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Measurement of Neighborhood-Based Physical Activity Bouts

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Abstract

This study examined how buffer type (shape), size, and the allocation of activity bouts inside buffers that delineate the neighborhood spatially produce different estimates of neighborhood-based physical activity. A sample of 375 adults wore a global positioning system (GPS) data logger and accelerometer over 2 weeks under free-living conditions. Analytically, the amount of neighborhood physical activity measured objectively varies substantially, not only due to buffer shape and size, but by how GPS-based activity bouts are identified with respect to containment within neighborhood buffers. To move the "neighborhood-effects" literature forward, it is critical to delineate the spatial extent of the neighborhood, given how different ways of measuring GPS-based activity containment will result in different levels of physical activity across different buffer types and sizes.

Keywords

Accelerometry; Geographic Information Systems; GPS; Neighborhood; Physical Activity

Introduction

Regular physical activity is a cornerstone of chronic disease prevention and treatment. The role of the physical or "built" environment in supporting or hindering physical activity levels in the population has garnered substantial attention over the last several decades (Barnett et

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Declaration of competing interest

None of the authors have any competing interests to declare.

al., 2017; Cerin et al., 2014; Cerin et al., 2017; Karmeniemi et al., 2018; King et al., 2019). For example, built environment correlates of walking, such as the presence of sidewalks, density of road network connections, and having utilitarian destinations within a short distance from the home, are well documented (Lee and Moudon, 2006b; Saelens and Handy, 2008).

Most research linking features of the built environment with health behaviors falls into the category of “neighborhood-effects” studies. An important limitation of this literature is that the location of the physical activity is not always specified in the studies; it is often unclear whether the activity occurred inside the “neighborhood” of residence or in other distal locations (Hillsdon et al., 2015; Hurvitz and Moudon, 2012; Hurvitz et al., 2014a). In fact, the definition of what constitutes a “neighborhood” is debatable. Most descriptions of “walkable neighborhoods” use a spatially-based definition framed on relatively close access to utilitarian destinations and urban form characteristics inside pre-selected “buffers” around the home address (e.g., 400 m, 800 m, and 1600 m, or roughly one-quarter to one mile around the home corresponding to a range of 5 to 20 minutes at typical walking speeds) (Lee and Moudon, 2006a; Moudon et al., 2006). We define neighborhood as the area that is readily accessible to a person from home. Areas that are not readily accessible to a person from home are considered outside the neighborhood. Defining what is meant by neighborhood is critical because the characteristics of pre-selected buffers, including their shape and size, often drive the relationships noted between neighborhood characteristics and physical activity levels (Forsyth et al., 2012b; James et al., 2014).

Here, we provide a more thorough review of important concepts in the field of epidemiology and neighborhood-effects studies to provide the theoretical underpinnings of the study. Our work is aligned with a generation of research referred to as “people-based” (Kwan, 2009), differentiated from the more common “place-based” approach used to measure exposure to the built environment. For example, earlier studies of associations between physical activity and the built environment used “place-based” exposure measures derived from publicly available administrative spatial data (e.g., census blocks or census tracts) to quantify specific environmental features. The assumption was that all individuals living in the same spatial setting or context had the same exposure to the built environment within that census block or tract (Riva et al., 2009). In contrast, “people-based” exposure relies on individual-level data and acknowledges potential individual-level differences in exposure to and the way(s) that the built environment can influence health-related behaviors. In the present study, we used various measures of areas that respondents lived in (i.e., their home neighborhood) to capture the locational opportunities potentially available as their base exposure. We also address the previously identified “uncertain geographic context problem” (UGCoP), which acknowledges uncertainty in how the size and shape of neighborhood areas exert different contextual and environmental influences on health behaviors (Kwan, 2012). We considered several “shapes” and “sizes” of the residential neighborhood, prerequisites to such studies of exposure, using the conventional Euclidian aerial buffer (with buffered areas defined as the “crow flies”) as well as more sophisticated street network buffers (with buffered areas defined as those accessible by a person traveling a specified distance from home along the street network) (James et al., 2014; Oliver et al., 2007). Furthermore, of the several ways to measure street network buffers, we specifically considered the novel sausage buffer. Forsyth and colleagues (Forsyth et al., 2012b) reported that their objectively measured built environment attributes and their self-reported physical activity and eating habits varied significantly by buffer type. However, the relationships between them remained similar, suggesting that buffer shape and size did not affect modeled associations between exposure and outcomes. Similarly, Frank and colleagues (Frank et al., 2017) compared the explanatory power of built environment measures using aerial and street network-based buffers and self-reported transportation- and leisure-related levels of physical activity and inactivity. They found that the coefficients of the different built environment measures did not differ significantly across buffering methods, and that associations of built environment measures with physical activity outcomes had the same level of statistical significance across buffer types. However, the sausage buffers yielded models where built environment measures coefficients differed in significance from the other models.

The results of the previous studies described above (e.g., James, Forsyth, and Frank) may have been biased by what has been termed the “residential effect fallacy” (Chaix et al., 2017). Using self-reported energy balance behaviors, as these studies did, makes it challenging to match behaviors spatially and temporally to the wide range of possible buffer shapes and sizes. Most certainly, spatially matching self-reported behaviors and exposure cannot be done precisely. The residential effect fallacy further stipulates that confounding from the urban-rural continuum, from the socioeconomic organizations of territories, and the resulting correlations between residential and nonresidential exposures, suggest that classically estimated residential neighborhood– physical activity outcome associations also capture nonresidential environment effects on physical activity, and overestimate residential contextual effects. That is, exposures outside of the home neighborhood are likely to affect behaviors, but these exposures are not captured by home-based buffers. This phenomenon is similarly described as the “neighborhood effect averaging problem” (Kwan, 2018), which is the observed attenuation of the neighborhood effect associated with people’s daily mobility patterns. Accordingly, the present study expands on the above body of work by using objectively measured (GPS- and accelerometry-based) physical activity and walking bouts, which are continuously timestamped and geolocated. Finally, the study uniquely tests different ways to precisely allocate physical activity spatially and temporally within buffers by describing activity bouts as continuous lines in space and calculating the precise location at which the line crosses a buffer. Overall, the present study offers approaches to spatially parcel out physical activity so that analyses can be carried out to distinguish between potential associations with exposure to the home neighborhood (inside the neighborhood) and those to the non-home environment (outside the neighborhood). Specifically, as described next, the study compares results from 16 different options to allocate physical activity to home neighborhoods.

Because neighborhood-effects studies focus on associations between exposures, such as the built environment, with health behaviors, such as physical activity, the careful matching of physical activity episodes (or bouts) with location (“where” does the activity occur?), often using accelerometry and GPS monitoring, is central to this research. Our group developed methods for integrating data from these devices using common timestamps into a single data structure (the *LifeLog*) (Hurvitz et al., 2014b). Here, we build on concepts described in our previous work and extend the neighborhood-effects literature by investigating how buffer type (shape), size, and delineations of neighborhood location of physical activity (i.e., the allocation of activity bouts inside buffers that represent the neighborhood spatially) produce different estimates of neighborhood-based activity. We hypothesized that buffer characteristics and delineations of neighborhood location of physical activity result in significant differences in physical activity levels measured inside of the home neighborhood. The study findings will be discussed in terms of how buffer characteristics result in different levels of quantifiable physical activity within home neighborhood locations, which has important implications for any study investigating associations between aspects of the built environment and physical activity levels.

