessment that has a low spatial and temporal resolution, with cities conducting tree assessment rarely (for example, every 3–5 years)[21]. In recent years, technology-assisted screening methods have been developed to complement manual methods, with trade-offs involved. Satellite-based imaging can provide data over large areas, with the data quality susceptible to external parameters such as availability of clear skies, depending on the type of sensor[22]. Yet, high spatial-temporal resolution (<10 m) is achievable through only targeted acquisitions, thus limiting the size of area covered[23]. Airborne sensing using unmanned aerial vehicles (UAVs) or aeroplanes leads to an increased spatial granularity[22], yet it involves high operational costs and may not be suitable in urban environments owing to aviation authority regulations. Furthermore, depending on the canopy density, both airborne sensing and satellite imagery can capture only the overhead view of the urban greenery. As a result, lower vegetation elements such as green walls, short trees or shrubs are often missed or misinterpreted in the gathered data[24]. In addition to traditional approaches, a number of research projects have investigated the use of low-cost alternatives to survey the presence and species of urban greenery. For instance, using Google Street View images to detect the presence of trees[24] or to calculate changes in tree species diversity in cities[25]. These projects are set within the field of opportunistic and low-cost sensing, aimed at developing environmental platforms that can be deployed and operated without the need for expensive infrastructures.

As the examples above demonstrated, the importance of urban greenery has been fostering the use of different methods and tools to quantify urban greenery and, more particularly, to assess tree health. They range from highly specialized and costly UAVs to engaging residents in citizen-science approaches. Scientific literature often presents detailed descriptions and discussions about one particular approach.

In this paper, we review research methods and tools to map the health of urban greenery on the ground. We highlight the types of attribute and information that can be mapped, and how technology-supported methods can complement traditional, labour-intensive approaches. We propose use cases for the methods reviewed and we discuss how scholars and policymakers can utilize greenery health data to support achieving SDGs at scale. We highlight existing research gaps with the aim at informing the development of new approaches.

Tree attributes and health

The health, survival and functionality of trees depends on three main aspects: (1) the ability of the root system to transport nutrients and dispose of pollutants, (2) functioning water conduits (xylem) transferring water and healthy sieve-tube elements (phloem) to all live organs; and (3) healthy leaves, the main site for gas exchange with the atmosphere through photosynthesis processes.

Early detection of conditions affecting these three components, such as cavities and diseases, can guide pre-emptive actions to maintain a tree's optimal functionality[26]. Unlike external physical damage, physiological stress and internal damage are often undetectable to the human eye, and severe damage can be reached long before symptoms become visible[27–29]. Furthermore, trees under stress reduce their transpiration rate to prevent excessive water loss, store less carbon dioxide and decrease their growth rate. Such trees have a weak defensive mechanism and their general health state is damaged, making them more vulnerable to the attack of parasites and diseases, thus increasing their chances of mortality.

Stressors affecting trees can be categorized as abiotic, that is, caused by non-living factors, and biotic, that is, provoked by living agents.

Abiotic stressors are often related to soil and sunlight factors. Soil health is a primary determinant of a tree health. Urban soils can have highly variable attributes such as different densities and different contents of organic matter owing to a patchy distribution of natural or human-made materials, such as gravel or construction waste. Furthermore, limited soil leads to restricted space for roots to develop, preventing proper tree growth and eventually reducing a tree's lifespan substantially[15]. Owing to the presence of pollutants, urban soils often have an increased salinity, which reduces the ability of the roots to extract water and nutrients. Many urban environments provide limited or irregular sunlight due to the shadows projected by buildings, which can prevent the tree reaching its optimum photosynthesis machinery[30]. In addition, the above-average air temperatures and heatwaves, which are increasingly occurring in urban environments[31], leads to trees losing an excessive amount of water. To counteract water loss, trees close their stomata—small pores in the leaves—reducing their beneficial ambient cooling effect. Another outcome of the 'life-saving' stomatal regulation is a reduction in the photosynthesis process; thus resulting in reduced growth.

