Methodological guidance for selecting buffers in greenspace–health studies

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Greenspace can promote health via diverse pathways. A common approach to assessing greenspace exposure is to estimate vegetation availability within buffers surrounding locations where people reside or spend time. However, no clear framework for informed buffer selection exists, and choices made show considerable heterogeneity, impeding evidence synthesis and causal inference. In this Personal View conducted by an interdisciplinary panel of experts, we aimed to establish a framework for informed buffer selection for epidemiological studies on greenspace. We began by reviewing available approaches for the selection of buffer types, which range from single fixed-location approaches to high-resolution mobility-based activity-space approaches, as well as different buffer sizes. We then summarised the determinants of buffer type and size selection including health outcomes and underlying mechanisms, study population, contextual factors, and data characteristics. Finally, based on these determinants, we developed recommendations for future research. Buffer type and size selection should be hypothesis driven, reflecting presumed greenspace–health mechanisms. Buffer selection should target activity-based approaches where feasible, and multiple buffer sizes should be tested. Overall, the assessment of greenspace exposure should shift from ad-hoc approaches to personalised, multiscale, and context-specific methods. We call for standardising and reporting the rationale for buffer selection to minimise bias and enhance comparability and evidence synthesis across studies.

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Introduction

The relationship between natural environments and human health has gained increasing recognition in recent decades, with accumulating evidence showing that green spaces promote both mental and physical wellbeing via multiple interconnected pathways.[1–3] These mechanisms include mitigating environmental hazards such as air pollution and extreme heat,[4–6] reducing stress and buffering against future stressors,[7] restoring attention and cognitive capacities,[8] facilitating physical activity and social contact,[9] and supporting microbiota diversity[10] (panel).

Greenspace exposure is commonly assessed around locations of interest (LOIs) where people reside[11,12] or spend time (eg, schools,[13] workplaces,[14] and commuting routes[15,16]). The standard approach of assessing greenspace exposure involves aggregating metrics such as average,[12] variability,[17] or percentage[18] of vegetation or vegetated land cover (eg, parks or tree canopy) within specific geographical boundaries surrounding each LOI. These geographical boundaries, collectively referred to as buffers, can be based on administrative units (eg, postal codes) or various shapes and sizes. For consistency, we use the term buffers to refer to all geographical boundaries surrounding LOIs, acknowledging that some might not strictly align with the conventional definition of the term.

The selection of buffer types and sizes is an important decision that directly influences the results of a greenspace exposure assessment.[19–21] Buffers define the boundaries within which exposure is measured, and, equally, where it is excluded. Despite the importance of buffers, limited theoretical or empirical guidance exists on how to select appropriate buffer types and sizes. Consequently, studies vary widely in how buffers are selected, with choices differing in size, type, and stated rationale.[19,20] This heterogeneity leads to inconsistent findings[22–25] by influencing both the magnitude and direction of the estimated greenspace–health associations,[22,23,26–28] limiting causal inference and cross-study comparison. This issue is closely linked to the modifiable areal unit problem (MAUP), where the shape and size of an analytical unit affect both exposure estimates and their associations with human health[29–32] (figure 1). Additionally, buffer selection is subject to the uncertain geographical context problem (UGCoP),[33–35] which highlights the inherent difficulty of accurately capturing dynamic, time-varying exposure patterns within static spatial boundaries.

Inconsistent approaches to buffer selection have become a substantial barrier to synthesising evidence on greenspace–health associations. Homogenising buffer selection approaches would help to resolve uncertainties regarding exposure effects and underlying mechanisms, supporting the establishment of causal pathways and mechanisms. Reducing methodological heterogeneity would also provide a more robust foundation for policy development and implementation. Although several studies have examined specific aspects of buffer selection,[22,36,37] these efforts have primarily focused on a limited number of determinants, addressing only single dimensions (ie, size

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Panel: Glossary of technical terms

- Activity space: the locations and places where participants spend time during their daily activities.
- Adaptive buffer sizes: the application of varying buffer sizes for different participants and contexts to address the constant-size neighbourhood trap.
- Adaptive circular buffers: the use of varying buffer distances to draw circular buffers around locations of interest.
- Adaptive kernel density estimation: a form of kernel density estimation in which the bandwidth varies by location or characteristics of the points.
- Administrative units: subdivisions of geographical areas or territories recognised by governments for administrative purposes.
- Buffers: discrete zones, measured in units of distance or time, which are superimposed onto the location of interest.
- Constant-size neighbourhood trap: a problem resulting from all participants having the same activity space, as defined by similar buffer sizes, without considering relevant determinants.
- Edge effects: the potential for exposure misclassification among participants living near the borders of the defined buffer (also known as boundary effects).
- Exposure misclassification: errors in how an individual's exposure to an environmental factor (eg, greenspace) is measured or categorised, occurring when the assigned exposure level does not accurately reflect the true exposure experienced by a person.
- Geographical masking: techniques used to deliberately modify or obscure the true geographical locations of individuals in spatial datasets to protect privacy and confidentiality (also known as geomasking).
- Greenspace: land that is partly or completely covered with grass, trees, shrubs, or other vegetation.
- Greenspace exposure: a term used for consistency with epidemiological literature, while recognising its limitations in capturing reciprocal human–nature interactions.
- Green space: a parcel of land covered with greenspace.
- Lacunarity: a scale-dependent measure of spatial heterogeneity or texture of a landscape used for spatial heterogeneity measurements.
- Modifiable areal unit problem: a source of statistical bias and uncertainty that arises when the spatial scale or boundaries used to aggregate geographical data are arbitrarily defined or modifiable.
- Neighbourhood effect averaging problem: the problem where participant mobility-based exposures to environmental factors tend towards the mean level of participants or the population of a study area, rather than their residence-based exposures.
- Positional error: inaccuracy in the measured or recorded spatial location of a feature due to errors in GPS, survey equipment, or georeferencing.
- Selective daily mobility bias: a bias in activity-space approaches where a participant appears to be more (or less) exposed to environmental characteristics (eg, greenspace) due to their personal decisions about activities and where to conduct them.
- Semivariance: one-half of the variance of the differences between all possible points spaced a constant distance apart.
- Shadow buffer: a buffer (also known as a buffered administrative unit) with a specific distance around the main buffer (eg, administrative unit) to compensate for edge effects among participants living near buffer boundaries.
- Trim distance: a distance that is added to the line drawn by network buffers or straight-line ellipses to create a polygon from lines (also known as trim buffer).
- Uncertain geographical context problem: the problem that findings about the effects of area-based attributes (eg, land use mix) on participant behaviours or outcomes (eg, physical activity) can be affected by how contextual units or neighbourhoods are geographically delineated.

or type, but not both), or reflected perspectives from a single discipline and geographical region.

To address these limitations, we assembled an interdisciplinary panel of experts representing diverse geographical contexts, from low-income and middle-income countries to high-income nations across all continents, to establish guidance for buffer selection in greenspace epidemiology. This guidance seeks to achieve five key objectives: (1) contextualising buffer selection within the continuum of location data granularity available for exposure assessment; (2) reviewing available buffer type delineation approaches; (3) examining buffer size considerations; (4) identifying and systematically organising the determinants that inform buffer type and size; and (5) developing recommendations for selecting buffers in future greenspace–health research. By providing this guidance, we aim to transition greenspace exposure assessments from ad-hoc approaches towards more systematic, hypothesis-driven, and context-appropriate methods.