Methods

Participants

This study included a sample of 375 individuals from the community-based Washington State Twin Registry (WSTR). Details regarding the WSTR are reported elsewhere (Duncan et al., 2019; Strachan et al., 2013). The parent study of the present cross-sectional analysis used objective measures of physical activity in space and time over two weeks of monitoring (accelerometry and GPS) under free-living conditions. The parent study was reviewed and approved by the local IRB.

Outcome measures

Participants wore a Qstarz BT-Q1000XT GPS data logger (Qstarz International Co. Ltd., Taipei, Taiwan) and Actigraph GT3X+ accelerometer (Actigraph Inc, Pensacola, FL) attached to an elastic belt worn around the waist for two weeks. Accelerometry data were stratified into “wearing” and “nonwearing” intervals using methods from the NCI (Troiano et al., 2008) operationalized within the “accelerometry” (Van Domelen, 2015) package in the R statistical programming environment. Nonwearing time was defined as intervals of at least 60 minutes allowing for up to two consecutive minutes with accelerometry values less than 100 counts per minute.

Physical activity was measured as moderate-to-vigorous physical activity (MVPA) bout minutes per week and walking bout minutes per week. Walking bouts were identified using a classification algorithm adapted from Kang et al. (Kang et al., 2013), described by us previously (Hwang et al., 2016) and in brief below, whereas MVPA bouts were identified as sustained intervals with 3D vector magnitude ≥ 2690 counts per minute (CPM) (Sasaki et al., 2011), using a modified 10-minute bout definition that allows for up to two minutes outside the specified CPM threshold (Troiano et al., 2008). Light-to-moderate physical activity (LMPA) bouts used vector magnitude thresholds between 2000 and 6166 CPM. Walking bouts were identified as a subset of LMPA bouts after accelerometry and GPS data were combined into “LifeLogs” using common time stamps (Hurvitz et al., 2014b). Walking bouts had (1) at least three records with GPS coordinates, (2) ≥ 20% of records with GPS coordinates, (3) median Doppler shift-based GPS speed between 2 – 6 kmh^{-1}, and (4) appropriate spatial configuration. The spatial configuration criterion calculates the inter-point distance for all GPS coordinates in the bout, and creates a minimum bounding circle (MBC) around the 95% most tightly clustered points in the bout; bouts with MBC > 20 m that met all other criteria were flagged as walking. Figure 1 (left panel) shows data for a single walking bout, indicating speeds 2 – 6 kmh^{-1} and vector magnitude 2,000 – 6,166 CPM; the map (right panel) shows the GPS track along a popular walking trail. The MBC criterion was used to differentiate LMPA episodes that took place in relatively confined spaces (e.g., gym, garden) from those that involved greater movement through space.

Exposure measures

Four different geometric buffers were constructed (Fig. 2) at two different radii each (833 and 1666 m, to represent the distance typically walked in 10 and 20 minutes, respectively) (Forsyth et al., 2012b; Frank et al., 2017; Hurvitz et al., 2014a; James et al., 2014; Oliver et al., 2007). Buffer construction used PostgreSQL/PostGIS, an open-source SQL database that includes support for geographic information system (GIS) data and a large set of standard functions for spatial analysis. The Euclidean buffer (Fig. 2a) was created by generating a circle centered at the home location (using 833 m and 1,666 m radii). The other three buffer types were based on network analysis using pgRouting (a PostGIS extension for network routing) with OpenStreetMap data from 2017, converted to PostGIS format using osm2po-core (FreeWare) (C. Moeller, Pinneberg, Germany, available at http://osm2po.de/), an application that parses OpenStreetMap data and makes it routable. The first step was to select all roadways which were traversable on the street network from the home location to the preset buffer size (833 m and 1,666 m) and which could be used by pedestrians; roads or streets that have limited access to vehicles (e.g., see Fig. 2, Interstate 5 shown in red while traversable streets within the distance tolerance are shown as cyan lines) were not included since they did not support physical activity or walking. The convex hull of a set of points is the smallest convex set that contains the points. Based on this definition, the convex hull buffer (Fig. 2b) was constructed by drawing a polygon that connects the outermost points in an area (e.g., the endpoints of the roads accessible by walking from home (833 m and 1,666 m) along the selected roadways) and contains the remaining points inside the polygon (Hasanzadeh et al., 2017), a procedure which is analogous to placing a rubber band around the terminal points of the accessible roads. A concave hull is a polygon which includes the full set of points, but has less area compared to the convex hull. The concave hull buffer (Fig. 2c) (Moreira and Santos, 2007), created with the PostGIS ST_ConcaveHull function, is based on the convex hull, but requires a user-defined percent of area to be removed from parts of the convex hull that have no traversable network segments. This is similar to the “trim” option in ArcGIS (e.g., see Forsyth et al. 2012a, Frank et al. 2017). Finally, the “sausage buffer” (Fig. 2d) (Forsyth et al., 2012b) was created by generating a Euclidean or “detailed-trimmed” buffer of 30 m along each side of the centerline of roads which were identified as being traversable by pedestrians from the network analysis. In a deviation from the Forsyth et al. method (Forsyth et al., 2012a), we filled in the “holes” created by areas larger than 60 m (the two 30 m buffers along street centerlines) in order to capture physical activity or walking bouts that may take place in areas such as gardens or parks located in the inner street-blocks of the home neighborhood. This approach was deemed preferable to using a trim dimension large enough to avoid creating holes, which, as discussed by Forsyth et al. (2012a and b), would create large extensions at the end of the buffered streets; however, our methods include the option to maintain holes, or to fill in holes below a user-specified tolerance. We used rounded street ends.

Activity bouts were delineated as linestrings (connected series of line segments) by joining the set of temporally sequential GPS points within the bout. Each activity bout linestring was overlain on each buffer type to estimate the total duration of MVPA and walking inside and outside of the home neighborhood buffer area. Containment of linestrings inside the buffer was determined by the different possible overlaps as shown in Fig. 3. We first used a "strict" delineation, which included only the activity bout linestrings that were completely inside the home neighborhood buffer, as represented by bout (a). We also used a "flexible" delineation, where a linestring was either completely or partially contained inside the buffer. Partial overlaps are illustrated by the portions of bouts (b), (c), (d), and (e) that are inside (solid portion of the line) the neighborhood buffer, whereas portions of bouts that are outside (dashed portion of line) of the neighborhood buffer did not count toward the calculation of the bout. The linestring represented by bout (f) is completely outside of the neighborhood buffer. Apportioning bout portions to inside or outside of the home neighborhood buffer was done using the temporal, rather than the physical dimension of the linestring, to correspond to the temporal measurement of physical activity. For each bout segment, the fraction of bout duration spent inside the buffer was estimated by multiplying the segment duration by the proportion of the segment inside the buffer (e.g., a 60 s segment with 40% of its length in the buffer would have 24 s inside the buffer and 36 s outside the buffer) (Scully et al., 2019). The durations of both complete and partially overlapping segments were summed to provide an estimate of the total time spent within and outside the buffer. These estimates were generated for both MVPA and walking bouts, and were normalized per participant as minutes per week to account for differences in the count of valid wearing days (i.e., a valid day was defined as a minimum of 10 hours of wearing time per day) across participants.