Biotic stressors are often related to the physiological response of trees to the attack of agents such as insects, fungi, viruses or bacteria[32]. Such response is usually expressed in a decrease in functionality and productivity that can eventually result in the death of the affected tree[33]. A tree's defence mechanism against biotic agents requires a functional and healthy internal state. If resources are limited, for example, owing to a pre-existing abiotic stress, the tree might succumb to the attack[18]. The development and fast-spreading nature of biotic agents, as well as species homogeneity of many urban environments, also contribute to the worsening of these biotic stressors[34].

If the health of a tree is poor, its contribution to the urban ecosystem is impaired. Unlike trees in natural or planted forests, rectification measures for urban trees are needed at a faster rate, owing to the rapid rate of changes in local conditions (for example, infrastructure, construction work, pruning) and owing to immediate implications such as potential physical damages to pedestrians and properties.

Inspection strategies for greenery health

We survey inspection strategies and tools using two lenses.

First, we scope popular sensing principles and technologies. The choice of these methods directly affects the type of health information that can be sensed, as well as the quality of the assessment. For example, hyperspectral and multispectral imaging (HMI) sensors are useful to estimate normalized difference vegetation index (NDVI) values, while thermal imaging sensors can be used to compute crop water stress index (CWSI) values. These strategies lie within three clusters: manual techniques, physical and chemical sensors, and imaging-based sensors.

Second, we discuss sensor deployment strategies to collect data. Different strategies affect the time and space resolutions that can be achieved. For example, although sensors embedded in a tree can provide data at a high time resolution (more than once an hour), achieving high space resolution leads to high deployment costs (one sensor per tree). However, remote-sensing techniques may lead to a higher space coverage more cost-effectively, yet with constraints on the time resolution (depending on the revisit rate of the sensor) and the influence of environmental parameters such as sky conditions.

We also highlight the level of automation required to collect data. For example, embedded sensors can work with little (periodic calibration) to no supervision for years, whereas airborne sensors require manual intervention as well as supervision to configure and deploy aeroplanes or UAVs over vast areas. A detailed list of the reviewed works is provided in Supplementary Information.

Manual techniques

As a first step, arborists measure the health of trees by visual inspection and utilizing non-invasive tools for screening, diagnostic or evaluation purposes[35,36]. Water limitations can be quantified by sensing air dryness (relative humidity and temperature) and by measuring the tree water consumption[37–39]. Insect-induced physical damage to the leaves and other elements can be detected visually[40–42]. However, external symptoms of decay may be absent even in the presence of internal decay[35]. In turn, this may lead to delayed actions taking place[43].

To provide more complete information, visual inspection might be supplemented by non-invasive methods such as electronic noise to detect fungal decay. However, these simple methods have low resolution and may miss small wooden decays or diseases at very early stages. Hence, for improved resolutions, arborists may also use invasive methods such as electrical resistivity measurements (attaching electrodes and passing an electric current through the trunk) or destructive instruments such as increment borers (tools for extraction of a wooden core sample from the trunk of the tree). Although effective, such invasive methods that require penetration in the living wood may create an entry path for pathogens or may alter the structural integrity of a tree. Finally, for the highest accuracy, high-cost methods such as electromagnetic or multi-path stress wave tomography may be used. Overall, arborists usually start with the method that causes the least damage, and successively apply more aggressive and costly techniques to get more accurate information[44].

Various manual inspection techniques exist and they are summarized in Supplementary Table 1 with their working principle, detection resolution, cost and invasiveness. The cost for each method has been estimated based on the scale in ref. 35. Further details on the in-depth principle of manual methods can be found in refs. 35,36,45.

Both invasive and non-invasive manual inspection techniques require intensive human labour as deployment medium, leading to low automation prospects. Thus, manual techniques usually lead to poor scalability, as highlighted in Fig. 1. In contrast, methods discussed in the upcoming sections, which are summarized in Supplementary Table 2 have different automation prospects and deployment media.

