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Review article

Preferred reporting items in green space health research. Guiding principles for an interdisciplinary field.

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ABSTRACT

The relationship between green spaces and health is attracting more and more societal and research interest. The research field is however still suffering from its differing monodisciplinary origins. Now in a multidisciplinary environment on its way to a truly interdisciplinary field, there is a need for a common understanding, precision in green space indicators, and coherent assessment of the complexity of daily living environments. In several reviews, common protocols and open-source scripts are considered a high priority to advance the field. Realizing these issues, we developed PRIGSHARE (Preferred Reporting Items in Greenspace Health Research). It is accompanied by an open-source script that supports non-spatial disciplines in assessing greenness and green space on different scales and types. The PRIGSHARE checklist contains 21 items that have been identified as a risk of bias and are necessary for understanding and comparison of studies. The checklist is divided into the following topics: objectives (3 items), scope (3 items), spatial assessment (7 items), vegetation assessment (4 items), and context assessment (4 items). For each item, we include a pathway-specific (if relevant) rationale and explanation. The PRIGSHARE guiding principles should be helpful to support a high-quality assessment and synchronize the studies in the field while acknowledging the diversity of study designs.

1. Introduction

Green spaces are attracting increasing societal and research interest, as a primary feature of the built environment capable of reducing the risk potential for non-communicable diseases (NCDs). The development in this area is due to the recognition of the multidimensional framework of health and the epidemiological transition towards NCDs as the leading cause of death (Hartig et al., 2014). Coupled with the focus on greening our cities to combat climate change and promote quality of life in cities in a rapidly urbanizing global population, this field of research has gained even more momentum. This is reflected in the sheer volume of research produced annually (R. Zhang et al., 2021), but more importantly in the shift from a monodisciplinary perspective of mainly epidemiology, psychology, human geography, environmental and health sciences to a multidisciplinary field that is on its way to becoming interdisciplinary (Hartig et al., 2014; R. Zhang et al., 2021). To this date, much of the available evidence on a variety of health outcomes points toward a positive green space-health relationship.

Bringing together the various fields of research in recent years has highlighted the multidimensional effects of green spaces on physical and mental health (WHO Regional Office for Europe, 2016). F or example, a recent review summarized the evidence on nature and mental health and reported a variety of likely positive effects of nature on increased positive affect, happiness, subjective well-being, positive social interactions, and a decrease in mental distress, among others (Bratman et al., 2019). Furthermore, evidence from longitudinal studies points towards a positive influence of contact with nature on cognitive function, memory, attention, impulse inhibition, school performance, imagination, and creativity (Bratman et al., 2019). Similarly, another recent review highlighted the evidence of positive effects of green space on physical health through reduced all-cause mortality, stroke-specific mortality, total cardiovascular disease morbidity, cardiometabolic factors, low birth weight, and physical inactivity (Yang et al., 2021). Yang et al. also reported there is limited evidence that green spaces may

Abbreviations: NCD, non-communicable diseases; QGIS, Quantum Geospatial Information system; LiDAR, Light Detection and Ranging; NDVI, Normalized Difference Vegetation Index; ED, Euclidean Distance; ND, Network Distance; BSA, Buffered Service Area; AU, Administrative Units; SES, Socio-Economic Status.

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reduce the risk of cancer, and respiratory-specific mortality, as well as influence hormone levels (Yang et al., 2021). Lastly, also negative health effects can emerge from green spaces through increased risk of allergies, infectious diseases, and harmful microbiota (Marselle et al., 2021).

However, bringing these different fields of research on nature, biodiversity, and green spaces from a variety of disciplines together has raised new questions. While layer after layer of the complex interrelations has been uncovered, questions about the quality and comparability of previous studies arise frequently in reviews (Gascon et al., 2015; Labib et al., 2020; Twohig-Bennett and Jones, 2018). Very high heterogeneity of study designs, exposure assessment, and outcomes are recognized. This heterogeneity of results is likely related to the different disciplinary skills but is partly also founded in the complexity of real-life settings, where the signal-to-noise ratio is very low (Hartig et al., 2014). Thus, to advance in the field, the overall comparability, quality, and rigor of the studies need to level up in precision, transparency, and robustness.

Consequently, one of the priorities is a joint baseline and agreeing on common wording, next to common quality standards, and sharing relevant theories. One important milestone in this regard was the foundational paper of a group of leading experts that identified three main pathways (Markevych et al., 2017). These widely accepted pathways are *Mitigation* (reducing environmental stressors such as air pollution, noise pollution, and heat island effects), *Restoration* (restorative effects of contact with nature through the restoration of attention and stress reduction), and *Instoration* (affordances of green spaces that encourage into more physical or socializing activities). This theoretical concept was later complemented with a fourth pathway *Causing harm* to summarize the negative effects that may arise, especially from the context of biodiversity and health (Marselle et al., 2021).

While the pathways are widely accepted, the methodological quality still needs to be improved through a precise common indicator definition within and across pathways wherever possible (Davis et al., 2021; Liu et al., 2022; R. Zhang et al., 2021). This includes especially a common understanding of green space itself, as the type, features, area, and perception of green spaces are diverse (Taylor and Hochuli, 2017). In this respect, a sensitivity analysis of multiple greenspace indicators is requested to better understand the mechanisms and the sensitivity in which they react to health outcomes or pathways (Davis et al., 2021; Labib et al., 2020). Lastly, the transparency of studies needs to be improved by the rigorous and precise definition and reporting of indicators and context variables to facilitate understanding in this interdisciplinary field (Browning et al., 2022; Collins et al., 2020; Markevych et al., 2017). It is a priority to translate identified risks of bias that are known in certain research fields into common protocols to ensure the quality and comparability of studies in the field, enabling not only meta-analysis but a truly interdisciplinary field.

This paper, therefore, aims to develop reporting guidelines to assess green spaces and report on green space research to assist the multidisciplinary field. PRIGSHARE (Preferred Reporting Items in Green Space Health Research) is designed as a transparent guide to help frame studies within or across pathways and assess relevant variables accordingly. It focuses on the flow of assessment decisions, starting with the objective of the study, the scope of the study, how to capture green spaces depending on the objective of the study, as well as the relevant contextual variables.

PRIGSHARE, therefore, distinguishes green space assessment in surrounding vegetation, contact with nature or accessible green space according to the theorized mechanistic pathways, where the *Mitigation* pathway aligns with the surrounding vegetation assessment, the *Restoration* pathway aligns with the contact with nature assessment, and the *Instoration* pathway with the accessible green space assessment. The *Causing harm* pathway will be included as a potential negative counterpart of the three other pathways since the appropriate assessment depends on the type of harm. This helps to communicate study designs in a common language and works as a guide to assess and report on green space health research. We have outlined this paper according to other successful guiding principles like PRISMA (Page et al., 2021). The maximum value is gained by using it together with the open-source script (AID-PRIGSHARE under review, see also S2). This script tackles the effort needed for sensitivity analysis. The QGIS script automatically generates different green space indicators at different distances based on land-use data and vegetation indices provided. While this reporting guideline focuses on assessments via land-use maps or satellite images, we acknowledge different views and possibilities of green space assessments, in the research field. We designed PRIGSHARE in a modular way to be enhanced by other techniques like the 3D street view visual assessments or the LiDAR technology (Light Detection and Ranging) for 3D scanning. Likewise, biodiversity assessments, biomass measurements, self-reported and perceived green space measures, wilderness experiments, and studies that research contact with nature as a treatment are not yet included. We encourage other authors to adapt or enlarge the reporting guideline for their purposes.

2. Development of PRIGSHARE

The PRIGHSHARE reporting guidelines are based on a non-systematic literature review of reviews of the field. Other relevant sources were included through snowballing and expert consultation. The first author developed the initial reporting guidelines and proposed the items to the co-authors. The proposal was discussed and refined within the core research team (all authors), which was then presented in a round of expert consultation from geospatial analysis, public health, and behavioral science. Following this consultation round, the core research team refined the guidelines.

Through the evidence in the current literature, we built a logical flow of assessment decisions for the theorized mechanistic pathways between green space and health, especially by distinguishing plausible green space assessments by pathway. We summarized identified risk of bias for each assessment section, and each item listed. To limit the length of the reporting guideline and the associated workload, we focused on land-use indicators as a proxy for accessible green spaces (*Instoration*) and satellite-based assessments as a proxy for greenness or natural environment (*Mitigation* and *Restoration*). Both assessment strategies can also be used to assess potential negative health impacts that may derive from vegetation, contact with nature, or behavior (*Causing harm*). To demonstrate the spatial risk of bias for different assessment decisions and data sources we used test data from the cities in the EU-funded URBiNAT project (Nantes-Nord, Porto-Campanhã, Sofia-Nadezhda, and Høje-Taastrup).