Statistical analysis

Descriptive statistics for duration of MVPA and walking bouts (min per week) were computed and reported by buffer size (833 m, 1666 m), buffer type (Euclidean, concave hull, convex hull, and sausage), overlap delineation (flexible, strict), and location (inside and outside the home neighborhood buffer). We used linear regression models to examine the extent to which the amount of MVPA and walking differed across the four buffer types for each buffer size, delineation, and location combination. Buffer type was used to estimate the amount of MVPA (or walking). As buffer type is a categorical variable, the linear regression model in which the buffer type is used to estimate the amount of MVPA (or walking) is analogous to a one-way Analysis of Variance (ANOVA). Eight comparisons were performed for MVPA and walking, respectively. A Bonferroni corrected alpha was used for multiple comparisons with $p < 0.006$ (i.e., 0.05 / 8 = 0.006) considered statistically significant in these comparisons. For comparisons that were statistically significant, post-hoc comparisons were performed using the Tukey Honestly Significant Difference (HSD) test to determine which buffer type comparisons were statistically different from each other. All statistical analyses were performed in the statistical program R 4.0.02.

Results

The devices were worn on average 10.8 ± 3.5 hours per day over 10.4 ± 3.4 days. Individuals' ages ranged from 23 to 79, with an average of 45.3 ± 13.0 years. The sample was 72.2% female, and a majority of the participants self-identified as White (90.3%) and non-Hispanic (95.7%).

Descriptive statistics of MVPA and walking bout duration by buffer type, size, and delineation of activity location are presented in Supplementary Tables S1 and S2, respectively. Comparisons between MVPA and walking bout levels inside and outside of the buffers, by delineation, are presented in Supplementary Tables S3–S6.

Differences in MVPA bouts across the four buffer types, by size, delineation, and location, are presented in Table 1 and illustrated in Fig. 4. The amount of MVPA was significantly different across the buffer types for the 833 m strict inside, 833 m flexible inside, 1666 m strict inside, 1666 m strict outside, and 1666 m flexible inside buffers, respectively (all $ps < 0.006$).

Table 2 presents the post-hoc comparisons for MVPA bouts. For the 833 m strict inside location, most of the pairwise comparisons were statistically significant ($p < 0.05$), except for the comparison between the convex hull and concave hull buffers. For the 833 m flexible inside location, the amount of MVPA in the Euclidean was higher than the concave hull (mean difference = 10.31, $p = 0.003$), convex hull (mean difference = 8.28, $p = 0.029$), and sausage buffers (mean difference = 15.25, $p < 0.001$). For the 1666 m strict inside location, most pairwise buffer type comparisons were statistically significant ($p < 0.05$), except for the comparison between the convex hull and concave hull buffers. For the 1666 m strict outside location, the amount of MVPA measured using the sausage buffer was higher than amounts in the concave hull (mean difference = 16.73, $p = 0.013$), convex hull (mean difference = 18.19, $p = 0.006$), and Euclidean buffers (mean difference = 277.48, $p < 0.001$). For the 1666 m flexible inside location, the amount of MVPA assessed using the Euclidean buffer was higher than that measured using the sausage buffer (mean difference = 16.60, $p < 0.001$).

Differences in walking bouts (minutes per week) across the four buffer types, by size, delineation, and location, are presented in Table 3 and illustrated in Fig. 5. The amount of walking was statistically different across the buffer types for the 833 m strict inside, 833 m flexible inside, 1666 m strict inside, and 1666 m strict outside buffers, respectively (all $p < 0.006$).

Table 4 presents the post-hoc comparisons for walking bouts. For the 833 m strict inside home location, all pairwise buffer type comparisons were statistically significant ($p < 0.05$), with the exception of the comparison between the convex hull and concave hull buffers. For 833 m flexible inside home location, the amount of walking measured with the Euclidean buffer was substantially higher than assessed with concave hull (mean difference = 5.96, $p = 0.012$), convex hull (mean difference = 5.10, $p = 0.045$), and sausage buffers (mean difference = 7.67, $p < 0.001$). For the 1666 m strict inside location, all pairwise comparisons were statistically significant ($p < 0.05$), except for the comparison between convex hull and concave hull buffers. For the 1666 m strict outside location, the amount of walking assessed using the sausage buffer was substantially higher than assessed using concave hull (mean difference = 11.76, $p = 0.014$), convex hull (mean difference = 12.56, $p = 0.007$), and Euclidean buffers (mean difference = 19.85, $p < 0.001$).

Discussion

The major new finding from the present study is that objective measures of physical activity inside the home neighborhood vary substantially depending on the buffer type constructed and the delineation of containment of GPS and accelerometry-based bout lines inside (and beyond) the buffer. Of the four types investigated, Euclidean buffers always resulted in the greatest, and sausage buffers in the lowest, levels of physical activity inside the home neighborhood. Invoking a “strict” delineation of inside the home neighborhood (see line (a) in Fig. 3) always resulted in lower levels of activity than the “flexible delineation” (see lines (b), (c), (d), and (e) in Fig. 3) within each buffer type. These findings were mostly consistent for both activity outcomes – MVPA and walking – with a few exceptions of statistical differences by specific buffer types, distances, and delineations of neighborhood location.

An application of the results from the present study is depicted in Fig. 6, which illustrates a single walking bout with geocoded home location and origin (square marker), destination (triangle marker), and walking bout (red line with white circles), and all four buffer types at 1,666 m radii. Descriptively, this bout started at home, with the individual walking to a distal location (e.g., a store or other utilitarian destination). Using a strict delineation of bout inclusion in the home neighborhood would identify the walking bout within the Euclidean buffer only, because the entire bout is contained inside that buffer, whereas there would be no detectable walking using the other three buffers because the bout line straddles the sausage, convex, and concave hull buffer boundaries. Thus, a strict delineation of bouts contained inside the home neighborhood leads to an “all or nothing” spatial allocation of activity.

However, the limitations of Euclidean buffers are known, chiefly among them being that not all of the space contained within these buffers is in fact “walkable”; note that much of the western half of the Euclidean buffer in Fig. 2a lies across a freeway with few overpasses (see the cyan lines in Fig. 2 b–d towards the top and bottom of the buffer diagram that cross the red colored freeway), and thus is not part of the walkable environment accessible to the individual. The network buffers (Fig. 2 b–d) address this limitation by explicitly capturing the actual walkable space available to individuals within the constraints of the available transportation network.