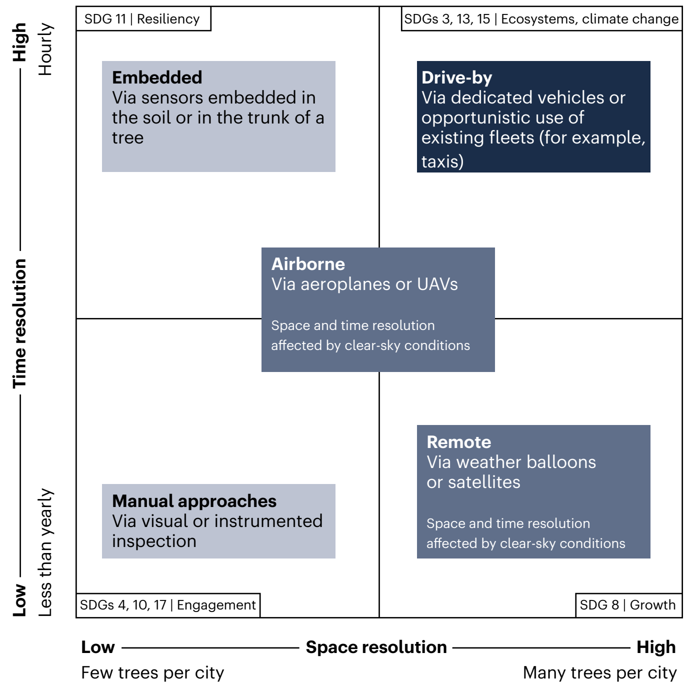

Fig. 1 | Space–time resolution of classes of methods with respect to SDG requirements. Each class has been evaluated for the time and space resolution the class methods can achieve. Each class has also been mapped to one or more SDGs the class methods can support based on the rationale described in the 'Relevance for the SDGs' section.

Physical, chemical and electrical sensors

These sensors are usually embedded into the bark (the protective outer sheath of the wooden parts of a tree) or in the soil. The physical property under scrutiny can vary, from the detection of sudden vibrations induced by the presence of parasites to the measurement of water uptake and transpiration. The data are generated at high temporal resolution with little or no human supervision required.

Accelerometer-based sensors can detect the presence of insects and larvae by monitoring sudden minimal vibrations provoked by the insects' activities such as feeding and locomotion[46]. Accelerometers can also be used in tandem with other sensors that measure moisture, light, temperature, humidity and air quality.

Electrical impedance spectroscopy is used to assess trees' physiological status by leveraging electrical impedance, a measure of the opposition of a material to the flow of alternating currents. Using a pair of electrodes placed in the trunk at diametrically opposite positions to measure impedance values, it has been demonstrated that it is possible to disambiguate between multiple health states and identify water stress and diseases[43].

Dendrometers are tools employed to measure trunk growth and shrinkage happening during long-term seasonal growth patterns, daily cycles of water uptake and transient conditions such as swelling after heavy rainfall. They could be either fully analogue tools, as simple as a metal strap that is affixed around a tree stem using a spring fastener, or fully digital tools based on contact or non-contact technologies. Dendrometers have been used for different purposes, including community-based monitoring using DIY techniques[47], for irrigation scheduling[48] and to assess the effect of climate change on *Pinus sylvestris*[49].

Internet of Things approaches are often adopted to monitor multiple health-related parameters at a high frequency and to provide real-time alerts[50]. Data from multiple embedded sensors can be used as features to train neural network models for health classification and early warning generation[51,52], and to develop aggregated health indexes combining dynamic ambient features (for example, light and wind exposure) with static or predictable features (for example, species, age)[16].