A continuum of location data granularity

Location data for greenspace exposure assessment exists along a continuum of spatial and temporal granularity, ranging from single-point locations to comprehensive activity-space approaches (figure 2). At the simplest end of this continuum are single-point LOIs, such as residential addresses, which are commonly used[38] but necessarily assume that exposure at a single location sufficiently captures most environmental exposures. Although these approaches lack temporal granularity, their spatial precision can vary depending on the geocoding accuracy and resolution of the address data.

Recognising that individuals move through multiple environments during their daily lives, more sophisticated approaches incorporate data from multiple locations to create more comprehensive assessments.[39] Such approaches include commonly visited locations beyond the home (or other single LOI), such as workplaces or recreational sites, to better account for daily movement patterns and construct an individual's activity space. Travel diaries and map-based questionnaires provide additional granularity by recording the time spent at each location, enabling time-weighted calculations that better reflect cumulative exposure patterns.

At the most detailed end of the spectrum are continuous mobility data, such as GPS or mobile phone location tracking. These data enable high-resolution spatiotemporal mapping of an individual's movement and real-time environmental context.[40] This approach has the potential to capture nearly complete exposure profiles, accounting for both locations visited and the duration spent in each environment, without the limitations of self-reported data. Still, a 2019 review found that single fixed-location approaches were used in approximately 53% of studies investigating the built environment and human health.[41] Meanwhile, another review on the relationship between nature and children's mental health found that only 1% of included studies used GPS tracking for their exposure assessments.[42]

The abundance of studies at the simplest end of this continuum reflects the ongoing challenge of balancing simplicity and feasibility on the one hand, with complexity and precision on the other (figure 2). This balance is shaped by the availability of data for a given outcome or population, as well as the time and resources required for data collection and processing. It is also influenced by the research question and underlying hypotheses about how greenspace is expected to influence outcomes. For example, high-resolution GPS data are typically available for a limited number of participants and miss frequently visited locations that fall outside the tracking period.[43] In contrast, online questionnaire data capture habitual locations across broader populations but are limited by the participants' ability to accurately recall where they went, for how long, and under what circumstances. Accordingly, studies focused on momentary or short-term exposures might be better suited to GPS-based approaches, whereas those examining cumulative exposure patterns over longer periods might benefit more from self-reported location histories.

An overview of buffer types

Buffers can be of different shapes and be flexibly combined with various types of location data. For example, network buffers can be applied to GPS-derived locations, whereas time-weighted or composite buffers can be constructed from diary-based or self-reported locations. In this section, we provide an overview of the buffer types commonly used in greenspace exposure assessments and how they are delineated based on the granularity of the available location data. We categorise the buffer delineating approaches into four main groups: (1) predefined-area approaches, in which boundaries follow predefined spatial units such as administrative areas[30] or grid cells; (2) single-location approaches, in which fixed distances or travel times are calculated from an LOI; (3) travel-diary or intermittently tracked location approaches; and (4) GPS tracking approaches, which incorporate continuous mobility data (figure 3).

Predefined-area approaches

Administrative units

Using administrative units is a well-established approach to delineating geographical boundaries.[44–46] In this approach, all participants with the same unit (eg, county, census tract, or postal code) are assigned the same exposure value. However, participants living near unit boundaries might be more influenced by adjacent areas (an edge effect), increasing the risk of exposure misclassification.[23,39]

The main advantages of administrative units include their relevance to policy decisions and their use as standard units for aggregating sociodemographic and health statistics. The main disadvantages include poor alignment with participants' activity spaces,[47–49] and exposure misclassification for participants living near unit boundaries.[11,50–52] Other limitations include the substantial variation in unit shapes and sizes, often related to population density,[53] as well as changes in unit boundaries over time.[23,54,55] Such variation might result in differing levels of precision for exposure assessments between participants in small (eg, urban) and large (eg, suburban or rural) units. Smaller units also increase the likelihood that participants spend substantial amounts of time outside their assigned area,[56,57] a limitation that might be less influential in specific populations (eg, older adults tending to stay closer to their residence). Conversely, larger units might encompass green spaces not actually visited by participants, reducing exposure contrast and limiting statistical power.[55]

Grid cells

This approach involves superimposing a grid on the study area and estimating participants' greenspace exposure based on the grid cell intersecting with their LOI.[58] Two common approaches for grid definition are used: (1) assigning values from image pixels (eg, 30 × 30 m pixels of Landsat satellites' images) and (2) using a predefined grid (eg, 500 × 500 m cells).

In the pixel-based approach, greenspace values from satellite or aerial images are directly overlaid onto LOIs, and the pixel value containing the LOI is used as the exposure estimate. In the predefined grid approach, the researcher creates a grid that is overlaid with the greenspace data (eg, satellite images or land cover), calculates the average greenspace value within each cell, and assigns that average to all LOIs within the same cell.

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In both cases, all participants within the same cell are assigned the same exposure value, regardless of their precise LOI locations. Although relatively easy to implement, this approach overlooks intracell variation. This limitation is particularly relevant when cells are large and the research question involves micro-scale exposures near the LOI. In such cases, the exposure estimates of LOIs near the edge of a cell might be misclassified due to their distance from the cell centroid.[59]

Single-location approaches

Circular buffers

Circular buffers, also known as Euclidean, crow-fly, radial, straight-line, or uniform buffers, are among the most common approaches to delineating buffers in greenspace–health research.[7,60–62] These buffers are defined as circles centred on an LOI, with a radius specified by the researcher. Greenspace exposure is typically calculated as the average value within the buffer area, assuming that all points within the boundary contribute equally to exposure.

A key limitation of this approach is the inability to differentiate the influence of greenspaces at varying distances within the LOI.[63] Since greenspace use often decreases with increasing distance from a participant's residence (although not always),[27,64] larger buffers may include areas that participants rarely or never visit. In these cases, applying a distance-decay function can help to model the declining likelihood of greenspace use with increasing distance.[65]

Similar to administrative unit and grid cell approaches, circular buffers also fail to account for physical barriers such as major roads, rivers, or private properties, which might restrict access to nearby greenspaces.[66,67]

Nested buffers

Nested buffers consist of a series of non-overlapping buffers of increasing size, designed to examine how the relationship between greenspace exposure and health outcomes varies with distance from an LOI.[36,68,69] Typically, the innermost buffer is a circular area closest to the LOI, whereas subsequent buffers take the form of concentric rings, also known as doughnut-shaped buffers[70] that represent specific distance bands (eg, 0–100 m, 100–300 m, 300–500 m).

Although most nested buffer approaches are concentric, they can also take irregular shapes. For example, a school catchment zone might exclude the school building and its grounds when estimating exposure for students who live nearby.[69,71] Several studies have compared nested buffers with overlapping circular buffers,[71–74] and a review recommended using nested buffers when the goal is to assess the independent contributions of greenspace at varying distances from an LOI.[36]

Network buffers

Network buffers approach estimates the area accessible within a specified distance or travel time from an LOI by tracing routes along street or footpath networks. Some approaches incorporate travel time, applying assumptions regarding average movement speeds.