In contrast to the strict delineation, when invoking the flexible delineation of inside the home neighborhood location, the amount of activity quantified for a given walking bout will be “parsed out” based on the buffer type. For example, referring back to Fig. 6, there is detectable walking in all four buffers. For the Euclidean buffer, all linestring data are included in the calculation of the total amount of walking because the bout is completely contained within the buffer, mirroring line (a) in Fig. 3. However, for the concave hull, convex hull, and sausage buffers, this specific walking bout corresponds to line (d) in Fig. 3 because the bout starts inside of the buffer (square marker) and ends outside those buffers (triangle marker). Analytically, only those linestring data that are contained within these buffers will be included in the calculation of the total amount of walking, resulting in a shorter duration walking bout (i.e., the leftmost linestring data shown in the inset of Fig. 6 will not be included in the concave hull, convex hull, and sausage buffers). Because Euclidean buffers cover a larger area than the other buffers, they capture more activity than the smaller buffers; it is expected that buffer type will follow the pattern Euclidean > convex hull > concave hull > sausage in terms of quantified activity bouts.

Based on the results of the present study, we make the following recommendations regarding the measurement of neighborhood-based physical activity bouts using accelerometers and GPS monitors. First, it is necessary to describe and justify the choice of buffer type in any study of neighborhood-based physical activity because the measured bouts will vary substantially based on choice of buffer. Euclidean buffers result in higher levels of physical activity being allocated to the home neighborhood, but network buffers are more justifiable for identifying features that individuals would have access to within their home neighborhood locations. Among the network buffers, the sausage buffer appears to have several strengths over the other types. For example, it is based on the physically accessible transportation network. The sausage buffer avoids the inclusion of potentially large inaccessible areas (as long as the holes are removed, as described in Methods), which can be present in all three other buffer types. It also contains the parcels and buildings closely adjacent to the road network that could be accessible by walking. Finally, the sausage buffer is highly replicable.

Next, regardless of which buffer type is ultimately chosen, the decision should be made in conjunction with the choice of location of activity bouts in the neighborhood (i.e., strict or flexible delineations of “neighborhood”). Using the strict delineation that only includes complete activity bouts in the neighborhood location will naturally lead to smaller physical activity bouts and great differences in bouts across the buffer types. The analyst may want to first specify the reasons for wanting to only consider complete activity bouts within the spatial context or, conversely, for including all “bits and pieces” of activity within the neighborhood that would be captured with a flexible delineation. As well, the choice of buffer type may be related to the local context. For example, studying populations living in dense (urban) or less dense (suburban) areas may affect the choice of buffer type. Specifically, a sausage buffer in a dense area will correspond to streets as the main accessible open space, whereas the same buffer in less dense areas could exclude open spaces away from streets but that are still accessible on foot. On the other hand, we acknowledge that sausage buffers may underestimate the accessible area in locations with low road density (Frank et al., 2017).

Strengths and limitations

A general strength of the current study is that the combined use of GPS and accelerometry provides objectively measured assessment of MVPA and walking, which reflects the actual physical activity levels of individuals, relatively free of self-report bias. Another general strength is that the 2-week assessment period included both weekdays and weekends, which may differ in the amount of physical activity and should thus both be included in any assessment of “usual” activity patterns. On average, participants had 10 valid wearing days over the 14-day assessment, which is a little over a week and generally exceeds levels reflective of "usual" activity patterns in adults (Cain and Geremia, 2011; Tudor-Locke et al., 2012).

A more specific strength is that our method of allocating bouts to inside or outside of the home neighborhood location can be refined to account for the direction of movement. For example, fig. 3 shows directional bouts, which would lend themselves to filtering activity that originates either within or outside the neighborhood location, and whether activity terminates within or outside the neighborhood location. In addition, the buffer generation methods were implemented completely within open-source GIS software, which can potentially support more tractable longitudinal analyses, as compared to the use of commercial, proprietary software, such as ArcGIS, whose algorithmic details may not be reviewable, and which may change across software versions (Forsyth 2012a). We recognize that PostGIS is not yet widely used, but to support other researchers, our team is in the process of creating complete documentation of our methods, which will be provided freely on the WSTR web page. This documentation will enhance replicability should other researchers choose to adopt our methods.

Although we took great care in developing our methods, in particular our choice of buffer types and delineations for home neighborhood locations (i.e., GPS containment), there are likely additional considerations, such as additional buffer types and sizes, availability of software platforms, and alternate delineations for home neighborhood locations, that we did not address in the present study. In addition, although accelerometers record continuously and generally are less prone to data loss (unless of course the participant forgets to wear the device), GPS data loggers are known to suffer from incomplete data due to factors such as cold starts and signal impedance from urban canyons or other obstructions. Therefore, GPS based bout linestrings may have shorter durations than the accelerometry-based bout if the GPS signal was lost at either end of the bout; this would result in less spatially referenced bout time than total bout time based solely on accelerometry data. Finally, our documentation of how to precisely allocate physical activity bouts within buffers can serve to reduce the risk of falling into the residential effect fallacy trap by insuring the accurate location of physical activity bouts with respect to the home neighborhood. Although beyond the scope of this paper, the buffer type (shape) and size options also acknowledge (but does not directly address) the UGCoP (Kwan, 2012).

Conclusions

The present study explored ways to spatially allocate accelerometer and GPS-based activity in a binary fashion, inside versus outside of a neighborhood location. We demonstrate different GIS-based approaches to buffering points of interest (typically home locations) and to stratifying activity bouts by type of containment within those buffers. Our focus on activity within and outside of a neighborhood is ostensibly aiming at built environment exposure near anchor locations, such as the home (i.e., features that are readily accessible in the proximal neighborhood) or workplace. GPS-based activity data, being continuous in space and time, have allowed research to move from place-based exposure to people-based exposure (Kwan, 2009). Buffering techniques continue to evolve by considering personal activity space (Kestens et al., 2012; Lee and Kwan, 2019; Zenk et al., 2011).

Analytically, the amount of walking in a neighborhood estimated from objectively measured data can vary substantially, not only due to buffer shape and size, but by how GPS-based bouts are allocated with respect to containment within the buffer. Based on the results of the present study, and consistent with Forsyth et al. (Forsyth et al., 2012b), we suggest using the sausage buffer for empirical studies that investigate associations between the neighborhood-built environment and physical activity in urban environments, with inclusion of the Euclidean buffer for comparison purposes. Clearly, buffer size must be described and justified, given that larger buffer sizes will always lead to more neighborhood-based physical activity than smaller buffer sizes. This is an important factor because one must consider how far people will travel to access different destinations using different transportation modes. Finally, it is critical to delineate what the spatial extent of “neighborhood” represents in any such study, given how different ways of measuring GPS based activity containment will result in different levels of physical activity across different buffer types and sizes.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Highlights

- Many studies do not clearly define and describe how “neighborhood-based” activity is measured.
- Neighborhood-based activity varies substantially by buffer shape, size, and neighborhood delineations.
- Delineations of spatially allocated accelerometer and GPS activity bouts are provided.
- Use of open-source GIS software and clear methods will increase replication across different studies.

