Accuracy of buffers and self-drawn neighbourhoods in representing adolescents GPS measured activity spaces: an exploratory study

Authors:

[1,2]Christensen, A., [1]Griffiths, C., [3]Hobbs, M., [2]Gorse, G., [1]Radley, D.

Affiliations:

[1]School of Sport, Carnegie, Leeds Beckett University, Leeds, LS6 3QT, UK

[2]School of Built Environment and Engineering, Carnegie, Leeds Beckett University, Leeds, LS6 3QT, UK

[3]GeoHealth Laboratory, Geospatial Research Institute, University of Canterbury, New Zealand.

Corresponding Author:

Alex Christensen
Alex.christensen@leedsbeckett.ac.uk
Leeds Beckett University, Fairfax Rm 230, Leeds, LS6 3QT, UK

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ABSTRACT

Background: There continues to be a lack of understanding as to the geographical area at which the environment exerts influence on behaviour and health. This exploratory study compares different potential methods of both researcher- and participant-defined definitions of neighbourhood reflect an adolescent's activity space.

Methods: Seven consecutive days of global positioning system (GPS) tracking data were collected at 15 second intervals using a small exploratory adolescent sample of 14–18 year olds (n=69) in West Yorkshire, England. A total of 304,581 GPS tracking points were collected and compared 30 different definitions of researcher-defined neighbourhoods including radial, network and ellipse buffers at 400m, 800m, 1000m, 1600m and 3000m, as well as participant-defined self-drawn neighbourhoods.

Results: This exploratory study supports emerging evidence cautioning against the use of static neighbourhood definitions for defining exposure. Traditional buffers (network and radial) capture at most 67% of activity space (home radial), and at worst they captured only 3.5% (school network) and range from capturing between 3-88% of total time. Similarly, self-drawn neighbourhoods captured only 10% of actual daily movement. Interestingly, 40% of an adolescent's self-drawn neighbourhood was not used. We also demonstrate that buffers capture a range of space (22-95%) where adolescents do not go, thus misclassifying the exposure.

Conclusion: Our exploratory findings demonstrate that neither researcher- nor participant-defined definition of neighbourhood adequately captures adolescent activity space. Further research with larger samples are needed to confirm the findings of this exploratory study.

Keywords: GIS, environment, perceived neighbourhoods

INTRODUCTION

The prevalence of children with obesity and the associated morbidities is an unparalleled public health concern (Agha and Agha, 2017); in 2016, 50 million girls and 74 million boys worldwide were obese (Abarca-Gómez et al., 2017). Along with the high prevalence of obesity, physical inactivity levels are also high among children and adolescents (Hallal et al., 2012). For psychological, sociological and physiological benefits (independent of obesity) including preventing and managing chronic conditions including: coronary heart disease, stroke, type 2 diabetes, cancer, mental health problems, and musculoskeletal conditions, children and adolescents should engage in 60 minutes of moderate-to-vigorous physical activity (MVPA) a day (Collins et al., 2012, Davies et al., 2011). However, many fail to meet this recommendation with over 80% of 13-15 years olds not achieving this guideline globally (Hallal et al., 2012).

While the causes of obesity and physical inactivity are multifaceted in aetiology, it is plausible that environmental influences such as the walkability of neighbourhoods or access to food may create or inhibit opportunities for healthy behaviours (Lakerveld and Mackenbach, 2017). Environmental influences on behaviour have gained increasing attention in both research and policy (Belon et al., 2014, Saelens, 2008). However, associations between environmental influences such as the availability of food outlets and dietary behaviours or green spaces and physical activity remain ambiguous in both adults and children (Wilkins et al., 2019, Bauman et al., 2012, Ding, 2012, Mackenbach, 2014). Inconsistent evidence has been attributed to, in part, methodological factors, including the variety of neighbourhood definitions that are used to estimate the area of geography which defines an individual's exposure to an environment (Kerr et al., 2013, Ding, 2012, Bauman et al., 2012).

The uncertain geographic context problem, defined as the spatial uncertainty in the actual area that exerts the contextual influences under study, is a persistent limitation in this area of research (Kwan, 2012). This uncertainty refers to the lack of understanding of the true causally relevant area at which the environment exerts influence on behaviour and health (James et al., 2014). Furthermore, the appropriate spatial context may depend on the relationship between the specific environmental factor and the specific health outcome. Research often relies on static definitions of neighbourhood such as administrative areas or predetermined buffers around a fixed point, often only the home location of an individual (Feng, 2010, Leal, 2011). A recent review (Wilkins et al., 2019) highlighted the high usage of static neighbourhood definitions within publications, showing that administrative boundaries and buffer metrics were used 242 times across the 113 studies. While administrative boundaries are critiqued for being too large and heterogeneous, buffers are commonly justified by suggesting they are a typical walkable or drivable distance (Almanza, 2012, James et al., 2014, Learnihan et al., 2011), however several distances between 100-4800 metres around the residence are used, due to lack of consensus on an appropriate distance (Crawford et al., 2014, Duncan, 2015, Frank, 2007, Laraia and Ammerman, 2007, Leal, 2011). Static measures have been continually critiqued as they do not account for individual behaviour and do not necessarily represent the area a person interacts with and could therefore underestimate the impact the environment has on health behaviour (Kwan, 2012, Cummins, 2007, Perchoux, 2013, Spielman and Yoo, 2009).