Polygon-based network buffers generate a polygon by connecting the endpoints of all possible routes along a network extending up to a given distance (eg, 800 m or a 15-min walk) from the LOI.[75] This approach is intended to more accurately reflect accessible areas compared with circular or administrative unit buffers. However, connecting street nodes with straight lines might misrepresent actual travel paths, particularly in areas with irregular street layouts or informal shortcuts.[67]

Line-based network buffers, also referred to as detailed, road-based, route-based, sausage, or trip buffers, use the set of all network lines from an LOI to endpoints within a specified distance.[69,76–79] These lines are typically buffered by a small perpendicular offset (a trim distance) before being intersected with greenspace parcels,[67,80] so that only greenspace within a specified proximity to the network is included. This approach might better reflect visible or accessible greenspace, particularly for pedestrians,[36] and is less likely than polygon-based buffers to capture large, inaccessible greenspaces.[63] One study found that line-based network buffers showed stronger associations with mental health outcomes then circular buffers.[81]

However, line-based buffers might still include private green spaces. Adjusting the trim distance can help to mitigate this issue, but might reduce comparability across studies due to differences in local conditions (eg, street widths) and map data formats (eg, polygonal streets *vs* centrelines).[77] Additionally, network buffers assume that participants travel only along roads or designated footpaths, omitting informal or off-network routes commonly used in real-world settings.[78]

Assumptions regarding travel mode (eg, walking, cycling, or transit) and average speed also influence the size and shape of network buffers and thus affect exposure estimates.[82,83] Although network buffer approaches allow for incorporating factors such as street sinuosity, slope, and perceived safety,[84] these considerations have rarely been applied in network-based greenspace exposure assessments, despite their potential importance for specific populations (eg, participants with mobility limitations).[15,85]

Travel diaries and intermittent location tracking

Standard deviation ellipses

The standard deviation ellipse (SDE) approach represents a participant's activity space by summarising the spatial spread and orientation of their movement or activity locations.[86] The SDE approach generates an ellipse based on the standard deviation of X and Y coordinates, typically using one or two standard deviations, to define the radius along each axis.[87] Ellipses can be constructed using anchor points[80] or GPS tracking data.[57] Although this approach provides a spatial footprint of activity, one study found that SDEs tend to overestimate the size of the actual activity space.[49]

Minimum convex polygons
The minimum convex polygon (MCP), also known as the minimum convex hull or home range,[88] is the smallest convex polygon that encompasses all recorded activity locations, with internal angles less than or equal to 180 degrees.[89] MCPs can be constructed from as few as three anchor points (eg, home, workplace, and a third routine location).[90] However, because the polygon is defined by the outermost points, this approach often overestimates the true extent of a participant's activity space, sometimes by a factor of 100 or more, making it poorly suited for most greenspace exposure assessments.[91]

Self-drawn neighbourhoods
The self-drawn neighbourhood (SDN), also known as a self-defined neighbourhood[92] or cognitive map,[93] is created by asking participants to draw the boundary of what they perceive as their neighbourhood on a map.[94] Although this approach offers data on each participant's perceptions of space, it has notable challenges, including variability across contexts, low familiarity with neighbourhoods, and challenges in replicability.[95,96]

SDNs can include areas not directly used in participants' daily routines. For example, a study in West Yorkshire, UK, found that SDNs captured only 10% of participants' actual daily movement, and 40% of the area within the drawn boundaries was not visited by participants.[94] Factors such as socioeconomic and demographic characteristics, physical and mental health, and transportation mode can influence the size and accuracy of SDNs.[92,97,98] For instance, longer residence duration, higher education and income, and greater neighbourhood engagement, have been associated with larger perceived neighbourhood areas.[99]

Importantly, the places participants recall when drawing their SDN might reflect locations that are particularly salient or meaningful. From this perspective, discrepancies between SDN and actual movement patterns might not be limitations, particularly in studies aimed at comparing different greenspace exposure mechanisms (eg, physical activity and attention restoration). This approach might be particularly relevant for health pathways that involve psychological benefits, where subjective perceptions play a central role.[100]

Daily path areas
The daily path area (DPA) approach delineates a participant's activity space by adding fixed-distance buffers around movement points (eg, GPS data) or lines (eg, participant-drawn travel routes). When high-resolution tracking data are available, this approach can, in principle, capture participants' cumulative greenspace exposure across their daily routines.[42,86,88] A time-weighted DPA can also be constructed by incorporating the duration associated with each location point.[42,49,70]

DPA-derived exposure estimates tend to correlate weakly with those based on residential neighborhoods[57] but show stronger correlations with estimates from MCPs and SDEs.[86] Limitations of this approach include low reproducibility due to the dynamic nature of human movement location, particularly when applied over shorter timeframes (eg, daily *vs* monthly). Additional challenges include participant recruitment, adherence, and retention, as well as the burden of having to track their movements placed on the participants.[101,102] Some of these challenges might be mitigated using passively collected time–location data, such as smartphone-based GPS tracking.[103]

GPS tracking: kernel density estimation
Kernel density estimation (KDE) is a statistical approach that transforms discrete point data (eg, GPS locations) into a continuous probability surface across a grid.[104,105] Each grid cell (or pixel) represents the weighted density of nearby points within a specific search radius, with weights typically decreasing with increasing distance from the cell.[105] KDEs can account for both the frequency and duration of visits to specific locations,[57] and are often used to identify clusters of activity points.[106]

An extension of this approach, adaptive KDE, adjusts the search radius based on the density of observation points and characteristics of the built environment.[107,108] Unlike standard KDE, which assumes a homogeneous background, adaptive KDE allows bandwidths to vary as a function of spatial context, enabling more refined modelling of activity patterns in heterogeneous environments.[109]

An examination of buffer sizes

A buffer's size clarifies the size of the spatial area within which greenspace is assessed, and the specific definition varies by buffer type. For circular buffers, the size refers to the radius; for network buffers, it is the distance measured along transportation networks; for DPAs, it is the offset distance around points or lines; for SDEs, it is defined by the number of standard deviations used to construct ellipses; and for KDE, it corresponds to the search radius used to create the density surface. Cell resolution serves as the spatial size in grid cell approaches, whereas MCPs are data-driven and do not require the selection of a buffer size.

Buffer sizes in greenspace epidemiological studies range widely, depending on the research question and hypothesised exposure pathways. This range spans from a few metres (eg, 20 m to develop a building proximity to greenspace[110]) to several kilometres (eg, 10 km for studies of greenspace and allergens[111]). This range can be categorised into three meaningful scales[23]: (1) personal scale (10–100 m), which captures immediate surroundings and direct environmental exposures around participant locations; (2) neighbourhood scale (100–2000 m), which encompasses areas where most daily activities occur, including local parks, neighbourhood green corridors, and accessible recreational spaces (eg, from a few hundred meters[112] up to around 2 km[113]); (3) city or district scale (>2 km), which includes broader urban green infrastructure that might influence air quality, temperature regulation, and regional environmental conditions.