3. How to use this paper

We present each checklist item (Table 1) followed up by an explanation and its rationale for inclusion based on current literature. The items are ordered by their ability to predefine other items and clustered in sub-topics. It is preferred, however not necessary, to report them in this specific order. Also, not all items are relevant for every study design, some will want to report their spatial assessment (items 7–13), and others their assessment of vegetation or natural environment (14–17). To support and keep track of item reporting, we provide a template for researchers in the supplementary material (S1). Whether researchers decide to do a vegetation assessment, a spatial assessment, or both, we encourage the use of the supporting open-source script which will produce several green space indicators (spatial assessment) and greenness indicators (vegetation or nature assessment) in distances from 100 to 1.500 m every 100 m (AID-PRIGSHARE - under review, see also S2). It is worth noting, however, that the validity of these indicators will depend on the extent to which the data entered have been checked for risk of bias (see Table 1 categories: scope, spatial, and/or vegetation assessment).

Table 1
Checklist of items to include when reporting research on green space health effects.

#	Section/Topic	Checklist Item
OBJECTIVE		
1	Health Outcome(s)	Specify the health outcome(s) being researched
2	Pathway(s)	Position the research within a theoretical pathway (Mitigation, Restoration, Instoration).
3	Green Space Focus	Provide a clear definition of green space features being researched, distinguishing between surrounding vegetation, contact with nature, and accessible green spaces.
SCOPE		
4	Type of Distance	Specify the type of distance used with rationale (Euclidean Distance (ED), Network Distance (ND), Buffered Service Area (BSA), Administrative Units (AU)).
5	Walkability Network	If accessibility to green spaces is part of the study design, indicate if the walkability network used to generate isochrones or buffered service areas has been checked for bias and how.
6	Distance	Give a rationale for the chosen distance and indicate if different distances were tested (Sensitivity Analysis).
SPATIAL ASSESSMENT		
7	Proxy for Exposure Variable	Define the spatial indicators used in research and indicate if different indicators were tested (Sensitivity Analysis).
8	Data Source	Indicate which database was used, the acquisition time, and if there has been an adjustment for potential bias (expert assessment).
9	Public Ownership Bias	Indicate if the dataset was controlled for the usability of green spaces from public-owned plots and how.
10	Residential Ownership Bias	Indicate how semi-public residential green spaces have been handled.
11	Classification Bias	Indicate how green spaces have been classified.
12	Usability Bias	Indicate if the usability of green spaces was checked and report inclusion/exclusion criteria.
13	Connectivity Bias	(Optional) Indicate if the database has been corrected for green space network connectivity and how.
VEGETATION AND NATURE ASSESSMENT		
14	Proxy for Exposure Variable	Specify the indicator(s) used to assess surrounding vegetation or nature and indicate if the sensitivity was tested.
15	Data Source	Provide the data source of the satellite images and their resolution together with important information such as image acquisition dates and cloud cover percentages.
16	Handling of Blue Spaces	Indicate how blue spaces have been handled.
17	Handling of temporal changes in vegetation indices	Explain how variance in vegetation indices due to seasonality or changes in the built environment was handled.
CONTEXT ASSESSMENT		
18	Personal Context	Give a rationale for the chosen personal context variables that have been tested or controlled for.
19	Local Context	Give a rationale for the chosen local context variables that have been tested or controlled for.
20	Urbanicity Context	Give a rationale for the chosen urbanicity context variables that have been tested or controlled for.
21	Global Context	Indicate in which climate, societal, and cultural setting the study was conducted. If several settings are part of the research explain how the results were controlled for potential confounding and tested for effect modification.

4. The PRIGSHARE items

4.1. Objectives

Item 1: health Outcome(s)

Specify the health outcome(s) being researched.

Explanation: A clear definition of the health outcomes that are the target of the research will guide the associated impact pathways and the overall study design. This is because most health outcomes are associated with one or more dominant pathways between green space and health. For example, the association between green spaces and cancer is thought to be primarily associated with the mitigation pathway of green spaces and secondarily with restoration effects (Porcherie et al., 2021). Cardiovascular health outcomes, including obesity, are primarily associated with the effect of green spaces to increase physical activity, with a secondary effect on psychological effects from being active in natural environments (Markevych et al., 2017). These psychological effects in turn appear to be primarily related to spending time in nature, mediated by restorative effects (Dzhambov et al., 2018; R. Zhang et al., 2021). Evidence for respiratory health effects associated with green spaces is still limited (Yang et al., 2021), but is theorized by the air pollution mitigation pathway, which is very well documented (Diener and Mudu, 2021; Ferrini et al., 2020; Xing and Brimblecombe, 2018). A possible combination of all these effects links a reduction in all-cause mortality to green spaces (Yang et al., 2021). Next to these positive effects, also negative health effects might be associated with certain dominant pathways, like allergic responses by surrounding vegetation (Marselle et al., 2021), infectious diseases by contact with nature (Lõhmus and Balbus, 2015), and increased unintentional injuries, especially for children, by accessible green spaces (WHO Regional Office for Europe, 2010). Overall, it appears that certain impact pathways dominate depending on the health outcome being researched and are often associated with other pathways. Researchers are therefore advised to clearly define their outcomes, position their research, and embed it in theory to facilitate understanding regarding the scope of the study.

Furthermore, the health effects occur after different exposure durations and may be interlinked over time. So far, these underlying complex mechanisms are still unclear and require further mechanistic studies to uncover (Yang et al., 2021). They are also thought to reinforce or attenuate each other, particularly through the factor of time (Hartig et al., 2014; Hunter et al., 2019; Markevych et al., 2017; White et al., 2020). One of the best-understood relationships is that between green space and physical activity. While it is unclear what duration of green space exposure is needed to encourage more physical activity, the activity itself has short-term effects on mental health and general well-being (Gascon et al., 2015), medium-term effects on obesity, and ultimately long-term effects on a variety of diseases that can lead to higher morbidity and mortality (Guh et al., 2009; Warburton et al., 2006). Since several of these temporal pathways are likely to exist, future studies should specify which type of impact it focuses on (short-term, medium-term, long-term). In addition, whenever possible, several sequential health effects over time should be included in longitudinal study designs to allow for a better understanding of potential relationships over time. Intervention studies are limited in this respect, as the usual short follow-up time means that medium-to long-term effects are not included (Hunter et al., 2019). However, the increased availability of high-quality longitudinal green exposure data also increases the possibilities for quasi-experimental designs that optimally use the natural variation across time and space in green spaces and greenness. In contrast, cross-sectional studies are not able to detect any causal relationships, which limits their potential in generating new evidence at this state of knowledge in the research field (Markevych et al., 2017). In summary, regardless of the study design, researchers should position their study in terms of the time of the effect, which reflects the health outcome(s) being studied. This will facilitate future meta-analyses and increase the possibility of categorizing the research findings.

Item 2: Pathway(s)

Position the research within a theoretical pathway (mitigation, restoration, instoration). *Explanation*: The choice of the pathway(s) considered pre-determines plausible definitions of green space indicators and the scope of assessment. Although the three pathways are likely to work simultaneously, the individual mechanistic pathways between green space and health are based on different aspects of green space.

Mitigation as a pathway is based on the mechanism of filtering, masking, and reducing environmental stressors through vegetation. In addition, replacing an emission source or creating distance through green space is often also categorized as a mitigation effect (Markevych et al., 2017). Depending on the study design, researchers may want to distinguish between an effect due to competing land uses, where a different type of buffer to the emitting source like a building, could lead to a similar effect, and a mitigation effect, due to the mechanism of vegetation in masking, filtering and reducing environmental stressors. Strong evidence for beneficial mitigation effects exists in the reduction of heat island effects (Iungman et al., 2022), the reduction of noise emissions (Van Renterghem, 2019), and the reduction of air pollution (Nowak et al., 2014, 2018). Additionally, a reduction in light pollution in urban areas is expected (Browning et al., 2022). Furthermore, the degree of vegetation correlates with reduced sealing in urban environments, which in turn mitigates the health risks of extreme weather events (Tidball and Krasny, 2014). Researchers interested in mitigation effects should therefore focus on indicators that can represent the degree of vegetation (4.4 Vegetation and nature assessment, items 14–17).

Effects via the *Restoration* pathway are assumed to develop through the experience of nature. There is a strong body of evidence that various types of nature experiences have positive effects on mental health, and reduce the risk of mental illnesses (Bratman et al., 2019). The dominant concepts are the Stress Reduction Theory (Kaplan, 1995) and Attention Restoration Theory (Ulrich, 1984). Recent research confirms that hearing natural sounds improves mental health (Van Renterghem, 2019). Seeing nature, even through a window or virtual through a screen increases recovery from injuries and releases stress (Marselle et al., 2021; Ulrich, 1984). Experiencing nature improves cognition, learning capabilities, and creativity (Marselle et al., 2021; WHO Regional Office for Europe, 2016). There is also a discussion of positive effects on immune defenses through direct contact with nature, but without evidence yet (Yang et al., 2021). Researchers interested in restoration effects should therefore focus on the assessment of nature experience, where vegetation indices might be an appropriate proxy (4.4 Vegetation and nature assessment, items 14–17), with special attention on blue spaces, as well as dose and frequency of contact with nature.