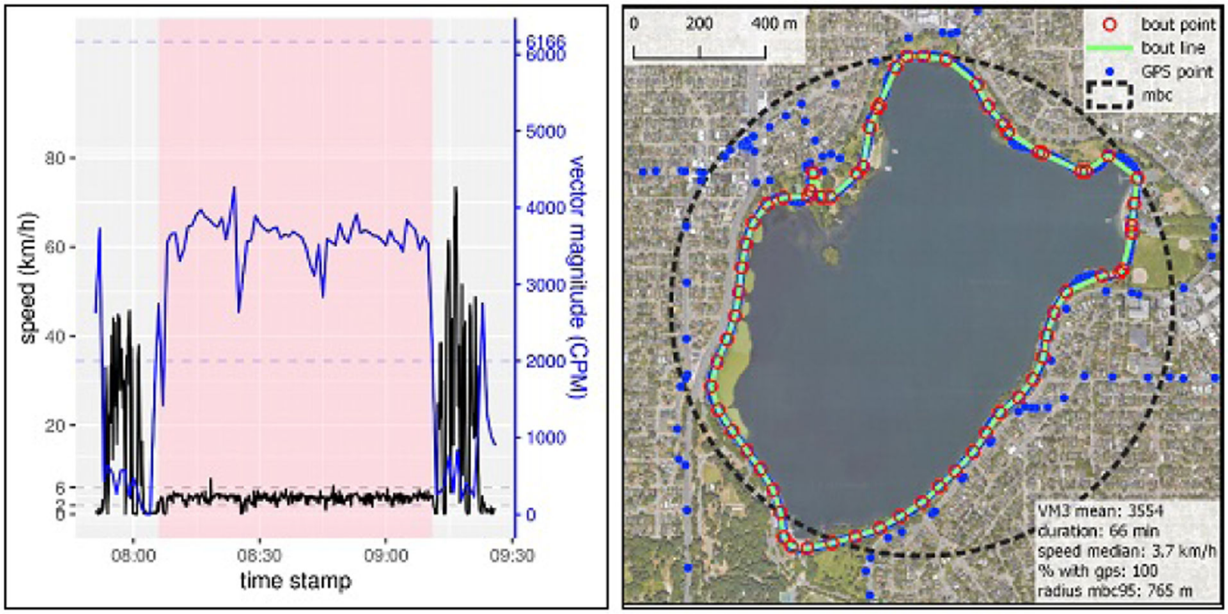

Figure 1.

Accelerometry profile for a walking bout, with bout interval shaded in pink (left panel); mapped GPS profile for the same walking bout (right panel).

"Bout points" are those GPS points that were measured during the walking bout.

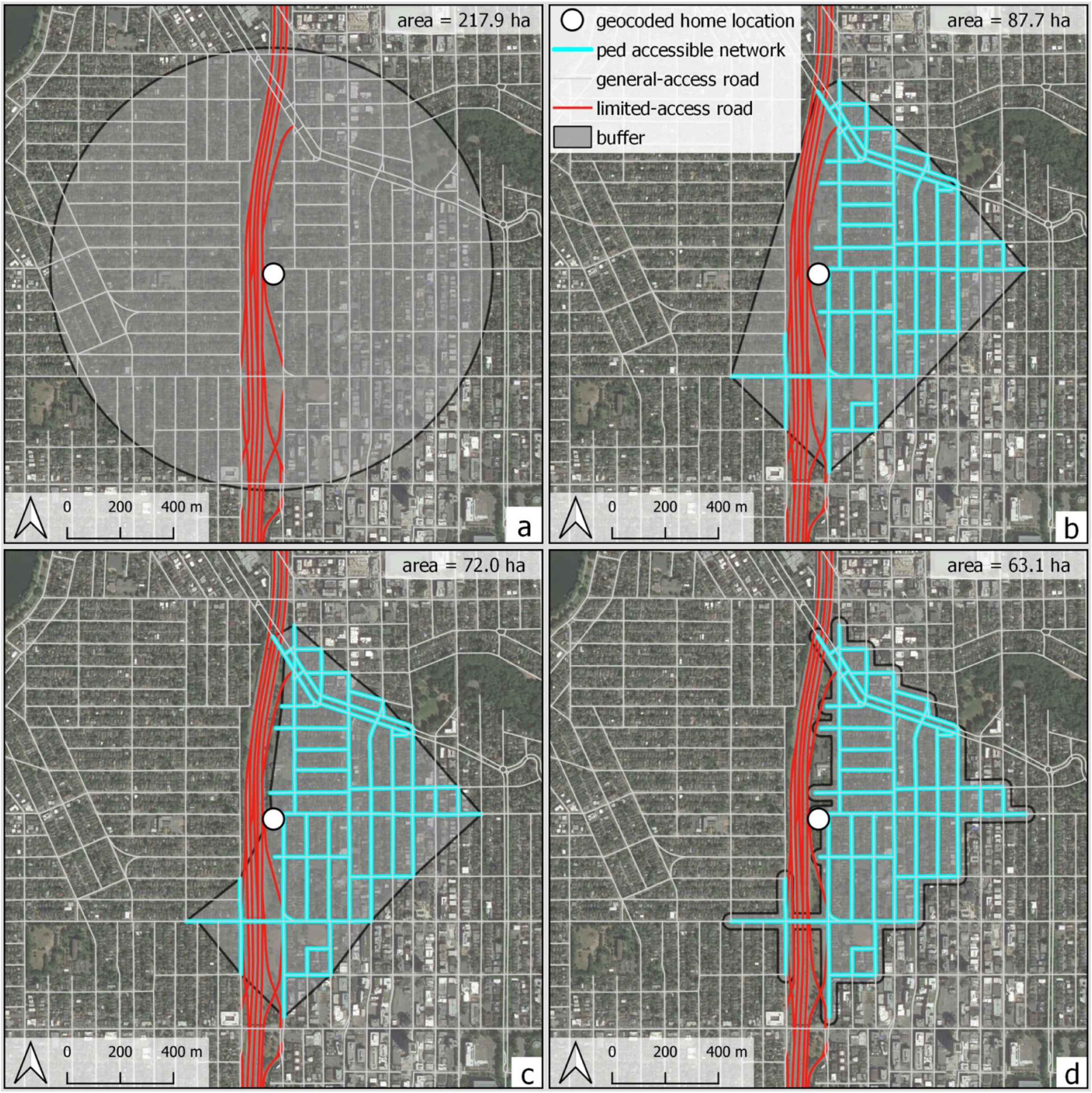

Figure 2.
Four approaches to delineating home neighborhood buffers.
Euclidean (a), convex hull (b), concave hull (c), sausage (d).
Unit ha = hectares.