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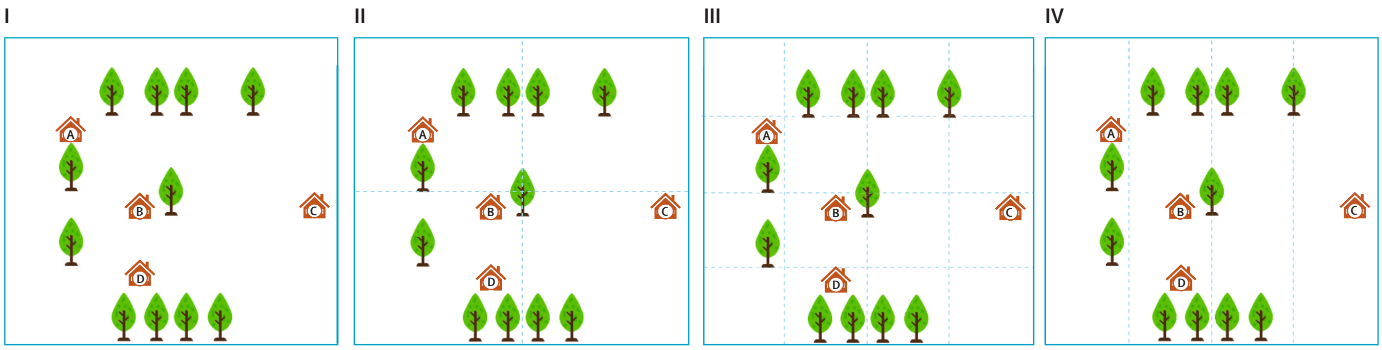

I

Participant	Buffer area	Greenness
A	16	0·69
B	16	0·69
C	16	0·69
D	16	0·69

II

Participant	Buffer area	Greenness
A	4	0·81
B	4	0·81
C	4	0·56
D	4	0·56

III

Participant	Buffer area	Greenness
A	1	1
B	1	0·25
C	1	0
D	1	2

IV

Participant	Buffer area	Greenness
A	4	0·50
B	4	1·12
C	4	0·12
D	4	1·12

***Figure 1:* Schematic representation of the modifiable areal unit problem (MAUP)**
(I) presents the study area with four participants (A, B, C, and D), residing in an area with 4 × 4 (i.e. 16) areal units. (II) presents four buffers with a 2 × 2 (i.e. 4) units delineation. The estimated greenspace exposure of participants (measured as the number of trees per area unit) ranges from 0·56 to 0·81. (III) shows the effect of scale (buffer size) in MAUP. By using a smaller buffer size, the exposure to greenspace ranges from 0·00 (for C) to 2·00 (for D). (IV) represents the effect of shape in MAUP. The buffer areas in II and IV are both equal to four units but have different shapes. The estimated exposure ranges from 0·12 to 1·12.

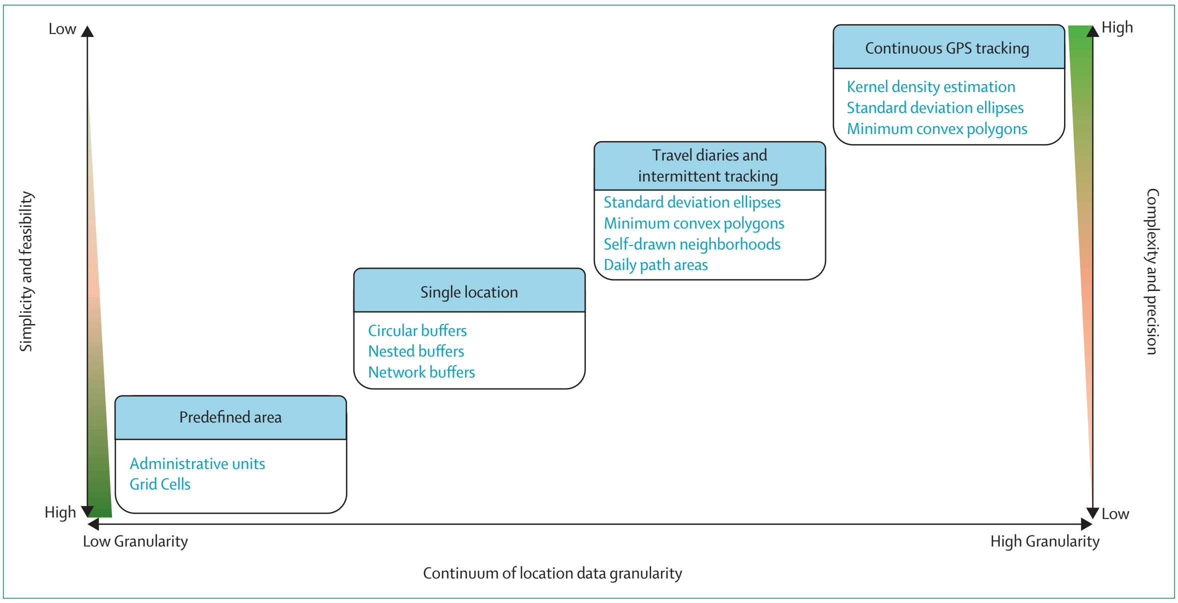

***Figure 2:* Continuum of location data granularity for greenspace–health studies**
The figure illustrates the trade-offs between granularity, spatial and temporal precision, and methodological complexity across different approaches to defining an individual's environmental context. Neighbourhood-level and single-location approaches (eg, administrative units) are simple and widely used but provide lower precision. Travel-diary and multiple-location approaches incorporate habitual mobility patterns, offering intermediate precision and complexity. The continuous GPS tracking approach offers the highest spatial and temporal resolution but requires advanced data processing, raising concerns regarding feasibility and privacy.

Pathway-specific considerations of buffer sizes

Different pathways by which greenspace benefit health are likely to operate at various spatial scales. Evidence suggests that measuring greenspace in smaller buffers produces stronger health associations for certain mechanisms, whereas large buffers might be more relevant for other mechanisms, such as physical acitivity.[7,114,115] In dense urban environments, for example, very small buffers around the home might be especially relevant for mental wellbeing, given the heightened importance of visual access to