In the *Instoration* pathway, green spaces are thought of as a behavioral setting that encourages people to engage in health-promoting behaviors such as physical activity or social interaction (Van Hecke et al., 2018; Wan et al., 2021). Researchers interested in these behavioral effects of green space should therefore assess those behavioral settings in people's daily living environment, through spatial indicators (4.3 Spatial assessment, items 7–13).

In contrast, green spaces can also cause harm. Vegetation not only reduces environmental stressors. It can also introduce new ones like airborne allergens, that may cause allergic symptoms (Marselle et al., 2021). In addition, trees emit volatile organic compounds (VOCs). Although VOCs from trees themselves are not particularly harmful to human health, they can react with other airborne chemicals to form air pollution (Duan et al., 2023; Gu et al., 2021). Furthermore, some tree species conversely form more ozone (O_3) than they remove and may negatively impact air quality and thus people's health (Sicard et al., 2022). Also contact with nature can potentially be harmful. Direct contact with nature can have negative impacts, e.g. through an increased risk of vector-borne diseases (Lõhmus and Balbus, 2015) and increased exposure to pesticides and herbicides (Marselle et al., 2021; WHO Regional Office for Europe, 2016). Lastly, accessible green spaces not only invite social and physical activity. They are also associated with an increase in injuries (Marselle et al., 2021; WHO Regional Office for Europe, 2016) and a potential increase in crime rates (Kimpton et al., 2017).

To summarize, the chosen pathway will limit plausible definitions of green space exposure (see Fig. 1). Furthermore, the chosen pathway will narrow down potential mediators to examine, if this is the target of the research. In addition, we suggest including positive and negative aspects into the three pathways linked through their main causing aspect of green spaces: being surrounded by vegetation (*Mitigation*), being in nature (*Restoration*), or having access to green spaces (*Instoration*). This categorization will support meta-analyses of these very different aspects of green spaces and make trade-offs visible. We, therefore, ask researchers to associate their research clearly and precisely with one or more of these impact pathways, as they pre-determine plausible green space indicators.

Item 3: green space focus

Provide a clear definition of green space features being researched, distinguishing in particular between surrounding vegetation, contact with nature, and accessible green spaces.

Explanation: A clear definition of green space itself forms the basis for the following assessment strategies. In green space health research, the term green space is often used interchangeably when spatially accessible features (green spaces) or the level of vegetation (greenness) is addressed, which is problematic since they associate with different theoretical pathways (Markevych et al., 2017). In addition, most research publications up to 2017 did not define precisely what they mean by green space (Taylor and Hochuli, 2017). When researchers defined green space, it was done very heterogeneously (Labib et al., 2020; Markevych et al., 2017; Taylor and Hochuli, 2017). The frequent use of the umbrella term "greenspace" (note the words being written as one in opposition to green space as two separate words) to simultaneously refer to both green space and greenness (Markevych et al., 2017) might have been a contributing factor in blurring the definition of these very different attributes of vegetation and useable green space. The interchangeable use of the term "greenspace" has the potential to add more noise to a research environment, which is known to have a low signal-to-noise ratio (Hartig et al., 2014). For example, measuring accessible green spaces using NDVI-like indices (Normalized Difference Vegetation Index, Tucker, 1979), can introduce noise into the data because it includes data on green structures that are not accessible, such as private gardens, slopes, or shrubs (Labib et al., 2020). Likewise, the measurement of greenness via land use indices undercuts vegetation in private green spaces and does not capture green elements such as trees in streets, leading to inaccurate results. This is reflected by recent studies that studied both greenness and green space and found significant effects on one indicator, while the other was insignificant (Browning et al., 2022; Davis et al., 2021; Gascon et al., 2018; Luo et al., 2020). Therefore, we recommend that a clear distinction is made between accessible green spaces, which lead to a spatial assessment via land-use indicators (4.3), and vegetation-based or nature-based variables, which can be captured through a vegetative assessment (4.4). This definition should be based on studied health outcomes and associated pathways and will also determine plausible buffer types and distances.

4.3. Scope

Item 4: Type of distance

Specify the type of distance used with rationale (Euclidean Distance (ED), Network Distance (ND), Buffered Service Area (BSA), Administrative Units (AU)).

Explanation: The type of distance is founded on the theoretical

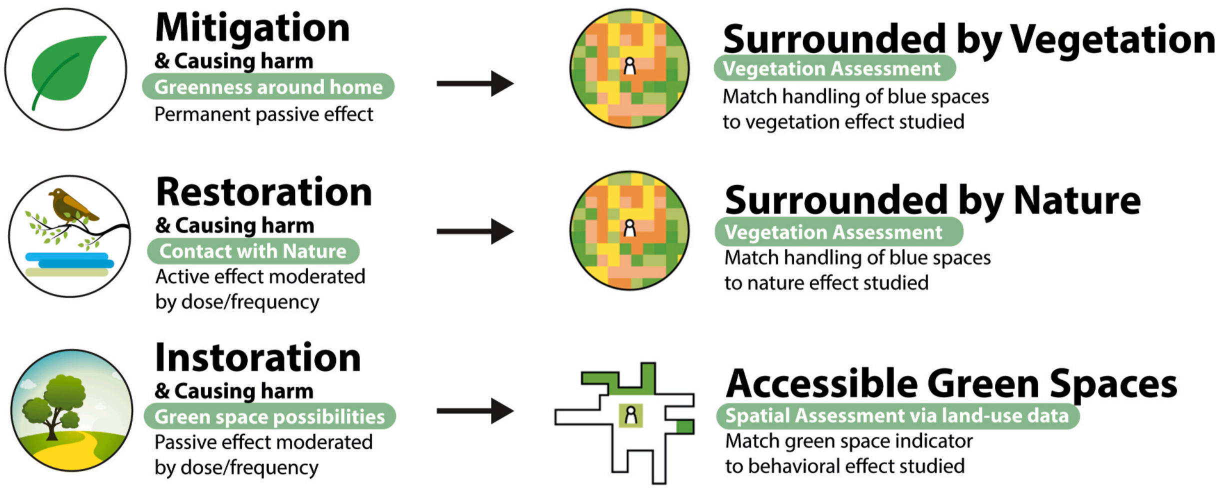

Fig. 1. Green space assessment by dominating positive effect pathway and potentially harmful effects.

pathways between green space and health. Depending on which pathways are being focused on, the effect is generated either by surrounding vegetation/nature or by accessible green spaces. Surrounding vegetation or nature can be measured using normal Euclidean buffers (ED), although they are limited in handling barriers like buildings (Ferrini et al., 2020). In contrast, accessibility should be measured in walkable distances (Labib et al., 2020; Markevych et al., 2017). To assess walkable distances, Isochrones that form a network distance (ND) is a widely accepted measure. Although it is known that Isochrones tend to be imprecise at smaller distances (Frank et al., 2017). This is because isochrones are constructed through a polygon stretched over the endpoints of the network, which adds inaccessible areas to the isochrone. A more accurate approach for smaller walkable distances may be a buffered service area (BSA), which reduces inaccuracy in the assessment but especially relies on an accurate walkability layer (see item 5). To demonstrate the differences, we constructed a test sample that compares different types of distances measurement for a distance of 500 m (Fig. 2). The total accessible area changes significantly starting from BSA at 100% to ND at 136% and ED at 335%. If surrounding vegetation or nature is the target of research and ED is assumed as 100%, ND