Besides being used in research, several sensing approaches have recently paved their way into commercial products, including non-invasive microneedle-based electrical impedance sensors, multi-sensory platforms for stability monitoring application, and sensors embedded in the soil to monitor moisture and acidity. A review of additional physical, chemical and electrical sensors is provided in ref. 53.

Similarly to manual techniques, physical, chemical and electrical sensors require physical access to trees.

Imaging-based sensors

Measuring infrared radiation emitted from biological materials, a technique called infrared thermography (IRT), is one of the emerging approaches for tree health monitoring.

The analysis of thermal images (Fig. 2, left) allows for early detection of various health conditions including cavities, bark necrosis and decay[54]. Thermal cameras are non-invasive and scalable tools, for example, when the camera is mounted on a moving vehicle. Differences in thermal patterns on the tree surface can indicate deteriorated areas: sections with cavities or physical damages show local cooler temperatures[44,55]; sections affected by infections caused by spores or bacteria show local warmer temperatures[56,57]. However, this approach requires a substantial amount of manual work to review the images by experts and it is often paired with manual inspections; the technique does not allow for the fully quantitative assessment that could enable scalability[54]. In addition, to provide optimal results, the bark should be shielded from direct sunlight, dry and free from moss—elements that could interfere with temperature readings, hiding potential damages. Although some of these factors can be mitigated by comparing temperature patterns within different parts of the tree expected to behave similarly[44], IRT performs well only to assess important external damages[58]. In addition, there are no generalized temperature patterns that can be used to detect damage across various species[36].

Fig. 2 | Examples of three imaging-based methods used to estimate urban greenery health attributes. From left to right: a thermal image captured using a longwave-infrared (at 8–14 µ) FLIR Lepton 3.5 camera, a multispectral image captured using a MAPIR Survey 3W camera (red at 660 nm, green at 550 nm, near-infrared at 850 nm); and a LiDAR point cloud captured using an Apple iPhone 12 Pro and the Polycam 3D Scanner app.

IRT can also be used to measure water stress[22]. Rather than bark temperature, the focus is on leaf temperature—a physiological trait that can be used as a proxy for tree irrigation[59,60]. For this specific application, thermal images are fused with red–green–blue (RGB) images, to use image segmentation algorithms to automate the extraction of thermal data from leaves only (for example, removing thermal data of the sky and the soil). The usefulness of IRT as a plant water stress indicator has been evaluated with different species, including persimmon and citrus trees[61], apple orchards[62] and conifers[63].

In HMI, various bands in the electromagnetic spectrum are captured. These data are used to calculate various vegetation indexes, including the NDVI. The NDVI synthesizes the ratio between the visible red radiation and the near-infrared radiation reflected by the vegetation. It leverages the property of chlorophyll in the leaves to absorb red light, and the cell structure of leaves to reflect near-infrared light. High NDVI values are a proxy for healthy photosynthetic capacity. Low NDVI values can be linked to overall poor health, the presence of stress or parasites, or the absence of greenery. The calibration of HMI sensors is an important aspect that affects the overall quality of results, especially for low-cost sensors[64,65]. Once calibrated, HMI sensors are highly reliable, at least when comparing NDVI values within the same species, as the ranges of healthy NDVI values can vary between species. Low-cost HMI sensor alternatives have been recently presented, for example, modifying regular RGB cameras to capture light outside the visible spectrum[66]. HMI sensors are usually deployed on satellites and drones[67,68], although static sensors also exist. In the latter case, the sensors are cheaper, but they need to be located in close proximity to the leaves. A sample HMI image is depicted in Fig. 2 (middle).