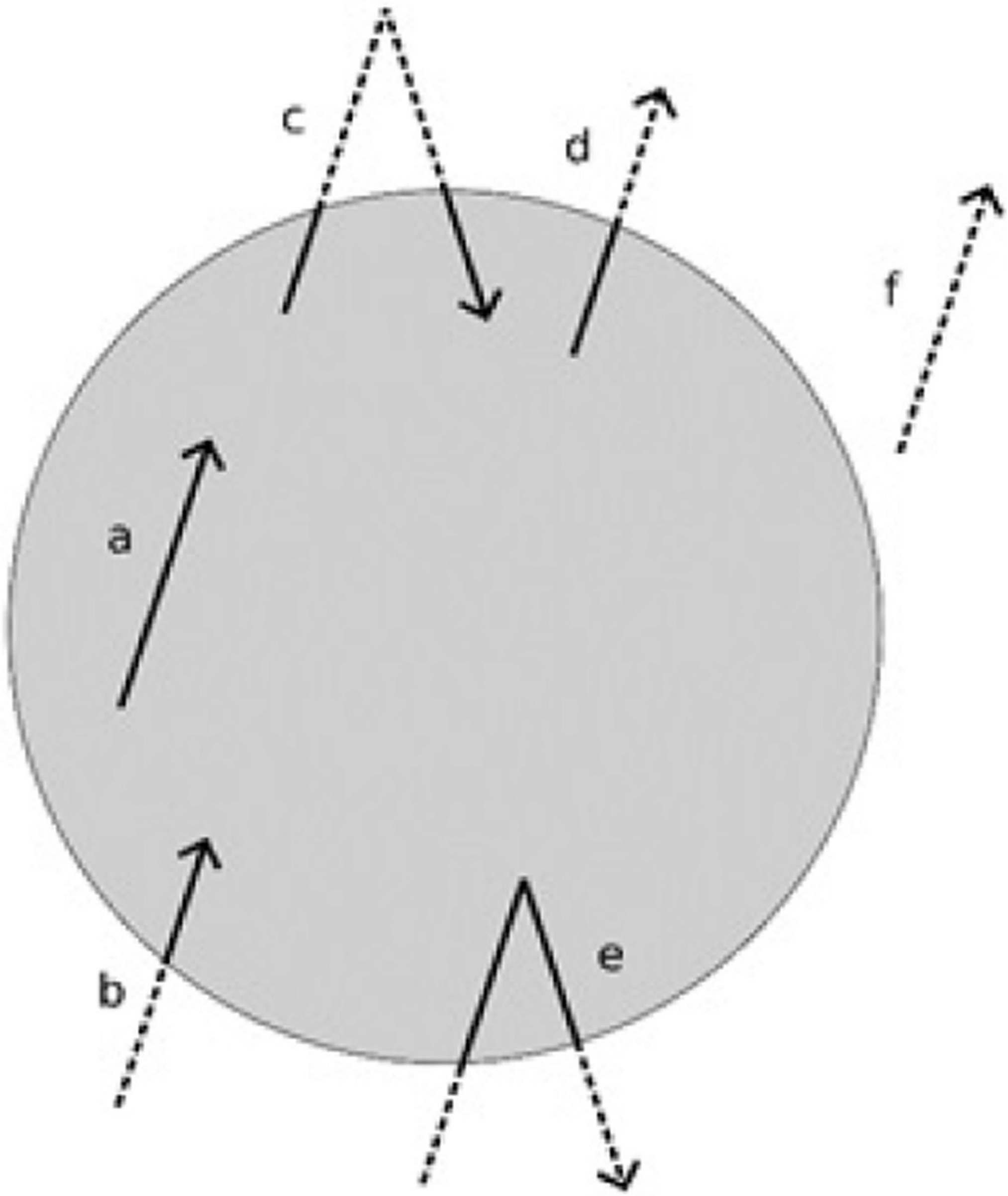

Figure 3.

Allocating bout level GPS linestring data to inside and outside home neighborhood locations.

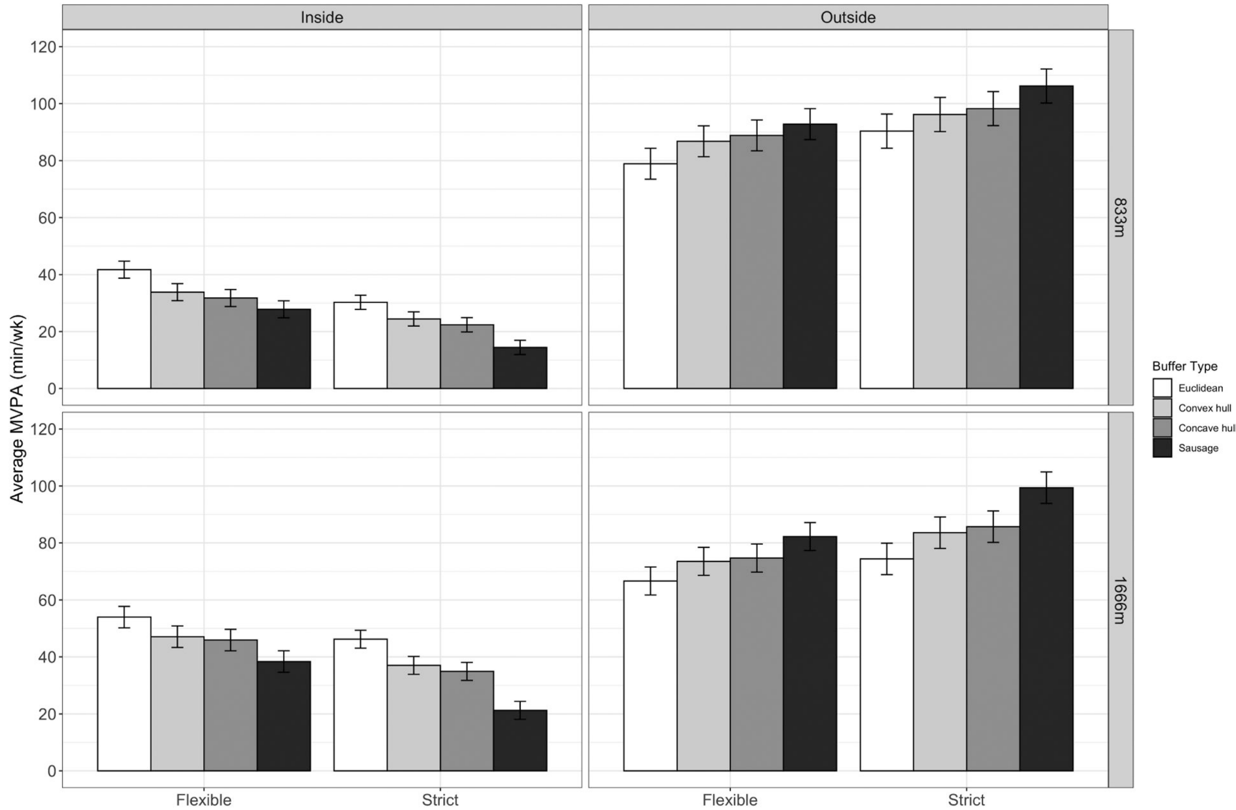

Figure 4.

Average moderate-to-vigorous physical activity (MVPA) (minutes per week) by buffer type, size, and location (inside and outside the home neighborhood).

Error bars denote standard errors.