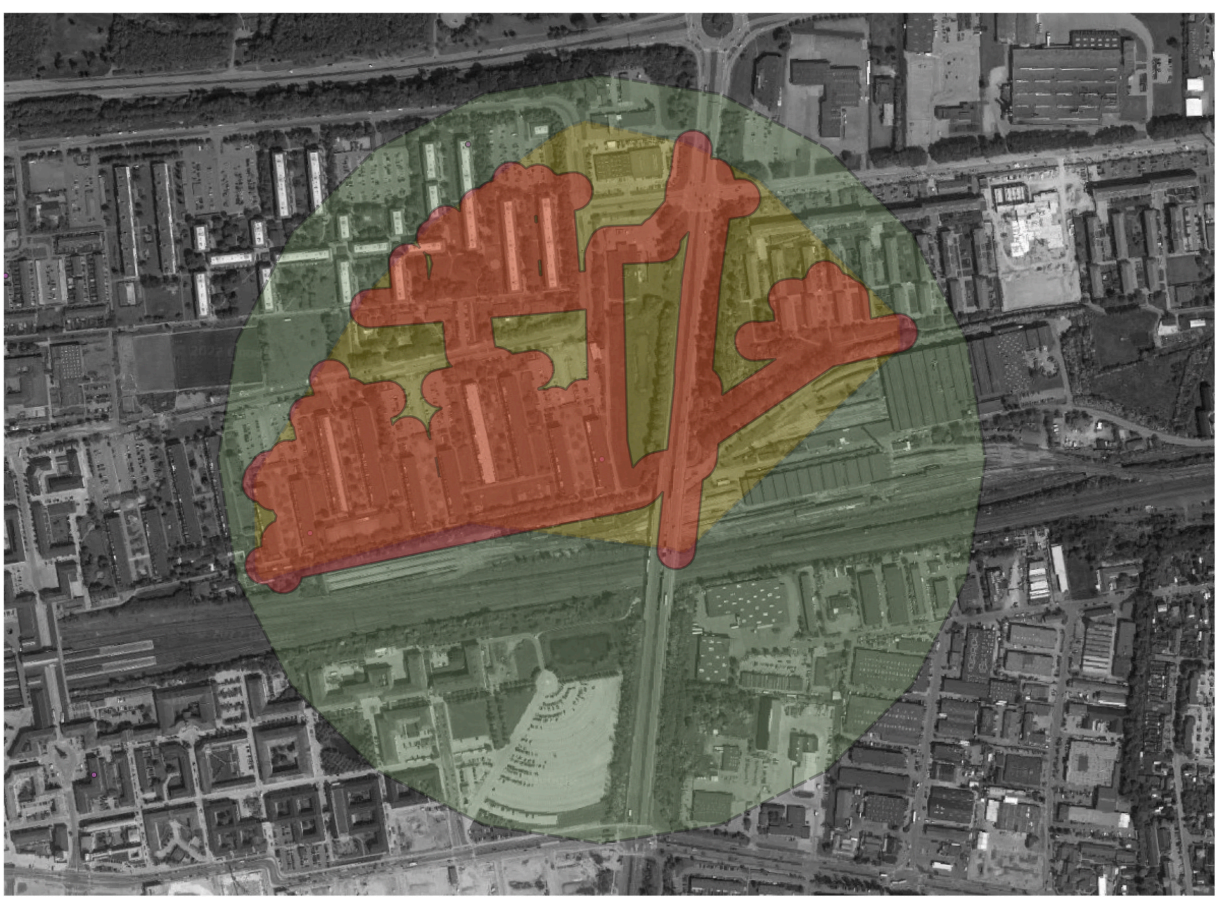

Fig. 2. Types of distance measurement: Types of Distance measurement and accuracy for 500 m in Høje-Taastrup. Red: 25 m Buffered Service Area (BSA), Yellow: Network Distance (ND), Green: Euclidean Distance (ED).

represents only 41%, and with BSA only 30% of the surrounding area is covered. A fourth approach, not further discussed here, is the use of administrative units (AU). An area calculation based on administrative units would introduce the modifiable area unit problem (MAUP) and also the workaround using centroids of administrative units is known to be an inaccurate proxy of the individual environment (Collins et al., 2020; Labib et al., 2020). In some cases, however, no other data quality is available. In these cases, the results should be interpreted with appropriate caution. We recommend researchers explicitly select and describe the type of assessment used in relation to the pathways considered.

Item 5: walkability network

If accessibility to green spaces is part of the study design, indicate if the walkability network used to generate isochrones or buffered service areas has been checked for bias and how.

Explanation: It is important to note that the accuracy of isochrones and BSA relies on the accuracy of the walkability network. This network is not equivalent to the available street network, with highways and railways being only the most obvious mobility types that act as barriers and need to be excluded. Another potential bias is missing or unconnected sidewalks, especially when primary roads are excluded from the network. Additionally, in some cases, informal paths are a substantial amount of the walkability network in a studied area. An analysis of the URBiNAT case studies showed that 5-13% of the total paths are informal and thus not in any database (Ferilli et al., 2019, p. 194). All of this has the potential to distort the accuracy of network distances. Thus, we encourage researchers to report the data source and specify if and how they checked the accuracy of the walkability network.

Item 6: scale

Give a rationale for the chosen distance and indicate if different distances were tested (sensitivity analysis).

Explanation: Depending on the pathways considered, the area of effect might vary greatly. The different effect pathways are associated with different effect ranges in which they operate (Browning et al., 2022; Labib et al., 2020). In addition, detectable health effects react very sensitively to the buffer distance chosen and modify the measured effect (Browning and Lee, 2017; Dzhambov et al., 2018; Hartig et al., 2014; Hu et al., 2021; Labib et al., 2020). While some of these findings can be explained by the low signal-to-noise ratio and heterogeneity in study designs, different ranges in the effect pathways are also hypothesized. It is plausible that the effect decreases at greater distances and varies between pathways. For example, mitigation effects might work in a larger radius than restoration effects. Restoration effects are tied to the range of human senses. They require direct contact with nature, unlike mitigation effects. Mitigation occurs between vegetation and environmental stressors. Human senses are only indirectly involved, which may lead to a larger effect range. That is why study designs with moving smaller buffers via GPS trackers are a promising approach to better capture the dose and frequency of contact with nature. In the case of Instoration, there is limited evidence of the nudging effects of green spaces operating at walkable distances of less than 1000 m (Labib et al., 2020). Although there are certain trends in the effect range of individual pathways visible, further studies are needed to verify these outcomes. Accordingly, if possible, sensitivity analyses of multiple distances should be included in the study design to facilitate meta-analysis, where the AID-PRIGSHARE tool might be helpful (AID-PRIGSHARE - under review, see also S2).

4.4. Spatial assessment

Item 7: proxy for exposure variable

Define the spatial indicators used in research and indicate if different indicators were tested (Sensitivity Analysis).

Explanation: There is no consensus on how to assess green spaces since it requires interpretation. Depending on the pathways considered, the approaches and results vary widely. There is an agreement, however, that simply surveying the quantity of accessible green spaces is insufficient to measure the instoration and restoration effects (Gascon et al., 2015; Labib et al., 2020; Markevych et al., 2017; Twohig-Bennett and Jones, 2018). Green spaces consist of several features and can vary in type, usability, size, and characteristics which influence the potential for different types of activity (Labib et al., 2020). For more information on the underlying mechanisms, we refer to Gibson's theory of affordances and the theory of behavior settings by Barker (Barker, 1968; Gibson, 1979). Gibson theorized that objects have perceived values and meanings beyond their visual appearance, which influence our interaction with that object (Gibson, 1979). Barker's Theory of Behavior settings, emphasizes that each spatial object or setting determines a plausible set of behavior that has to be learned and can differ by culture (Barker, 1968). It is plausible that bigger continuous green space networks nudge people differently than a small pocket park (Markevych et al., 2017). In addition, pocket parks will most likely have a different effect depending on their usability, design quality, and who uses them (Wan et al., 2021). While for adults, bigger green spaces or chained networks of green spaces might invite physical activity, smaller green spaces tend to invite socializing activities. These relations plausibly differ by age group. Children can be nudged into active physical activity on small playgrounds, while adults will probably be nudged into sedentary activities through benches. Thus, the amount or diversity of uses in green spaces might be suitable to measure effects on socializing activities, while the connectivity of green spaces might be best suited to measure effects on physical activity. Therefore, we encourage researchers to provide a clear definition of the exposure variable in connection to the measured health outcomes and targeted population groups. In addition, we highly recommend a sensitivity analysis to compare different green space indicators, as well as testing of composite green space indicators that incorporate more than one feature of green spaces in future studies (again, the open-source script might be helpful, AID-PRIGSHARE - under review, see also S2).

Item 8: data source

Indicate which database was used, the acquisition time, and if there has been an adjustment for potential bias (expert assessment).

Explanation: Common European data sources for green spaces, like Urban Atlas, recommended by the WHO (WHO Regional Office for Europe, 2016) and OpenStreetMap often provide a low level of accuracy of the information required in this field of research. For the behavioral pathway, it is required to construct a green space indicator that can validly represent the behavioral setting that leads potentially to more physical or socializing activity. Therefore, research cannot rely on greenness but should construct an indicator that uses publicly accessible green spaces and/or their usability. For this, land-use datasets are needed. However, they have a high risk to be biased, as they are not designed for this kind of research and are based on cadaster maps. Fig. 3 shows OpenStreetMap and Urban Atlas data on an area in Høje-Taastrup, Denmark, and how this often leads to incomplete and misleading green space data. A comparison between Urban Atlas and OpenStreetMap shows different types of misinterpretation and a general overestimation of available green spaces compared to an expert assessment. Setting the expert map at 100%, OpenStreetMap overestimates green spaces by 23% and Urban Atlas by 59%. From this test sample, OpenStreetMap seems more accurate but should be treated with caution as well. Since it is open source, the added green spaces by the GIS community might vary greatly from city to city. That is why land-use data sets usually require expert knowledge to preprocess before they should be used in spatial and statistical analysis. In addition, OpenStreetMap data is especially likely to change over time. This causes problems in longitudinal study designs when observed changes in the dataset are likely to reflect changes in the reporting/assessment of the environment, rather than changes in the actual environment.