Like IRT sensors, HMI instruments can be deployed in tandem with other sensors, most commonly, with light detection and ranging (LiDAR) instruments. LiDAR uses the time of flight of pulsed laser light to determine the distance between the sensor and an object or a surface. LiDAR is used for greenery health applications to measure geometrical parameters such as the number of leaves surrounding a branch, the crown diameter and the leaf area index (LAI). The LAI is computed by measuring the total area of leaves per unit of ground area and it is directly related to the amount of light that can be intercepted by a tree. Although neither the geometrical properties of a tree nor the LAI is a direct measure of greenery health, they can be used to assess the development of a tree over time with respect to target growth goals for each species. LiDAR combined with HMI sensors have also been useful for species identification[69]. Similarly to other imaging-based methods, LiDAR and HMI sensors have been deployed using airborne[70] and ground-based approaches[71]. A sample LiDAR point cloud is depicted in Fig. 2 (right).

Street-view images captured for mapping and navigation purposes have been recently used to quantify the extent and the location of urban greenery[72,73], their species[25] and shading effect[74]. Although the extraction of health parameters from street-view images is still to be investigated, information about the location and coverage can be combined with a city's inventory of trees to provide an indirect health assessment.

Finally, several methods can be combined in multi-sensory approaches to provide a higher-fidelity assessment of a single parameter; for example, combining LiDAR and hyperspectral cameras[75]. This strategy also serves to map how a single stressor impacts different aspects of a tree[63].

Imaging-based methods can allow for more flexibility compared with manual and chemical, physical and electrical methods. They can be used to map greenery in remote areas, when deployed on drones or satellites, and in areas where frequent physical access to greenery might be precluded due to safety reasons, for example, along highways. Furthermore, the output of these sensors, such as the NDVI index, can be used to assess the conditions of greenery beyond street trees, including plants, grass and shrubs.

Relevance for the SDGs

Large-scale monitoring of urban greenery can deliver hyper-local data useful for a broad range of applications, tailored on issues of specific geographical areas. Hyper-local data have a fine-granular space–time resolution and are meaningful to address (greenery health) issues that are relevant to very specific and small geographical areas (for instance, at the street level or at the level of individual trees). This section highlights use cases and their relevance for the SDGs. Each use case (UC) has a numerical identifier (for example, UC1), a title and a mention to the SDG(s) it relates to.

SDG 15 proposes "Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss". We identify at least two advantages of having hyper-local data on greenery that can help cities to achieve this goal.

UC1 selective watering (SDG 15)

Currently, irrigation of urban trees is irregular and inconsistent or absent[76,77], resulting in trees being over-irrigated (which may lead to anoxia) or under-irrigated (which may lead to soil drought). This issue mainly occurs owing to high heterogeneity in water consumption by individual trees and soil hydraulic properties. Data at high temporal and spatial resolution can help create the feedback loops necessary

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to implement selective watering strategies, optimizing irrigation as a function of each tree's water use. In turn, data-driven urban irrigation (a practice that is becoming common in agriculture[78]), can save water and improve trees' overall health along with soil fertility. Methods and tools capable to capture CWSI information, including electrical impedance spectroscopy[43] and IRT[22], can be applied.

UC2 early detection of diseases (SDG 15)

Diseases and parasites lead to a reduction in tree health and increased mortality[79]. Detecting diseases at an early stage can prevent permanent damage and mitigate the risk of mortality. For instance, some early signals can be detected using parameters generated by multispectral/hyperspectral images[42], as well as continuous measurements via embedded sensors[27]. These methods can also be used to measure the efficacy of pest treatments over time, via repetitive measurements. Furthermore, data from multiple parameters at high temporal and spatial resolutions can serve as training datasets to allow the development of machine-learning algorithms for the automatic identification of specific parasites.

SDG 11 proposes "Make cities and human settlements inclusive, safe, resilient and sustainable".

UC3 continuous monitoring (SDG 11)

Long-term monitoring data are essential to understand changes over time, including trends in tree growth, health and mortality. Without detailed data collected over time, it is not possible to implement effective management solutions and measure their success rates, estimate urban forest value or inform policy-making[80]. Yet, the frequency of monitoring campaigns is hampered by resource limitation and specifically the lack of staff time[81]. Several recent survey methods have an elevated degree of automation (as reported in Supplementary Table 2), which enables long-term monitoring campaigns. In addition, advances in artificial intelligence allow for training machine-learning algorithms that can perform tasks such as sensor calibration, calculation of geometric property of trees and pattern identification based on multi-sensory input[51,52]. Although human judgement is still required at certain stages of the process, artificial intelligence has the potential to decrease human involvement in repetitive and trivial tasks and reduce the number of site visits.