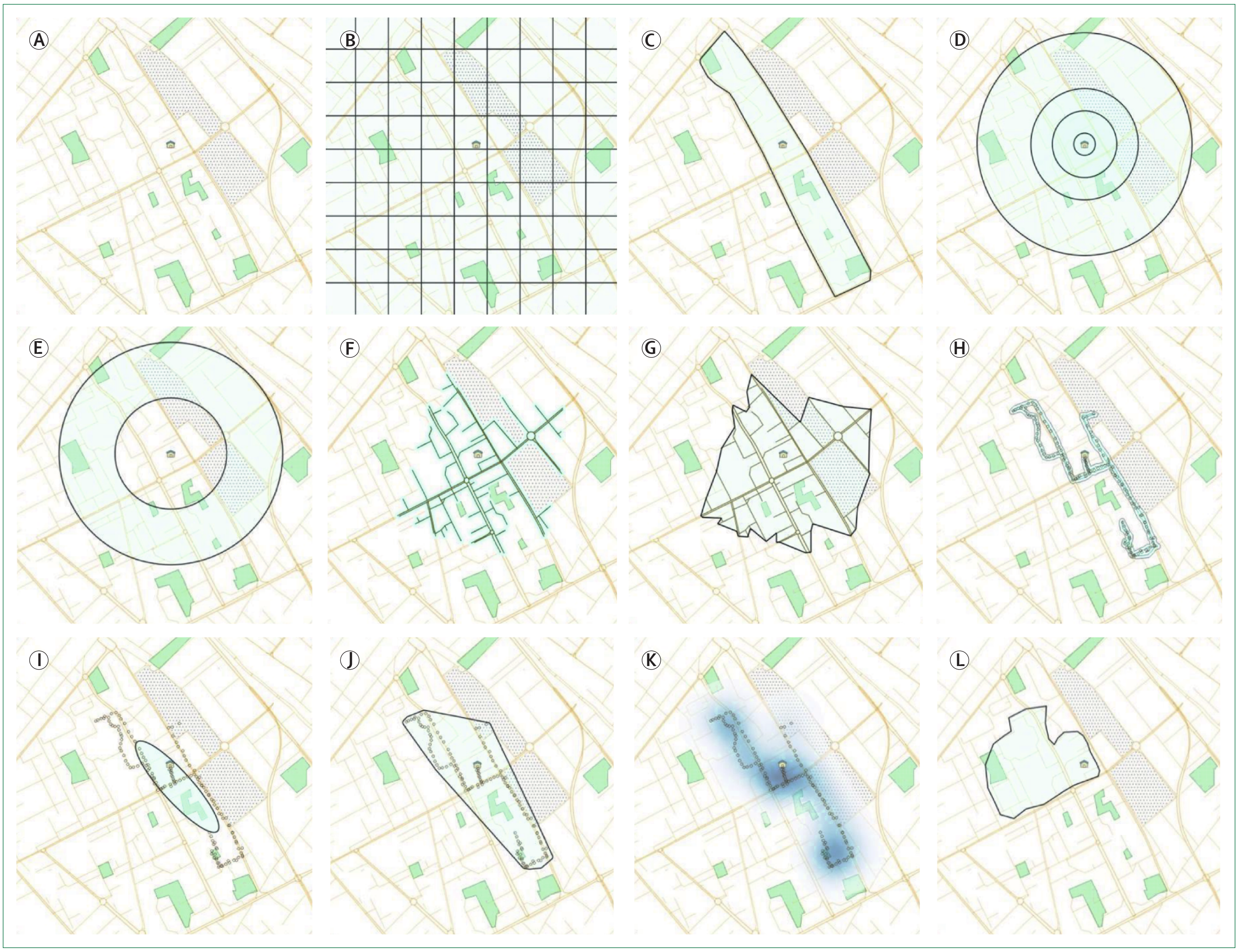

Figure 3: **Buffer types of greenspace–health studies**
(A) The study area; (B) Grid cells; (C) Administrative units; (D) Circular buffers; (E) Nested buffers; (F) Line network buffers; (G) Polygon network buffers; (H) Daily path areas; (I) Standard deviation ellipses; (J) Minimum convex polygons; (K) Kernel density estimations; (L) Self-drawn neighbourhoods.

greenery. These micro-scale exposures can support stress reduction and psychological restoration, particularly when larger green spaces are inaccessible. Research in Singapore has showed curvilinear relationships between greenspace and mental health across increasing buffer sizes for circular, network, and nested buffer approaches.[72] However, findings across studies remain heterogeneous, with some reporting consistent associations across multiple buffer sizes, even among subpopulations with varying mobility patterns.[116]

Methodological challenges of large buffer sizes

Larger buffer sizes introduce several analytical challenges. They can mask spatial heterogeneity in greenspace exposure at finer scales,[117,118] reducing variability in exposure estimates.[119] This problem is particularly pronounced in dense urban areas where participants' large buffers might overlap substantially, creating spatial autocorrelation that should be addressed by specialised regression techniques.[20,120]

More generally, every environment has an upper limit for buffer sizes, beyond which buffers are unlikely to capture meaningful exposures.[30,59] The lacunarity curve, a spatial scale-dependent measure of heterogeneity, can help to identify this upper boundary, based on evidence from a preprint paper and a research article.[30,121] For example, research in Manchester, UK, identified upper bounds for normalised difference vegetation index variance at approximately 640 m for Sentinel-2 imagery and 480 m for Landsat-8 imagery.[30]

Concluding thoughts on buffer sizes

Given these considerations and challenges, no universally correct buffer size exists. The optimal choice depends on multiple factors, including the specific health outcome(s), hypothesised causal pathway(s), study population characteristics, and local environmental context. Because lacunarity analysis only guides the selection of the largest buffer size, Bayesian model averaging has been proposed to address contextual uncertainties by pooling greenspace effect estimates across multiple buffer sizes within appropriate upper boundaries.[122]

Determinants of buffer selection

Although there is no single formula for choosing buffer type and size, researchers can rely on several key determinants to inform their choices.

Health outcomes and underlying mechanisms

The hypothesised mechanisms linking greenspace to health outcomes should guide buffer selection. For example, when examining neighbourhood social phenomena (eg, social capital or crime rates), perceived areas through SDNs might be most relevant. Circular or network-based buffers can conceptually represent individual exposure environments, but their application becomes statistically constrained when outcome data are only available at a coarser spatial resolution. In such cases, all buffers within the same administrative unit receive identical values, leading to non-independence of observations, pseudoreplication, and artificial inflation or deflation of statistical power.[123] This spatial mismatch between exposure and outcome can bias effect estimates and limit interpretability.

The assumption that network buffers are always more appropriate than circular buffers should also be questioned. For health outcomes not limited to travel and roads (eg, air pollution and pollen exposure), circular buffers might be equally appropriate or superior.[1,124] Network buffers are generally more beneficial when outcomes relate to greenspace accessibility and behaviours such as physical activity.[68,125,126] However, observed associations between greenspace exposure and outcomes do not necessarily indicate that greenspace within road network buffers increases physical activity. Instead, this could be explained by physically active individuals selecting routes with more green space, also known as a selective daily mobility bias.[126]

Small buffers might be more appropriate for outcomes related to psychological restoration, stress reduction via visual access to greenspace, noise annoyance, or individual microbiota enrichment.[127] For mechanisms operating through visual access, residential building density is an important consideration.[128] In dense urban areas, residents on ground floors might only see a few metres of greenspace, whereas those on higher floors might have substantially farther views, warranting larger buffers for residences on higher floors.

For outcomes hypothesised to relate primarily to physical activity, purposeful visits, or greenspace use, buffer selection is challenging given the highly variable nature of human behaviour. A 300-m radius represents approximately a 5-min walking distance, whereas 500-m radius represents 5–10-min distance and 1000-m radius represents 10–15-min distance.[10,129] Although some studies suggest greenspace use declines rapidly beyond 100–300 m from home,[27,65] larger buffers have also been better predicted to improve physical health and loneliness.[7,61] Browning and Lee's systematic review found that buffer sizes between 1000 and 1999 m showed more consistent protective associations between greenspace and physical health (including physical activity) than smaller or larger sizes.[36] Buffer-based metrics, such as the percentage of area covered by green spaces or parks, can be useful for opportunities for green space access and use. Still, alternative metrics, such as straight line or network distance to the nearest park of a specified minimum size, might be equally relevant for physical activity-related hypotheses; however, these distance-based measures are beyond the scope of this Personal View.