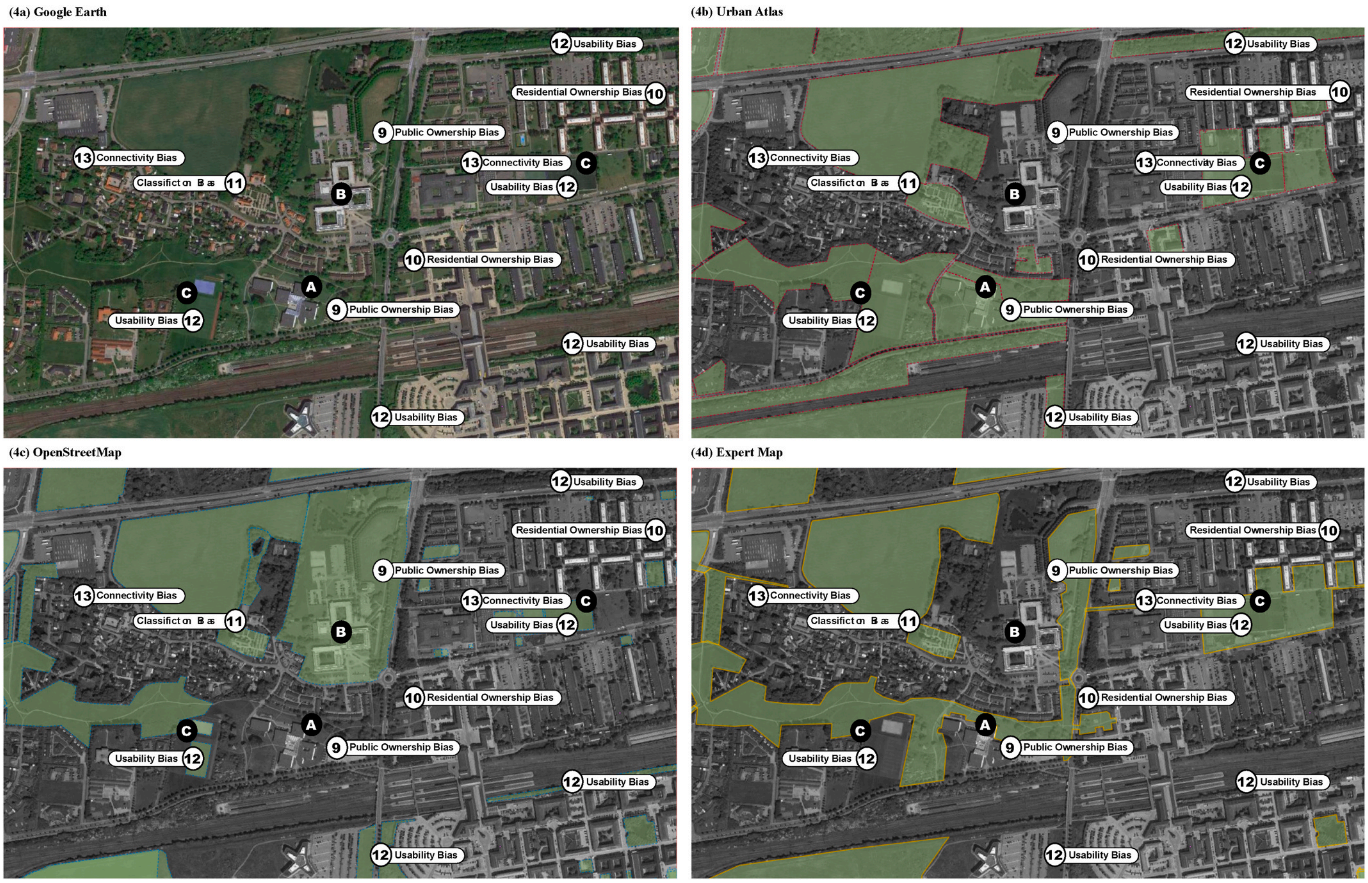

Fig. 3. Green space data quality: Differences in green space quantity by data source and associated errors demonstrated with sample data from Høje-Taastrup: (9) Public Ownership Bias (10) Residential Ownership Bias (11) Classification Bias (12) Usability Bias (13) Connectivity Bias; (A) Gymnasium, (B) Town Hall, (C) Sports Field; (4a) Maps Data: Google, © 2022 (4 b) Urban Atlas –159%, (4c) OpenStreetMap - 123%, (4 d) Expert Map – 100%.

Furthermore, it makes it important to report the acquisition time. We, therefore, encourage researchers to report the data source, if and how the data was harmonized in longitudinal studies, as well as how the dataset was preprocessed to avoid bias (see 4.3.3–4.3.8).

Item 9: Public Ownership Bias

Indicate if the dataset was controlled for the usability of green spaces from public-owned plots and how.

Explanation: Because land use maps are categorized according to the ownership of a particular plot of land, rather than its usability or green space coverage, misclassification often occurs. We recommend that researchers pay particular attention to modernist public buildings, whose building structures often sit within a substantial green space of local importance (see Fig. 3). Since the categorization of the plot can refer to the function of the building or the function of the green space on the plot, it is frequently over- or underrepresented. In the test sample of Høje-Taastrup, this effect can be seen twice in a rather small area (in this example a gymnasium and a town hall). The example in the south shows a gymnasium (A) that is incorrectly categorized by both Urban Atlas (too much space) and OpenStreetMap (none of the space). The example further north shows the town hall (B), where this misclassification also occurs, but this time Urban Atlas does not capture the green space at all, while Open Street Map includes too much of the plot. This leads to an overall bias in the green space indicator, triggering particularly high biases in the smaller buffers. We encourage researchers to check land use maps for these errors and report this clearly.

Item 10: Residential Ownership Bias

Indicate how semi-public residential green spaces have been handled.

Explanation: Besides publicly accessible green spaces, semi-public green spaces can play an influential role in the everyday activities of people and likely introduce bias if not handled correctly. In some countries, semi-public green spaces are considered private, and in others public, while it can be argued that they are neither. These residential green spaces, especially in highly urbanized areas, are an important extension of the private space of their residents, which was especially visible during the lockdowns during the COVID-19 pandemic (Labib et al., 2022). At the same time, they generally create perceived residential ownership which likely leads to non-use among non-residents, creating this semi-public phenomenon. This effect is plausibly related to the urban morphology (e.g. closed block vs. point high-rise structures) which determines the openness of the residential green space and its connectivity to the overall green space network. For the green space assessment, this leads to a necessary individual expert assessment, of whether these places belong to the public green space network or if they should be considered private for residents. In the Høje-Taastrup test sample (see Fig. 3) this assessment discovered a very important entry to the local green space network (center of the map) and divides the social housing residential green spaces (north-east of the map) into publicly used and privately used. We suggest that researchers report how they handled residential bias to reduce noise in the dataset.

Item 11: Classification Bias

Indicate how green spaces have been classified.

Explanation: Public green spaces in land-use maps do not equal publicly used green spaces. According to Labib et al. (2020), issues remain regarding which green spaces should be considered in the

Instoration pathway. Some studies focus on public parks only (Reyes--Riveros et al., 2021), while others include forests, cemeteries, and agricultural land (Discher et al., 2022). To complicate things further, it must be added that the consideration of green space typologies will depend on the cultural context of the study (see also 4.5.4 Global Context). Contrary to most cemeteries in northern societies, cemeteries are rather grey (not green) in southern societies and should be treated differently depending on the cultural context. In principle, however, we argue that a pure extraction of public green spaces from land use databases would exclude (semi-) natural environments that are being used to walk, cycle, or meet. In Fig. 3, a typical cluster of agricultural land, forest, and a cemetery is shown that is used by the residents and would not be captured if only public parks would be considered. Thus, if only public parks are the target of research, we still recommend capturing other (semi-) natural environments and testing for effect modification, as these spaces might explain partly the observed effect (see 4.5.2 Local Context). Researchers should clearly define and explain the classification of included and excluded green spaces.

Item 12: Usability Bias

Indicate if the usability of green spaces was checked and report inclusion/exclusion criteria.

Explanation: Green spaces in land-use maps are not all useable for residents, most commonly because of inaccessibility or non-usability. A potential bias concerns fenced green areas, which are often found around sports fields, but also around cemeteries and sometimes around agricultural areas (see Fig. 3). In the example of Høje-Taastrup, the southwestern sports field is fenced and exclusively for students, while the northwestern sports field is open to everyone (C). In addition, it can also be seen that green areas around sports fields are often not properly classified, as they are also subject to ownership bias. More typical issues in land-use maps are the inclusion of green areas on steep slopes, green areas consisting exclusively of dense vegetation such as shrubs, and non-useable greenery between street lanes or along railroad tracks (see Fig. 4). It is worth noting however, while these types of non-useable green spaces are not able to create an inviting behavioral setting themselves, they might be able to increase the inviting character of existing settings nearby, e.g. by reducing environmental stressors or the addition of natural sounds and scenery. Depending on the presence of these types of green spaces and the research question, this may substantially affect the measured results.