In addition to SDG 11, we highlight how hyper-local, continuous monitoring can also benefit SDG 8: "Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all."

UC4 quantifying cost-gain balances (SDGs 8 and 11)

The global cost for tree maintenance exceeds US$2 trillion worldwide[16,17]. Yet a comprehensive quantification of the economic benefits provided by urban greenery is tangled by the multifaced nature of the ecosystem benefits as well as the lack of models (and data) for several regions around the globe[82]. Data on urban trees' location, species, health and age can help develop economic models to assess the value of urban trees in relation to their environmental risk mitigation, public health and energy-saving benefits, as well as their aesthetic and cultural relevance.

Another application that can be improved with hyper-local data is the mitigation of UHI effects and carbon removal, which we argue is connected with SDG 3 ("Ensure healthy lives and promote well-being for all at all ages") and SDG 13 ("Take urgent action to combat climate change and its impacts").

UC5 mitigation of UHI effect (SDGs 3 and13)

Urban surfaces, such as façades and road pavements, play an important role in the UHI effect[4]. UHI happens when dense urban environments show higher local temperatures than suburbs and rural areas[83,84]—and this condition is being exacerbated by climate change. Increased greenery is associated with a reduction in land-surface temperature and reduced risk for pedestrian heat exposure[85,86]. By quantifying the cooling effect for different species as a function of their health statuses, such as canopy density, tree height and leaf thickness, guidelines for planting and maintenance strategies tailored to specific UHI risk areas can be defined.

One of the key applications that can be improved with hyper-local data is community engagement, which is present in several SDGs. We particularly highlight SDG 4 ("Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all"), SDG 10 ("Reduce inequality within and among countries"), SDG 11 and SDG 17 ("Strengthen the means of implementation and revitalize the Global Partnership for Sustainable Development").

UC6 community engagement (SDGs 4, 10, 11 and 17)

Citizen involvement in the monitoring of urban greenery can complement traditional approaches conducted by government agencies, companies and research institutes. This action can build on several methods and tools in the field of citizen science—the inclusion of non-experts in research efforts[87–89]. In addition to providing data to public administrations, it increases public awareness of the benefit provided by urban greenery, fostering a sense of stewardship and appreciation[90], and steering public debates around equity and environmental justice. Community engagement also fosters lifelong learning, as the volunteers need to be trained to collect data[80]. This approach has been demonstrated by several campaigns such as the 2015 TreesCount! inventory in New York City and the i-Tree Eco assessment in London, England. Novel low-cost and open-source greenery health mapping tools[24,47,65,66,91] can facilitate the work of citizen scientists, enabling them to collect quantitative evidence in a cost-efficient way, which is of particular relevance for low-income communities.

We believe that collecting hyper-local data, although an absolute optimum, could be unnecessary for certain use cases. For example for SDGs 4, 10 and 17 addressed in the 'community engagement' use case, accessibility (for example, open-source code) and cost of implementation are the main drivers for the selection of a method. For SDGs 8 and 11, the priority might be the degree of automation of the methods. More in detail, we believe that hyper-local data are relevant for UC1 to understand water consumption at the tree level, UC2 to have a big dataset to train machine-learning algorithms for disease detection, UC3 to allow for evaluation of changes or interventions over time, and UC5 because UHI is a hyper-local phenomenon itself. However, we believe that hyper-local data are less relevant for UC4 whereas widespread coverage is a priority, as well as UC6 where cost and open access to data and analysis tools could be more relevant.