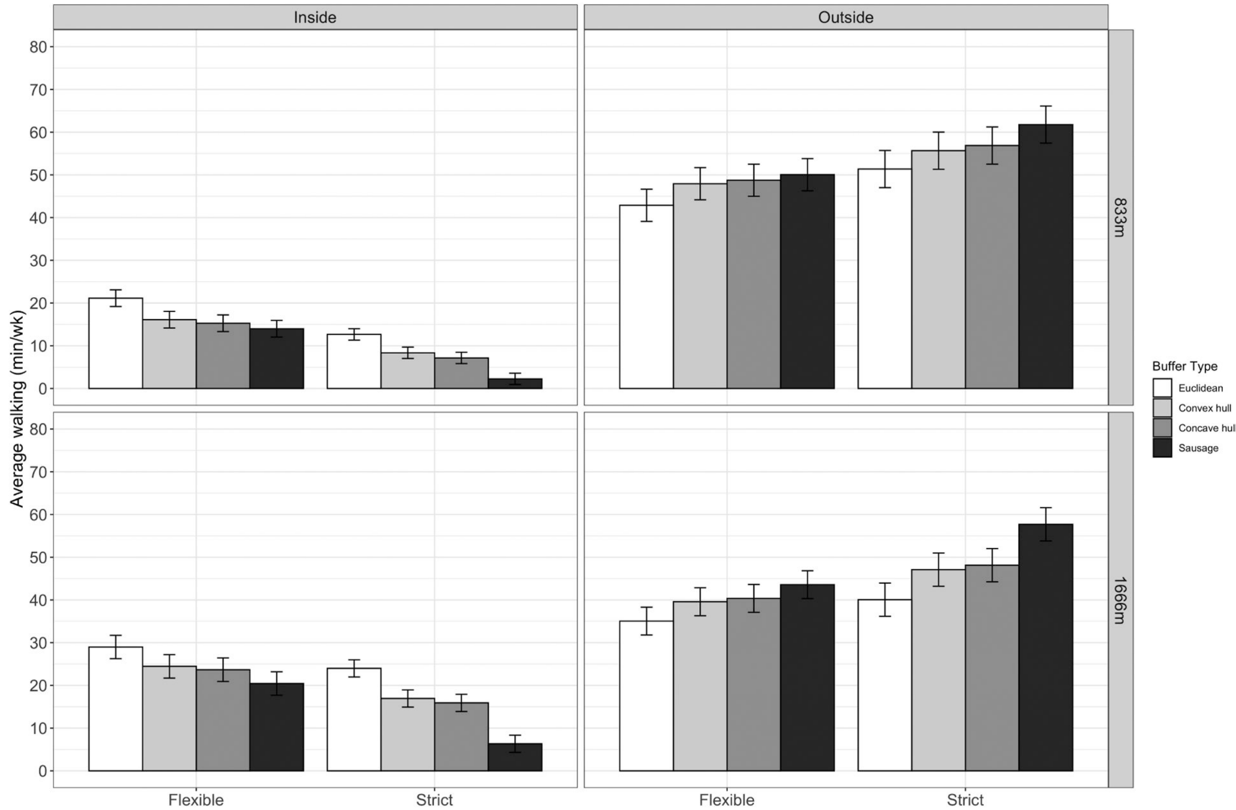

Figure 5.
Average walking (minutes per week) by buffer type, size, and location (inside and outside the home neighborhood).
Error bars denote standard errors.

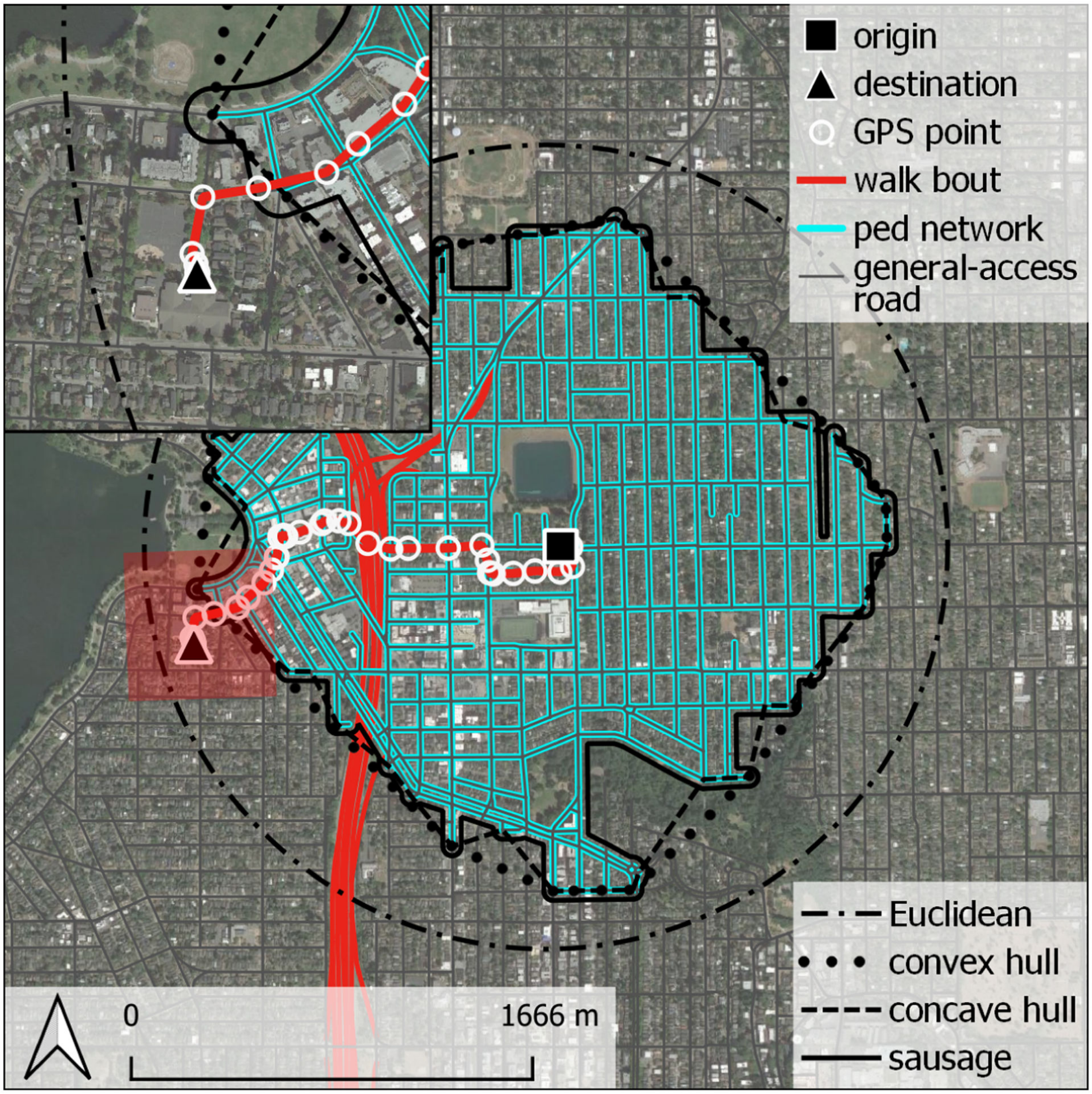

Figure 6.
Illustration of four buffer types (1,666 m distance) and flexible delineations of bout level linestring data to inside and outside home neighborhood locations.
Note that GPS points (white circles) are included for illustrative purposes only; the determination of physical activity inside the neighborhood location is based on linestring measures.