Consequently, it is important to use site visits, local expertise, and/or tools such as Google Street View to specifically check the dataset for this susceptibility to error. Although this might not be feasible in study designs that include larger spatial areas., researchers should be aware that these non-accessible green spaces will introduce noise in the dataset. Researchers should therefore check the land-use dataset for usability and state the rationale for inclusion and exclusion in the dataset.

Item 13: connectivity bias

(Optional) Indicate if the database has been corrected for green space network connectivity and how.

Explanation: If physical activity is a goal of the research, the connectivity of green spaces as a potential network for green mobility is an important factor to consider. It seems plausible that the more destinations can be reached by green mobility, the higher the incentive to use this network (Roscoe et al., 2022). It is recommended to investigate linear green spaces, which are often not part of the databases but are essential for the local green network. In the example from Høje-Taastrup, two of these linear connections are present, turning fragmented green spaces into a green network (see Fig. 3). In addition, to map this indicator correctly, polygonal structures interrupted by roads or railroad tracks must be reconnected manually where pedestrian crossings exist. Other possible indicators might be the total line length of pathways within green spaces. We encourage researchers, therefore, to investigate this and report whether they corrected their dataset for connectivity bias.

4.5. Vegetation and nature assessment

Item 14: proxy for exposure variable

Specify the indicator(s) used to assess surrounding vegetation or nature and indicate if the sensitivity was tested.

Explanation: Different vegetation assessments can lead to different results and need to be adapted to the pathway researched. Vegetation indices, like NDVI, are the most used proxy for green spaces in general and not only for greenness, thus largely independent of the pathways. But they produce different results depending on the vegetation index used (Markevych et al., 2017). In addition, it remains unknown which of these indices provides the most accurate results (Labib et al., 2020). Other possible assessment strategies are land cover maps, processed street view visuals through computational tools, and 3D assessments with LiDAR technology. Land cover maps like CORINE ignore green areas smaller than 25 ha, including all street trees and private green areas (Labib et al., 2020), making them less suitable as a proxy for vegetation. Indicators based on processed street view images are limited in their applicability in the interdisciplinary field, because of the expert knowledge required in handling and processing (Markevych et al., 2017). LiDAR technology is a promising technique, enabling the measurement of vegetation in 3D using point clouds. However, LiDAR datasets are not yet widely available. Furthermore, the calculation of the indicators is significantly more complex than 2D vegetation indices, so

Fig. 4. Usability bias: Left, unusable greenery slopes in Porto Campanhã, Portugal, right, unusable street greenery between lanes in Porto Campanhã, Portugal (Maps Data: Google, © 2022)

the application is limited here as well. The major advantage of 3D measurement is seen mainly in the better distinguishability of trees and grassed areas since trees are said to have a greater health effect (Schmidt, 2022). In a recent study, Giannico et al. compared traditional 2D NDVI from Rome with a 3D vegetation index, developed with the LiDAR Technology, and highlighted the differences through low Pearson correlations between 0.33 at 50 m buffer 0.47 at 300 m buffer between the two indices (Giannico et al., 2022). Although, a large part of the differences might be explainable through the rather low resolution of the 2D indicator of 30 × 30 m. The recent availability of high-resolution satellite images of e.g. Sentinel2 in 10 × 10 m resolution might lead to a higher similarity between LiDAR and satellite-based spatial indices. Therefore, to justify the higher effort of the 3D measurement, more tests are needed to verify the hypothesized improvement in data quality through LiDAR. Especially since green walls that cannot be captured with 2D indices are still rare in urban settings. Thus, in the following, we will only refer to the robust and dominantly used vegetation indices and how to adapt between measuring natural (green-blue) environments compared to pure greenness (only vegetation). Lastly, we would like to explicitly encourage sensitivity analyses of different indicator types or indices (AID-PRIGSHARE - under review, see also S2).

Item 15: data source

Provide the data source of the satellite images and their resolution together with important information such as image acquisition dates and cloud cover percentages.

Explanation: It is well documented that low resolutions of satellite images lead to inaccurate vegetation indices. Low resolutions are not capable to capture smaller green areas (Labib et al., 2020; Markevych et al., 2017) and might not be capable to distinguish between grass and trees. With the introduction of Sentinel 2 for Europe, 10 × 10 m resolutions are becoming standard, increasing the accuracy and robustness of this greenness assessment. To evaluate the quality of the greenness indicator used, researchers should provide the satellite and its resolution together with contextual information such as image acquisition dates and cloud cover percentages.

Item 16: handling of blue spaces

Indicate how blue spaces have been handled.

Explanation: Blue spaces in vegetation indexes can be a source of bias. They should be treated differently in mitigation compared to restoration pathways. In the restorative pathway, blue spaces are also associated with positive effects on health (White et al., 2020). That is why blue spaces are often manually edited in vegetation indexes, trying to represent the natural environment instead of just greenness when restoration effects are studied. If left untouched, blue spaces will receive lower scores in NDVI than buildings or streets. Water has a low reflectance in red and almost none in near-infrared, which leads to low NDVI values (e.g. Nantes Test Sample: -0.2 for a bigger river compared to +0.2 for a building with a grey roof). Thus, blueness can conceal the presence of greenness, while they are working together as a restorative natural experience. Within the mitigation pathway, blue spaces likely have a different impact depending on the environmental stressor of interest. Blue spaces might be less impactful in reducing air pollution or in noise mitigation, but they play an important role in temperature reduction. Leading experts usually recommend setting waterbodies to zero or missing when greenness is the target of research to avoid a lower mean vegetation index through the presence of “blueness” (Markevych et al., 2017). Both strategies will increase the mean NDVI value but to a different extent. However, blue spaces should not be ignored completely as they can lead to spurious relations and should instead be included as a stand-alone indicator. For example, present water surfaces may seemingly increase the temperature reduction effect of vegetation. Besides this, blue spaces might be treated differently depending on their size. Small water streams can potentially be ignored since they will not substantially alter the vegetation index and serve as an inherent feature of the natural environment, in which they are located in. For larger water bodies like rivers, lakes, and oceans researchers need to decide if blue spaces are set to missing, to zero, or left untouched. Researchers should base their decision on the research question and the definition of green space used. In any case, we encourage researchers, to report on how they treated blue spaces to increase study transparency and facilitate meta-analyses.

Item 17: handling of temporal changes in vegetation indices

Explain how variance in vegetation indices due to seasonality or changes in the built environment was handled.

Explanation: Vegetation indexes vary by season and by year. Depending on the study design and timestamp of health outcome variables, a pure snapshot of greenness might not be sufficient. With the installment of Sentinel-2, the availability of cloud-free satellite images at any time point in the year has become a lot easier. Before the Sentinel-2 database with daily images was available, most of the research only used a single summer day image to produce the vegetation index (Markevych et al., 2017). But, calculating the vegetation index from one satellite image potentially introduces bias, in particular during harvest times (Barbati et al., 2013). In addition, seasonality in general can affect the calculated values. Depending on the study design satellite images should be assessed at several time points and merged into one image before calculating a vegetation index. The vegetation index may also differ in different time stamps because of the transformation of the built environment. Green spaces might be demolished for a new residential area, or an old industrial site might be transformed into a park during a longitudinal assessment, which should be seen as a potential to study causal relations with quasi-experimental methods or fixed effects analysis. In any case, we encourage researchers to specify how a potential variation in vegetation indices between different time stamps has been handled or exploited.

4.6. Context assessment

The context of the study is important, and each study should carefully consider which confounders should be controlled for and which effect modifiers should be tested. A confounder is a variable that is not on the causal pathway and can introduce a spurious or confounded association if not controlled for because it affects both the health outcome and the green exposure (Szklo and Nieto, 2014). An effect modifier (moderator) is a variable that influences the relationship between green space exposure and the health outcome; a certain effect may be more pronounced in certain contextual situations compared to others (Szklo and Nieto, 2014).

Item 18: personal context

Give a rationale for the chosen personal context variables that have been tested or controlled for.

Explanation: At the personal level, many confounding factors and effect modifiers are considered in environmental studies. Generally, socioeconomic status (SES), age, gender, employment, and disability are considered. For example, neighborhood SES is not only thought to have a dominant influence on people’s health but is also associated with the level and quality of green spaces in the residential environment, making it a confounder in most of the research designs in the field (Browning and Lee, 2017; Markevych et al., 2017; M. van den Bosch and Ode Sang, 2017). Furthermore, since study designs are predominantly about the surrounding green space around an individual’s home, a broad consensus has emerged that an important moderating effect is the actual frequency and duration of exposure (Gascon et al., 2015; Hartig et al., 2014; Markevych et al., 2017). Here, occupation and age groups can serve as proxy variables. These variables can measure potential differences in the duration and frequency of exposure in the neighborhood. For example, this may explain, in part, why neighborhoods with a high proportion of unemployed people have been shown to benefit more from green spaces (Dadvand et al., 2012).