Outlook

Owing to the high costs involved with manual approaches, cities survey their urban greenery once every few years, with several cities that have never carried out a census. The development of highly scalable and reliable approaches is necessary to acquire a large amount of data about the health of urban greenery, which fosters in achieving various SDGs.

Achieving scalability is complex. The health attributes monitored are dictated by the type of sensing technology employed, and the deployment strategies affect the potential for scalability. For instance, physical, chemical and electrical sensors can be embedded into only the trunk or in the near proximity of a tree. They generate continuous streams of data at high temporal resolutions; however, the spatial resolution might be limited—embedding sensors on every tree in the city will result in high costs. On the contrary, imaging-based sensors can be used handheld during manual inspections, or deployed on satellites, UAVs or even terrestrial vehicles. While satellite and airborne-based remote-sensing approaches can cover large areas[22], the data are generated at a low temporal resolution, mainly constrained by the revisit rate of the vessel and the availability of clear skies. Airborne sensing using

UAVs or aeroplanes leads to an increased spatial granularity[22], yet it involves high operational costs and may not be suitable in highly urbanized environments due to aviation authority regulations. Furthermore, these approaches can provide only a bird's eye view of the greenery, ignoring information about the trunk as well as shorter elements such as shrubs and green walls that might lie hidden under larger trees. On the other side of the spectrum, street-view-based methods[73,74,92,93] are highly scalable, but they are able to quantify only the presence and species of urban greenery rather than its health, and are limited to mapping public spaces. Yet, ground-based sensing can look at urban greenery in a more holistic manner. The deployment of sensors in a drive-by scheme has the potential for high scalability[94]. In this research strand, only a few studies[22] have investigated ground-based monitoring approaches with HMI and thermal imaging. Although scalability can be increased by deploying sensors on vehicles, most research initiatives, except very few[22,63], still require manual judgement and processing by humans on the data collected. Finally, imaging-based methods deployed as drive-by platforms or handheld devices may raise privacy or ethical concerns[95], although several techniques are available to tackle this issue; for example, by pedestrians' thermal fingerprints[96].

The high heterogeneity of the urban landscape also affects the choice of method used for monitoring. For example, trees may be accessible via pedestrian-only routes, public or private roads, or be confined in private backyards. Drive-by methods (Fig. 1) can be applied to only trees close to private or public roads. Physical access to trees for visual inspection, installation and maintenance of embedded sensors could be limited by safety barriers; for example, trees along busy roads, informal settlements or in high-crime neighbourhoods. Remote sensing is less suitable when green and grey structures[11] are tightly nested due to occlusion.

Another challenge concerns the validity of the studies available in the literature. Most of the reviewed techniques, except for a few[16,54,55,97], have been evaluated on a few dozen trees, in a controlled environment. It is still unclear how factors such as the weather, climate and interference from elements of the built environment might affect the validity and performance of the techniques. Finally, the transferability of methods across species has not been achieved. Most methods still require a substantial amount of manual work, either for analysing the data, for example, in the case of thermal images, or for sensor deployment and operations, as in the case of operating UAVs.

Scalable methods and tools for urban forest monitoring are necessary to support SDGs for all. We hope that this Review will spur interest and collaboration among different stakeholders, ranging from urban planners and policy advisors to environmental engineers and computer scientists. For the first group, our work can be used to inform planting strategies, measure the outcome of greenery maintenance practices and foster community engagement. For the latter group, it can be used as a foundation to overcome the trade-offs and challenges related to the scalability, robustness and transferability of the methods and tools currently available.

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Conceptualization: A.G., S.M. and Y.P. Data curation: A.G. Methodology: S.M. Formal analysis: A.G., S.M. and Y.P. Writing—original draft: A.G., S.M., Y.P. and F.D. Writing—review and editing: A.G., S.M., Y.P., F.D., V.P. and C.R. Supervision: S.M. Project administration: S.M., F.D. and V.P. Funding acquisition: C.R.

Competing interests

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Additional information

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