For pollen exposure conditions, a New York study reported that pollen levels correlated with tree cover in radial buffers of around 1000 m, more specifically between 250 and 500 m, depending on the plant species and pollen size, shape, and weight.[130]

Buffer size selection also depends on the cooling effects of green spaces near an LOI. The strongest ambient air temperature and heat stress reduction occurs at closer distances to (< 380 m, and likely, strongest within 150 m).[5] However, cooling distance depends on park size, shape, and climate, with parks smaller than 10 000 m^2 often showing no notable cooling effect.[131]

Population characteristics

Study population characteristics substantially influence buffer selection. Health and health-related behaviours (eg, pregnancy, disability, fitness level), sociodemographic characteristics (eg, age, gender, ethnicity, socioeconomic status, employment), and preferences related to greenspace (eg, professional joggers, nature enthusiasts) affect mobility capacities, opportunities, needs, choices, and societal constraints (including those generated by stigma and structural discrimination).[132] These characteristics should therefore guide buffer type and size selection.[88]

Age-related mobility patterns are particularly relevant. Children and older adults typically travel shorter distances than adolescents and younger adults; an average 5-min walk is approximately 200 m across all ages compared to 300 m when excluding older adults and 320 m when additionally excluding children.[133,134] Similarly, pregnant women's activity spaces tend to shrink in late pregnancy.[91] For these populations, smaller circular or network buffers centred around the residence might be most relevant.[135,136]

Highly mobile populations (eg, employed individuals, younger participants, high-income participants, car owners) can pose challenges related to the neighbourhood effect averaging problem when using solely residence-based approaches.[137] For these populations, approaches using travel diary, intermittent location tracking, or GPS data (eg, DPA or KDE) might provide more accurate assessments.[48,138] Personal preferences, such as connectedness to nature, can also affect buffer selection, as people with higher levels of connectedness might travel greater distances to access greenspace.[139] These findings highlight the potential value of participant preferences when selecting buffer types and sizes.

In summary, for studies focusing on a specific subpopulation (eg, pregnant women, children), buffer type and size should prioritise the group characteristics and mobility patterns. For studies with heterogeneous populations, applying multiple buffer sizes and types relevant to the included population groups (as sensitivity analyses) and testing interactions between buffer sizes and types can help to evaluate whether exposure affects population groups differentially.

Contextual factors

Study setting

Study area characteristics such as urbanicity and climatic zone affect should to be considered in buffer type and size selection.[138,140,141] Beyond greenspace, buffers often include non-green elements such as roads, buildings, or pollution sources that can influence health or potentially alter or confound the mechanisms through which greenspace exerts its effects. In historical areas with dense, irregular forms, a single fixed-location approach (typically home) might capture built-up residential environments, compared to an activity-space approach that captures more distant greenspace.[140] However, these approaches answer different research questions—buffers at single fixed locations reflect greenspace accessibility or availability, whereas activity-space approaches measure realised exposure based on behaviour. The opposite pattern might apply to residents of suburban areas who travel to dense urban centres for work or education, leading to mismatches between residence-based and actual greenspace exposure. Such scenarios exemplify the neighbourhood effect averaging problem, where relying on residential-based exposure can mask true individual variability due to daily mobility patterns.

Urbanicity also influences the relevance of the buffer size. A Hong Kong study across six regions with varying urbanicity found that associations between greenspace and perceived general health differed by buffer size across settings. In highly urbanised areas, statistically significant associations were observed within smaller buffers (100–500 m), whereas in less urbanised regions, stronger associations emerged at larger buffers (2000–5000 m).[142]

Beyond urbanicity, characteristics of greenspaces, such as size, shape, public access (ie, hours, entrance fees), and qualities, might modify buffer size recommendations when nearby greenspaces do not meet residents' needs. Climatic conditions also matter—in extreme or arid climates, accessibility and availability of nearby greenspaces can change seasonally, potentially justifying larger or more flexible buffers to capture seasonally preferred or distant locations. Conversely, in tropical or temperate zones with evergreen vegetation, greenspace use tends to be more consistent year-round, meaning that buffer selection is less affected by season and data collection timing. However, in large-scale studies (eg, continental or national level), using small cell sizes (eg, dozens of metres) might have computational limitations.[143]

Additionally, the LOIs included in a study shape buffer selection. Activity-space approaches include LOIs accessible through commuting and travel modes (eg, cycling, walking, transit). However, if a study focuses on particular associations in predefined settings, buffer approaches using multilocation data might not provide additional benefits over those centred on single locations.

Planning policies

Buffer selection can influence how easily research findings inform decision making.[144] The European Commission defines access to greenspaces as living within a 300-m distance from a green space of at least 5000 m^2.[145] Therefore, some studies have used a 300-m circular buffer around homes to extract surrounding greenspace in line with this indicator.[146–149] Other examples of greenspace thresholds include a 10-min walk to a park, widely used in the USA,[150] the 15-min city framework, and the 3–30–300 rule.[149,151] Considering these thresholds when selecting buffers can aid studies motivate and monitor greenspace access initiatives.

Since administrative boundaries are often more relevant for policy makers, studies intended to inform policies might be justified in using this buffer type.[24,152] Conducting analyses across administrative boundaries at different scales might tailor findings to decision making at various levels of government, ranging from local to national.[117]

Data considerations

Characteristics of data sources

Greenspace quantification traditionally relies on grid-based raster files or land cover and land-use maps with specific pixel sizes, minimum mapping units, or geometric accuracies.[153] When greenspace data is raster-based, pixel size (spatial resolution) measures the minimum usable buffer size. For example, applying a 100-m buffer is not recommended if the greenspace raster data has a 500-m resolution. Similarly, due to geometric accuracy in land cover maps (eg, approximately 100 m for CORINE Land Cover[154]), smaller buffers carry a higher risk of exposure misclassification compared with larger buffers. High-resolution raster data or land cover and land-use maps with higher geometric accuracy and smaller mapping units warrant applying smaller buffers. Comparing spatial heterogeneity metrics such as lacunarity, local variance, semivariance, and scale variance at different sizes might be useful for buffer selection.[155]

Emerging data sources, such as street-view imagery, social media, and social-sensing data, now complement traditional remote sensing approaches to greenspace assessment.[156–159] Street-level imagery (eg, Mapillary, Google

Street View, Baidu Street View), when combined with machine-learning techniques, enables quantification of visible greenness through indexes such as the Green View Index.[159,160] Unlike satellite-based metrics, Green View Index captures human-scale, vertical, and facade-level vegetation, offering more realistic approximations of visual greenery experienced by pedestrians. Social media and social-sensing platforms, such as X (formerly Twitter), TripAdvisor, Instagram, and Foursquare, provide user-generated data with insights into subjective perceptions of greenspace.[161,162] For example, sentiment analysis and a hedonometer of X posts have been associated with park visits with positive emotional responses.[163,164] Such emerging data sources might enhance our understanding not only of greenspace quantity but also of quality, accessibility, and user experience.

Data accuracy and availability

Location geocoding accuracy varies by approach and geographical area.[165,166] Street geocoding is among the most common approaches in epidemiological studies,[167] with reported positional error for street geocoding ranging from approximately 40 m to 75 m.[167]

Another approach uses GPS devices or smartphone applications, such as NatureDose^{TM}, to geocode participants' activity spaces.[168] GPS devices used in epidemiological studies usually have positional errors ranging from 10 to 20 m.[169] The buffer size should not be smaller than the expected geocoding error.