In addition, pathway-specific context variables should be considered. On the Instoration (behavioral) pathway, it is particularly important to locate indicators that can affect the relationships between the stimulus character of green spaces and behavior. For example, owning a dog potentially changes the measured stimulating effect of green spaces, from a stimulated to a required activity. In addition, owning a private green space likely modifies the measured relationship between green spaces and health (Labib et al., 2022; X. Zhang et al., 2021). Private gardens enable an effortless transition between inside and outside, which potentially leads to more but shorter doses of nature and may affect the ability of public green spaces to invite owners to physical or socializing activities. In the same way, different cultural habits in everyday behavior may also change the exposure to green spaces or the relationship between green spaces and behavior. It is also discussed that subjective evaluation of green spaces, such as perceived safety or perceived quality, modifies the effect, which might result in differences between men and women (Gascon et al., 2015; Markevych et al., 2017). The restoration pathway relies on stress levels or attentional fatigue to measure the restorative effects of greenness, which may differ by age group, occupation, and SES, as well as personal living conditions and stress levels at home (Amerio A et al., 2020). The mitigation pathway passively reduces environmental stressors around the residential environment. These environmental stressors tend to be more frequent where rents are low, as they reflect the low quality of the living environment (Li et al., 2018). In addition, the quality of buildings, whose purpose is to protect against environmental stressors, is often lower where rents are low, reflecting the lower quality of housing. Surprisingly little is known about the modifying effect of the quality of the building envelope in the green space mitigation pathway, even though the very function of buildings is to protect against external environmental impacts. It is therefore plausible that the measured mitigation effects differ significantly between buildings of different epochs, construction types, and degrees of renovation. This could explain part of the effect in socially disadvantaged areas, where a stronger correlation between green spaces and health is often found (Dadvand et al., 2012). Thus, we encourage authors to carefully reflect on the personal context domain that may lead to a necessary adjustment for confounders and testing for (pathway-specific) effect modifiers.

Item 19: local context

Give a rationale for the chosen local context variables that have been tested or controlled for.

Explanation: Green space itself is embedded in an anthropogenic local context that influences other metrics. First, green space assessment can hardly be isolated from the living environment in which it is located. Especially in the behavioral domain, other influences likely affect the measured relationship. The most commonly considered factors are neighborhood walkability, the mix of uses, and access to public transportation (Labib et al., 2020). It is also plausible that perceived neighborhood safety has a strong influence on general open space use (van den Bosch and Ode Sang, 2017). Second, the spatial distribution of emitting sources in relation to green spaces and the individuals of the study may cause spurious relations or conclusions. Depending on the studied area, it is possible to measure the influence of a third variable, e.g. the absence of artificial light, rather than the effect of green spaces due to competing land uses (Stanhope et al., 2021). But since confounders and mediators are statistically identical and can only be distinguished based on the underlying theory (Mackinnon et al., 2000), it may vary how those competing land uses are included in the study design (see also item 2: Pathway(s)). Third, the choice of place of residence is a highly segregating process, leading to more or less segregated environments with distinct tendencies in key personal health determinants. In fact, a local environment can often be assigned to one or more milieu-specific settings. This carries a high risk that omitted variables such as socioeconomic status will bias research findings (Browning and Rigolon, 2018; Gascon et al., 2015). Fourth, spatial artifacts can occur and bias the measured association between green space and health outcomes. The closer individuals in the study live together, the more their daily living environments overlap. This results in very similar green space measurements, especially at larger buffer distances. These forms of spatial autocorrelation or geographical bias can be tested with Moran's I in GIS, a form of geographically weighted regression (Labib et al., 2020). Researchers are therefore encouraged to control for local confounding variables, test for potential (pathway-specific) effect modifiers, and discuss possible limitations. This should be dependent on their study design, while particular care should be taken in the Instoration pathway.

Item 20: urbanicity context

Give a rationale for the chosen urbanicity context variables that have been tested or controlled for.

Explanation: The degree of urbanization may moderate the measured impacts. First, the environmental stressors that occur are significantly more prevalent in more urban environments, which influences the need for, and likely the measured strength of, mitigating and restorative effects (Browning et al., 2022). It is also likely that the relationship between the amount of available green space and specific health benefits is not linear and approaches a certain threshold asymptomatically. This would mean that more green space no longer has the same effect on human health beyond a certain amount of green space. This might explain partly the measured differences between rural, suburban, and urban areas. Second, daily routines, particularly for working age groups, are different in rural and suburban areas compared to urban structures. Daily habits are highly dependent on the urban context in which daily life takes place. Density and mix of uses determine to a large extent the number of jobs, infrastructure facilities, leisure, and mobility opportunities and can thus be understood as incentives for pedestrian mobility instead of car-dependent mobility, which will lead to more time spent outdoors (Gehl, 2013). In addition, the degree of urbanicity acts as a proxy for the time needed to reach the destinations of daily life (Montgomery, 2013) and thus of the remaining leisure time after work that can potentially be spent in green spaces. Therefore, it seems only plausible that green spaces develop different affordances in each case. To summarize, the urban context should always be reported and included as a moderating variable when different settings occur in the study design. For example, population density seems to be a suitable measure for this purpose.

Item 21: global context

Indicate in which climate, societal, and cultural setting the study was conducted. If several settings are part of the research explain how the results were controlled for potential confounding and tested for effect modification.

Explanation: Cultural settings, societal conditions, and climate vary widely around the world and thus influence the comparability of individual local study results.

Firstly, climate zones arguably determine the necessity for intensive or less intensive mitigation of environmental stressors, especially heat. In addition, the potential negative impacts of green spaces through disease vectors vary for different climate zones (Rossati, 2017). It is important to note that those climate classifications can vary significantly even within larger countries like the United States (for more details on the Köppen-Geiger climate classifications, we refer to Kottek et al., 2006). Secondly, because of different climate zones, different urban morphologies, architectural designs, and cultural habits have evolved. These behavioral settings also likely influence daily habits, like the amount and intensity of physical activity (Merrill et al., 2005) and social interaction outdoors. Thirdly, the diversity of individual societies also leads to different starting points concerning other health determinants (Dahlgren and Whitehead, 1991, 2021). These include the health care system as well as other social, economic, and environmental conditions.

In addition, there is also evidence that the stress levels of societies might be different (Gallup, 2019). To summarize, different global contexts have different conditions in environmental stressors (Mitigation), seem to have different starting conditions in stress levels and well-being (Restoration), as well as different behavioral settings and habits (Instoration). Global contexts also differ in potential negative health impacts of green spaces and in different societal conditions that influence a variety of health outcomes. Thus, different global contexts will likely add another layer of noise and complexity to the data, whether in a direct comparison within a study or a later evaluation by a review. Therefore, we invite researchers to indicate how they address these contextual factors, for example, by stratifying the data set by city samples or by adding the city as a confounding variable into the model. However, even if only one case study is part of the study design, researchers are asked to report the global context in terms of climatic and cultural conditions to aid the interpretation of the results and facilitate comparisons and future meta-analyses.

5. Discussion

PRIGSHARE (Preferred Reporting Items in Green Space Health Research) was developed to structure important items to consider and report in the green space health research field into an ordered reporting guideline. This was a returning demand from the field to upscale the quality and robustness of studies (Browning et al., 2022; Davis et al., 2021; R. Zhang et al., 2021). The developed checklist guides researchers from the research question to a precise definition of green space, depending on the dominant mechanistic pathway, to an appropriate