Table 1.

Differences in moderate-to-vigorous physical activity bouts (minutes per week) across the four buffer types, by size, delineation, and location.

Size	Delineation	Location	Predictor	Sum of Squares	*df*	Mean Square	*F*	*p*
833 m	Strict	Inside	Buffer type	165859.79	3	55286.60	21.92	<0.001
			Error	8110550.45	3216	2521.94		
		Outside	Buffer type	165861.58	3	55287.19	3.84	0.009
			Error	46264709.33	3216	14385.79		
	Flexible	Inside	Buffer type	97494.26	3	32498.09	9.04	<0.001
			Error	11558431.29	3216	3594.04		
		Outside	Buffer type	97495.65	3	32498.55	2.74	0.042
			Error	38157747.26	3216	11864.97		
1666 m	Strict	Inside	Buffer type	315879.81	3	105293.27	26.46	<0.001
			Error	12799106.41	3216	3979.82		
		Outside	Buffer type	315890.07	3	105296.69	8.60	<0.001
			Error	39375442.08	3216	12243.61		
	Flexible	Inside	Buffer type	111796.88	3	37265.63	6.49	<0.001
			Error	18474575.49	3216	5744.58		
		Outside	Buffer type	111802.65	3	37267.55	3.84	0.009
			Error	31227969.28	3216	9710.19		

Table 2.

Post hoc comparisons of the mean differences in moderate-to-vigorous physical activity bouts (minutes per week) by buffer type, size, delineation, and location.

Size	Delineation	Location	Comparison	Mean difference	*SE*	p_{tukey}
833	Strict	Inside	Convex hull - Concave hull	1.76	2.50	0.896
			Euclidean - Concave hull	9.09	2.50	0.002
			Concave hull - Sausage	10.97	2.50	<0.001
			Euclidean - Convex hull	7.34	2.50	0.018
			Convex hull - Sausage	12.72	2.50	<0.001
			Euclidean - Sausage	20.06	2.50	<0.001
833	Flexible	Inside	Convex hull - Concave hull	2.03	2.99	0.905
			Euclidean - Concave hull	10.31	2.99	0.003
			Concave hull - Sausage	4.94	2.99	0.349
			Euclidean - Convex hull	8.28	2.99	0.029
			Convex hull - Sausage	6.96	2.99	0.091
			Euclidean - Sausage	15.25	2.99	<0.001
1666	Strict	Inside	Convex hull - Concave hull	1.45	3.14	0.967
			Euclidean - Concave hull	10.74	3.14	0.004
			Concave hull - Sausage	16.73	3.14	<0.001
			Euclidean - Convex hull	9.29	3.14	0.017
			Convex hull - Sausage	18.19	3.14	<0.001
			Euclidean - Sausage	27.48	3.14	<0.001
1666	Strict	Outside	Concave hull - Convex hull	1.45	5.52	0.994
			Concave hull - Euclidean	10.74	5.52	0.208
			Sausage - Concave hull	16.73	5.52	0.013
			Convex hull - Euclidean	9.29	5.52	0.332
			Sausage - Convex hull	18.19	5.52	0.006
			Sausage - Euclidean	27.48	5.52	O.001
1666	Flexible	Inside	Convex hull - Concave hull	1.00	3.78	0.994
			Euclidean - Concave hull	8.07	3.78	0.142
			Concave hull - Sausage	8.54	3.78	0.108

Size	Delineation	Location	Comparison	Mean difference	*SE*	p_{tukey}
			Euclidean - Convex hull	7.07	3.78	0.241
			Convex hull - Sausage	9.53	3.78	0.057
			Euclidean - Sausage	16.60	3.78	<0.001

Table 3.

Differences in walking bouts (minutes per week) across the four buffer types, by size, delineation, and location.

Size	Delineation	Location	Predictor	Sum of Squares	*df*	Mean Square	*F*	*p*
833	Strict	Inside	Buffer type	62273.08	3	20757.69	29.23	<0.001
			Error	2283753.56	3216	710.12		
		Outside	Buffer type	62272.95	3	20757.65	2.73	0.043
			Error	24493851.75	3216	7616.25		
	Flexible	Inside	Buffer type	26312.03	3	8770.68	5.72	<0.001
			Error	4930509.86	3216	1533.12		
		Outside	Buffer type	26311.92	3	8770.64	1.54	0.202
			Error	18329246.65	3216	5699.49		
1666	Strict	Inside	Buffer type	162889.43	3	54296.48	33.60	<0.001
			Error	5197260.25	3216	1616.06		
		Outside	Buffer type	162891.07	3	54297.02	8.90	<0.001
			Error	19619394.55	3216	6100.56		
	Flexible	Inside	Buffer type	36616.94	3	12205.65	4.03	0.007
			Error	9742047.72	3216	3029.24		
		Outside	Buffer type	36617.62	3	12205.87	2.85	0.036
			Error	13796219.13	3216	4289.87		

Table 4.

Post hoc comparisons of the mean differences in walking bouts (minutes per week) by buffer type, size, delineation, and location.

Size	Delineation	Location	Comparison	Mean difference	*SE*	p_{tukey}
833	Strict	Inside	Convex hull - Concave hull	0.83	1.33	0.924
			Euclidean - Concave hull	5.82	1.33	<0.001
			Concave hull - Sausage	6.54	1.33	<0.001
			Euclidean - Convex hull	4.99	1.33	<0.001
			Convex hull - Sausage	7.37	1.33	<0.001
			Euclidean - Sausage	12.36	1.33	<0.001
833	Flexible	Inside	Convex hull - Concave hull	0.86	1.95	0.971
			Euclidean - Concave hull	5.96	1.95	0.012
			Concave hull - Sausage	1.71	1.95	0.817
			Euclidean - Convex hull	5.10	1.95	0.045
			Convex hull - Sausage	2.57	1.95	0.552
			Euclidean - Sausage	7.67	1.95	<0.001
1666	Strict	Inside	Convex hull - Concave hull	0.79	2.00	0.979
			Euclidean - Concave hull	8.09	2.00	<0.001
			Concave hull - Sausage	11.76	2.00	<0.001
			Euclidean - Convex hull	7.29	2.00	0.002
			Convex hull - Sausage	12.56	2.00	<0.001
			Euclidean - Sausage	19.85	2.00	<0.001
1666	Strict	Outside	Concave hull - Convex hull	0.79	3.89	0.997
			Concave hull - Euclidean	8.09	3.89	0.160
			Sausage - Concave hull	11.76	3.89	0.014
			Convex hull - Euclidean	7.29	3.89	0.240
			Sausage - Convex hull	12.56	3.89	0.007
			Sausage - Euclidean	19.85	3.89	<0.001