Positional errors in urban areas and more densely populated regions tend to be substantially smaller than those in rural areas.[170,171] However, GPS receiver accuracy is context-dependent as they regularly fail to record indoor positions and are less accurate when signals are obstructed, for example, by dense canopy cover[171,172] or tall buildings.[173,174] Geocoding accuracy is often higher in urban areas than in rural areas, allowing the application of smaller buffer sizes with greater confidence in urban settings. Apart from introducing exposure misclassifications, geocoding errors can considerably bias travel estimates (eg, network buffers results) and lead to imprecise accessibility estimates.[175,176] Excluding participants due to unavailable geocoding accuracy at desired buffer sizes can introduce selection bias. A better approach is to report results for these participants using a group with multiple, larger buffer sizes.[165]

Data ethics and privacy

Some data related to socioeconomic deprivation and health are available only in aggregated form to preserve anonymity and privacy.[177] For this data type, using the same aggregation area (ie, administrative unit) to assess greenspace is recommended. When administrative areas are small or population mobility is likely to extend beyond residential units, using a shadow buffer might provide a more accurate representation.[178] Given the privacy concerns and data protection regulations, some health data sources intentionally introduce random errors in participant geolocation, a process known as geographical masking.[179] In these cases, the buffer size for extracting greenspace should be at least as large as the induced error size.

Guidelines for buffer selection in greenspace–health research

The selection of appropriate buffer types and sizes is an important methodological decision that directly influences the validity and interpretability of research findings. Rather than relying on arbitrary or conventional selections, researchers should adopt a systematic, hypothesis-driven approach grounded in the determinants outlined above and depicted in the table (for selecting buffer types) and figure 4 (for selecting buffer sizes). The following guidelines provide a framework for making these decisions while acknowledging that no single buffer approach is universally optimal.

General principles

(1) Apply a determinant-driven approach: buffer selection should be explicitly justified based on key determinants, including health outcomes and underlying mechanisms, study population characteristics, contextual factors, and data considerations. This rationale should be clearly articulated in study protocols and publications; (2) Implement sensitivity analyses: given the inherent uncertainties in buffer selection, researchers should examine multiple buffer types and sizes as sensitivity analyses. This approach not only strengthens the robustness of the findings but also provides insights into the spatial scale dependence of greenspace–health associations; (3) Avoid model fit-based selection criteria: the choice of buffer types and sizes for primary analyses should not be determined by statistical model performance metrics (eg, R^2, Akaike information criterion values). Model fit might not accurately reflect the true extent of greenspace influences on health outcomes and can lead to post-hoc rationalisation of methodological choices.[180] Instead, determinant-informed approaches should guide buffer type and size selection; (4) Prioritise buffer type before size: although both buffer type and size are important, buffer type should be selected first based on relevant determinants. Size can then be flexibly selected within plausible ranges.

Buffer type selection

(1) Prioritise activity-space approaches when feasible and appropriate: high-granularity activity-space approaches (eg, GPS tracking) better capture actual exposure patterns than single-location approaches and should be preferred for primary analyses when resources and data permit; (2) Maintain single-location approaches for comparability: even when

	Recommended applications	When to avoid	Best practices
Administrative units	Ecological studies, when health data are only available aggregated at administrative levels, informing policy	Individual-level analyses with fine-resolution data	Use shadow buffers to compensate edge effects, report limitations of this buffer type
Grid cells	Raster data with matching resolution	Large cells when fine-scale exposure is needed	Use higher-resolution grids
Circular buffers	Visual access, studies of greenspace mitigating harmful exposures	When access is important for study context, population, or pathways	Use distance decay weighting, combine with network buffers when appropriate
Nested buffers	Exploring distance decay or effect variation by distance, sensitivity analyses	As sole measure of exposure	Use alongside other buffer types to explore gradient effects, specify rationale for each distance band
Network buffers	Studies focused on accessibility and use, physical activity studies	Outcomes unrelated to mobility	Incorporate travel modes, street attributes (eg, safety, topography), adjust trim distances contextually
Standard deviation ellipse	Rarely recommended due to large activity space overestimation	As main buffer type for exposure assessment	If used, use constraints or filters to exclude unused areas
Minimum convex polygon	Large-scale movement pattern studies, exploratory studies	As main buffer for exposure assessment	Combine with time-weighting or other restrictions
Self-drawn neighbourhood	When perceptions or subjective definitions of neighbourhoods are the key focus of studies	Precise spatial exposure assessments	Compare with actual activity space, analyse discrepancies to explore perceptions versus reality
Daily path area	Using high-resolution tracking data to assess actual exposure along routes	Studies without reliable tracking data or if participants cannot provide consistent paths	Use time-weighted approaches, supplement with other buffer types
Kernel density estimation	Studies with fine-grained tracking data, when estimating exposure probability surfaces	Sparse data or low point densities	Use adaptive kernel density estimation to incorporate environmental characteristics, adjust bandwidths appropriately
Vertical or 3D buffers	Dense high-rise urban settings, visual exposure assessments	Low-rise or open contexts in which vertical dimensions are less meaningful	Integrate with horizontal buffers, combine LiDAR or other 3D data when possible