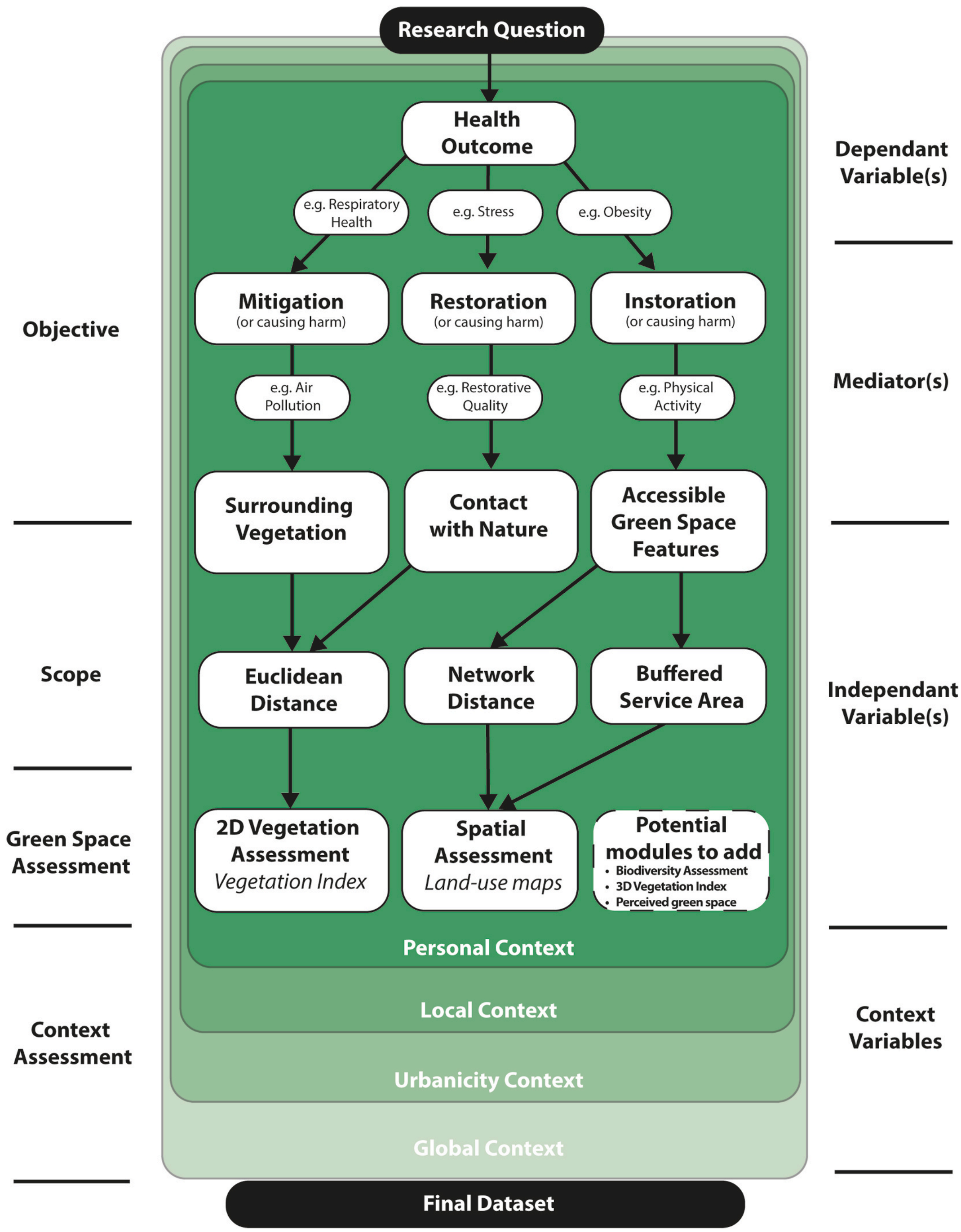

Fig. 5. Flow of assessment: The suggested flow of assessment decisions depending on health outcome(s) and associated pathway(s).

approach to scope, green space indicators, and inclusion of important contextual variables (Table 1). At each step, examples of misconceptions and inaccuracies in data collection, as well as confounding variables and possible effect modifications, are discussed (see also Figs. 1–4). This should help researchers achieve a high-quality, transparent, and understandable study design and thus consequently robust study outcomes.

5.1. The flow of assessment decisions

An important achievement is the transparent and guided flow of assessment decisions from the health variable to the theoretical impact pathways and the definition of green space indicators. Until now, this decision tree has often been applied implicitly and subsequently could not be correctly repeated by others, leading to a variety of incomparable approaches. The PRIGSHARE reporting guideline is an attempt to make these dependencies visible (see Fig. 5). Rather than justifying the chosen distance in a study design with policy recommendations, as a recurring previous practice pointed out by Labib et al. (2020), PRIGSHARE guides by the theorized underlying mechanisms of the pathways in choosing buffer types and distances. At the same time, it also makes clear that one green space indicator is not enough to investigate all impact pathways and supports researchers with a tool for sensitivity analysis, to further advance the understanding of the area of effect of specific green space health mechanisms (AID-PRIGSHARE - under review, see also S2). In summary, PRIGSHARE's flow of assessment illustrates how different mechanistic pathways translate into different decisions regarding assessment methods and chosen variables. PRIGSHARE will make it easier to categorize and compare studies, and potentially streamline the assessment by pathway thus fostering review quality through comparability and available meta-information.

5.2. The modularity of the green space assessment strategy

Another strength of the PRIGSHARE reporting guideline is the modular use of green space assessment strategies, allowing other researchers to add new modules, e.g. for 3D visual assessments via street view applications, perception of green space, 3D vegetation indexes based on LiDAR Technology, or a module for active tracking of green spaces dose and frequency via GPS. Because of the discussed weaknesses of established assessment strategies and the simultaneous impact of green space components, new assessment strategies are likely to be adopted. Therefore, PRIGSHARE establishes a robust framework where these assessment strategies can be added or exchanged without affecting other modules of the reporting guideline. For this reason, we encourage other researchers to enhance and adapt PRIGSHARE further to their needs by adding green space assessment modules, preferably published in open access and scripts in open source.

5.3. The robust framework and its potential to include new research areas

PRIGSHARE is also able to include new sub-fields in greenspace-health research that are emerging. These new areas derive in parts from the nature-based solutions movement (European Commission et al., 2021a; 2021b). Firstly, there is increasing recognition in this research field of the already known disaster risk reduction potential of green spaces (Hartig et al., 2014), able to mitigate the risk of injuries and lives lost due to extreme weather events. Secondly, there is a potential that green spaces and trees in particular are able to reduce exposure to artificial light pollution at night. Both can be categorized as mitigation effects where greenness is an appropriate proxy. Thirdly, contact with the microbial biodiversity of nature is considered to strengthen the immune system (Markevych et al., 2017; Sandifer et al., 2015). It can be argued that this fits into the restoration pathway since it requires actual contact with nature. In summary, the robustness of the reporting guidelines allows for the expansion and refinement of existing impact pathways without substantially affecting the guideline structure. Theoretically, even additional pathways could be included.

5.4. Risk of bias assessment

While PRIGSHARE is not a quality assessment tool, it helps assess the constructed dataset's appropriateness, accuracy, and completeness to answer the research question. The reporting guideline provides an overview of a set of potential noise in the data set that arises from inaccuracies or missing effect modifiers and confounding variables in the research field. This overview will support the existing risk of bias assessment tools like OHAT (OHAT, 2015) that are used in systematic reviews to assess the study quality. Thus, PRIGSHARE will help make future reviews in the research field more robust overall.

5.5. Feasibility for different study types

The feasibility of PRIGSHARE for larger cohort or registry-based studies on the Instoration pathway might be limited. Instoration pathway studies require a spatial assessment via land-use data which is associated with a substantial correction effort compared to vegetative assessments. Due to the wide spatial spread of participants in cohort or registry-based studies, the spatial correction effort becomes unfeasible. This limits the applicability of parts of PRIGSHARE in larger cohort studies if available green space data is not greatly improved. Currently, researchers usually have to decide between a high level of precision in spatial data to increase the validity of the results on the one hand and feasibility on the other hand. In addition, manually editing spatial data will negatively affect the reproducibility of the study. To tackle both problems, we suggest an open-source green space layer, where these corrected expert maps can be stored and shared. In general, the low data quality of existing databases should be taken as an opportunity to look for new standards to increase the precision and usability of green space data.

5.6. Analytical processing

The PRIGSHARE reporting guidelines are limited in their guidance about conducting and reporting the analytical process that is to follow the data assessment. In section 4.5, we encourage researchers to carefully consider potential confounders and effect modifiers but there are of course also other aspects of the data analysis that are important. Although we acknowledge that data analysis is an inherent part of the publishing process, we consider extensive guidance on this topic as out of the scope of this paper. For guidance on mediation analysis, which seeks to better understand the pathway mechanisms, we refer to the review on analytical approaches in green space health research of Dzhambov and colleagues (Dzhambov et al., 2020). Furthermore, general reporting guidelines in public health can support more universal reporting needs, including analytical processes, specific to the used study type such as the STROBE statement for observational research (Von Elm et al., 2007) the CONSORT statement (Schulz et al., 2010) for trials or the TRIPOD statement (Collins et al., 2015) for prediction studies.

5.7. Limitations

The PRIGSHARE reporting guideline was tested with data from four European cities. We acknowledge that there will probably be differences in terms of general data quality, data accessibility, and types of errors for non-European cities. In addition, the green space data quality of Urban Atlas and OpenStreetMap was only demonstrated for one city to show the general principle. While we are confident that these data quality issues are measurable everywhere in Europe, the error tolerance accordingly represents only a general direction. In addition, due to the wide science area, the discussed confounders and effect modifiers should only be seen as frequent examples rather than a comprehensive list.

6. Conclusion

The PRIGSHARE reporting guideline brings together knowledge from different disciplines to support a high-quality assessment of green spaces and to synchronize the studies in this interdisciplinary field while acknowledging the diversity of study designs. PRIGSHARE has the potential to support reducing the heterogeneity in assessment and outcomes which will advance the overall understanding of green space health pathways. Although PRIGSHARE stemmed from identified problems from existing reviews in the field, it is not yet possible to prove that this reporting guideline can achieve its ambitious goal of synchronizing the field and uplifting the quality of studies. It will largely depend on the uptake and use of PRIGSHARE and its frequent update in a rapidly growing field of research.

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Declaration of competing interest

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

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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