***Table:* Buffer type selection guidelines for greenspace and health studies**

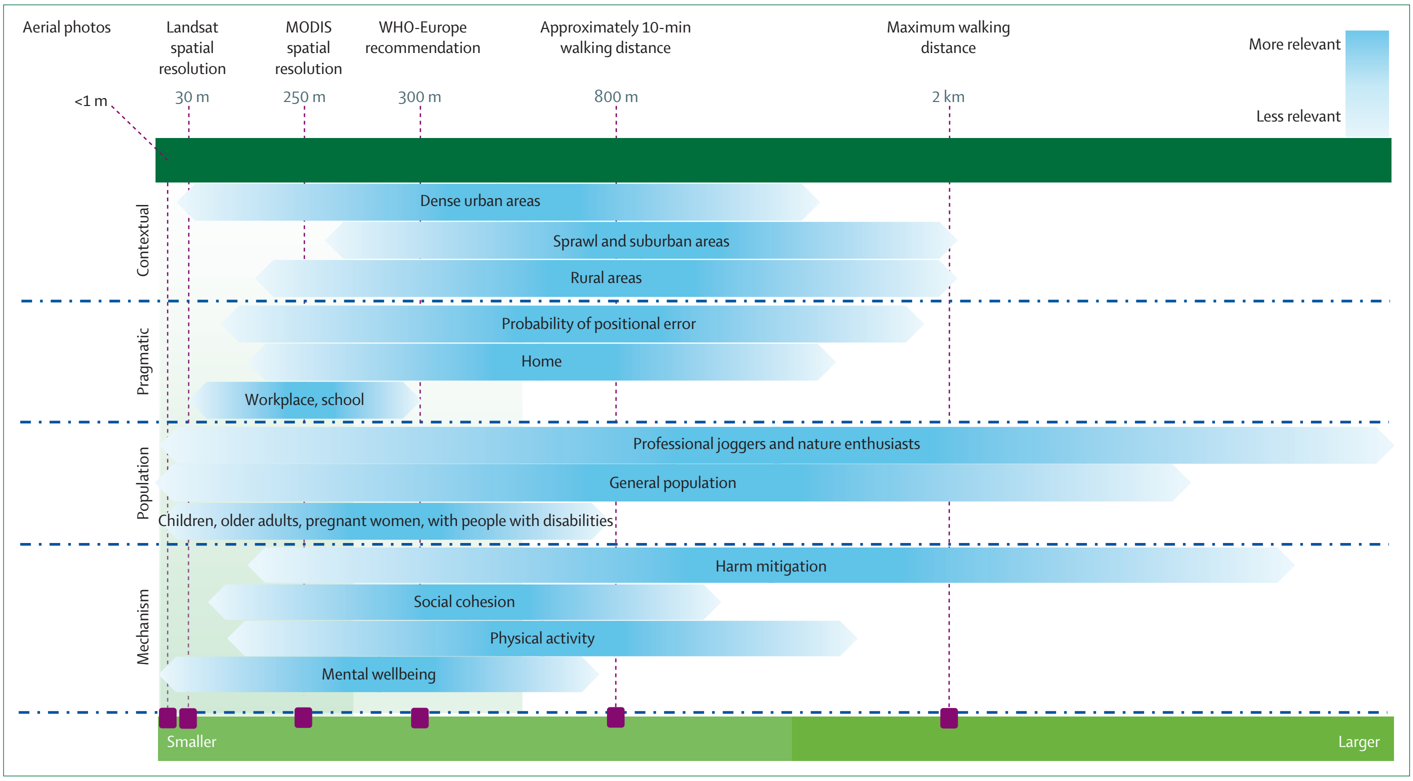

***Figure 4:* Illustrative framework for selecting appropriate buffer sizes based on contextual, pragmatic, population, and mechanistic considerations**

The horizontal axis indicates buffer size (from smaller to larger), referencing spatial resolutions (eg, aerial photos, satellite imagery) and common distance thresholds (eg, WHO-Europe recommendation of 300 m and a 10-min walking distance of 800 m). The vertical axis organises criteria into four domains—contextual (eg, urban density), pragmatic (eg, positional error), population-specific (eg, vulnerable groups and physical ability), and mechanistic (eg, mental wellbeing and physical activity). The colour gradients indicate the relative relevance of the buffer size within each domain; the more saturated colours represent a higher relevance.

using activity-space approaches, researchers can report results for single-location buffers (typically residential areas) to facilitate comparisons across studies; (3) Use multiple locations when activity-space data is unavailable: when comprehensive mobility is not feasible, incorporating LOIs (eg, home, work, school, commuting routes) is preferable to relying solely on residential addresses. This helps to avoid spatial misclassification from the uncertain geographical context problem; (4) Exercise caution with administrative unit approaches: avoid administrative units and other predefined spatial units for individual-level analyses, as they often poorly represent activity spaces and exposure patterns. However, these approaches remain valuable for ecological studies where exposure and outcome data are aggregated at the same administrative level, and when it is necessary to directly inform or monitor greenspace policies (eg, the 3–30–300 rule); (5) Limit the use of standard deviation ellipses and minimum convex polygons: given their tendency to overestimate activity spaces and include unvisited areas, SDEs and MCPs should not serve as primary buffer types unless combined with additional constraints or filtering methods to exclude unused space; (6) Use nested approaches for mechanistic studies: nested or doughnut-shaped buffers can effectively examine how greenspace–health associations vary with distance from LOIs, providing insights into the relative importance of different mechanistic pathways; (7) Consider perceptual approaches for psychological outcomes: self-drawn neighbourhoods and other perceived approaches can offer insights into mental health and health-related behavioural outcomes, as subjective perceptions might be more relevant than objective spatial boundaries; (8) Explore 3D approaches in dense urban environments: in cities with extensive high-rise development and vertical greenspace (eg, Singapore, Hong Kong), consider 3D buffer approaches that account for green walls and elevated vegetation, particularly for greenspace visibility mechanisms; (9) Consider temporal weighting in activity-space exposure assessments: when using GPS or other mobility-based approaches, future studies should incorporate not only spatial location but also time spent in each place. Time-weighted exposure estimates better reflect actual exposure patterns.

Buffer size selection

(1) Define size ranges based on multiple determinants: rather than selecting single buffer sizes, researchers should identify the lower and upper thresholds that encompass the relevant spatial scales for their study population, hypothesised mechanisms, and outcomes. This approach avoids the constant-size neighbourhood trap and acknowledges the possibility that greenspace affects human health at different scales; (2) Use data considerations to establish sizes: buffer sizes should respect the limitations of the data. Minimum sizes should exceed the resolution of greenspace data, geocoding accuracy, and positional errors. If the applied buffer size is smaller than the greenspace data resolution, adjacent buffer values become correlated or identical.[181] Maximum sizes can be informed by lacunarity curves and model averaging,[122] local variance, semivariance, and scale variance at different lags, indicating sizes that allow for sufficient variation in exposure assessments.[155] Overly large buffers might fail to capture local greenspace variability and important spatial details;[182] (3) Align buffer sizes with mechanistic hypotheses: different health pathways operate at different spatial scales. Mechanisms that involve visual access, such as psychological restoration, require smaller buffers, whereas larger buffers might better capture physical activity and urban heat island effects. Air quality and allergen exposure might require multiple scales to account for both localised and broader effects; (4) Report results across multiple, standardised buffer sizes: rather than selecting a single optimal size based on the association strength, researchers should analyse and report results across at least three buffer sizes. Recommended metric distances include 25, 50, 100, 300 m (preferable to 250 m, as 300 m is closer to an adult's 5-min walking distance and used in greenspace policy[149,151]), 500 m, 800 m (approximately a half-mile walking distance), 1000 m, 1·5 km, and 2 km. We encourage researchers working in settings where non-metric units are used (eg, the USA, the UK) to adopt metric units for comparability; (5) Implement distance-decay approaches when appropriate: for proximity-sensitive mechanisms (eg, visual access), use distance-decay or fuzzy-distance approaches that weight exposure based on distance from LOIs. Traditional circular buffers can serve as a basis for sensitivity analyses to ensure comparability between studies.

Future directions

As greenspace–health research evolves, new determinants might emerge that influence buffer selections. The guidelines presented here reflect best practices based on current evidence and expert consensus, but should be updated to reflect new methodological and data developments. We acknowledge that this guidance primarily focuses on individual-level data and exposure assessments. Although ecological studies have value, our recommendations are intended to support individual-level epidemiological analyses. Although our focus was on greenspaces, the principles and guidance presented here might also inform methodological developments in other domains of spatial epidemiology research, such as blue space–health studies, where similar challenges exist in exposure assessment. Ultimately, the aim is to transition from ad-hoc buffer selection to systematic, hypothesis-driven approaches that enhance the rigour and reproducibility of greenspace–health research while supporting evidence-based policy and practice.

Contributions

MJZS, MB, KS, MH, and PD led the conceptualisation and writing of the original draft. MJZS, MB, and KS contributed towards figure creation. All other authors contributed to the conceptualisation of the work and participated in reviewing and editing the manuscript. All authors reviewed the final version of the manuscript and approved it for submission. This work did not entail any data curation, data analysis, project administration, resources, software, or validation. All authors had full access to all the data in the study and had final responsibility for the decision to submit for publication.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT to improve the clarity in some parts of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of interests

We declare no competing interests.

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