There are limited solutions to this problem as appropriate data, for instance on where people typically purchase foods or are physically active, to inform such measures are scarce (Thornton et al., 2017). Evidence has shown that food purchasing behaviours or physical activity occurs beyond the boundaries of the static residential neighbourhood (Zhao et al., 2018, Kwan et al., 2019). For example, within adults (n=56), Australian evidence shows that many food purchases (n=952) occur outside what is traditionally considered the residential neighbourhood food environment, with purchases occurring a median of 3.6km from participants' homes (Thornton et al., 2017). While many studies often include objective measures of health outcomes, there is often less emphasis on accurately capturing actual exposure to the environment (Perchoux, 2013, Kwan, 2012). Current research suggests that individualised measures of the environment, such as using GPS, could lead to different and a more accurate understanding of environmental exposure (Chaix, 2013, Perchoux, 2013). Improving upon previous methods, to understand the geographical area at which the environment exerts influence on behaviour and health, will help improve evidential consistency (Hobbs and Atlas, 2019, Hobbs and McKenna, 2019).

Research has attempted to solve the uncertain geographic context problem by using activity spaces, which represents an individual measure of spatial behaviour by determining all locations an individual has direct contact with as a result of their day-to-day activities (Perchoux, 2013, Golledge and Stimson, 1997). However, activity space has also been represented in several ways including standard deviation ellipse (Zenk et al., 2011), minimum convex polygon (Villanueva et al., 2012), daily path (Zenk et al., 2011), and kernel density estimation (Jankowska et al., 2015). There is currently no consensus on the best method to use in determining activity space. It remains unclear what the most appropriate spatial context is for understanding the relationship between the environment and health (Kwan et al., 2019, James et al., 2014). To improve our understanding of how health interacts with place, we compared the use of radial, network, self-drawn and ellipse buffers in an adolescent population. Although research has begun to assess the use of buffers within both adult (Holliday et al., 2017) and older adult (Laatikainen et al., 2018) populations, it is likely adolescents use and interact with their environment differently (Villanueva et al., 2012). This exploratory study aims to compare different potential methods of researcher- and participant-defined neighbourhoods, used in environmental health research, reflect an adolescent's actual activity space.

METHODS

PARTICIPANTS, SETTINGS AND PROTOCOL

Adolescents aged 14-18 years were recruited from secondary schools and colleges in West Yorkshire, England. Recruitment took place between May 2017 and March 2018; students were informed about the study during school assemblies or during class time. Students who expressed an interest to take part were asked to attend a short meeting to receive details on the project. Sixty-nine participants (24 male, 45 female) provided consent/assent to participate in the study. Data collection occurred in two waves, autumn (September/October 2017) and spring (March/April 2018). Individual demographics data on age, gender, postcode, and ethnicity (amalgamated into White British and all other ethnic groups due to small sample sizes in other ethnic groups) were collected using an online questionnaire developed in Qualtrics (Qualtrics, Provo, USA). Institutional approval was received from Leeds Beckett Research Ethics Committee.

DAILY MOVEMENT

To objectively collect individual's daily movement, participants either wore a GPS device (Garmin Forerunner 401) (n=39) or ran a proprietary GPS smartphone application (Tracker) (n=30) for seven consecutive days, collecting data over 15 second epochs (Jankowska et al., 2015). Participants were instructed to wear the GPS device during all waking hours, except if they were participating in a water activity (i.e. swimming or bathing). GPS data were visually inspected and cleaned to ensure that any data outside of the study period were removed. Furthermore, data were separated by days, using time stamps, and total daily wear time was calculated. Using a similar approach to Quigg (2010), upon inspection of participants' GPS wear time, prior to data analysis, but after data collection, it was decided a 5 hour wear time criteria, which includes a trip from home to school, would be used in this study; this maximised data inclusion, but additionally provided a cut-off for insufficient compliance. Less than five hours was considered insufficient compliance and was therefore excluded. Data adhering to the wear time criteria was uploaded and visually inspected within ArcGIS (v. 10.6.1) to ensure the data was of good quality (i.e. logical GPS path, data within the study area, etc).

RESEARCHER- AND PARTICIPANT-DEFINED NEIGHBOURHOODS

Radial, network and ellipse buffers

Within ArcGIS (v. 10.6.1), 30 types of buffers were created, centred around the home (based on postcode) and school of each participant. Radial and street network buffers, as well as two novel types of buffers, a straight line ellipse (SLE) and network line ellipse (NLE) were created at five buffer sizes (400m, 800m, 1km, 1.6km, 3km). Straight line and road network paths (based on the shortest network route) between the home and school were used to create ellipse buffers. Table 1 provides examples of each buffer type for clarity.

Activity space

Activity space has been represented in several ways in previous research. This includes using a minimum convex polygon (Villanueva et al., 2012), standard deviation ellipse (Sherman et al., 2005), daily path (Zenk et al., 2011), and kernel density estimation (Jankowska et al., 2015). Table 1 describes these methods and provides strengths and weaknesses of each. There is currently no consensus on the best method or approach to use in determining activity space.

Table 1. Activity Space methods used in research

Activity Space Method	Description	Strengths	Weaknesses
Minimum Convex Polygon	A polygon area that contains all GPS points (Rundle et al., 2016). It is an area-based geometry tool used to describe the geographic extent of an individual's daily activity pattern (Villanueva et al., 2012).	-Contains all GPS points -Captures space: can analyse by what is in the polygon, i.e. built environment traits within polygon	-Does not provide information about the frequency in which different parts of the area were used (Rundle et al., 2016). Also includes vast amount of space not used/accessed by the individual.
Standard Deviation Ellipse	Covers approximately 68% of all GPS points and is centred on the mean centre of the point pattern. Its long axis is in the direction of maximum dispersion, its short axis is in the direction of minimum dispersion (Zenk et al., 2011).	-Captures main GPS orientation - Captures a space: can analyse by what is in the ellipse, i.e. built environment traits within ellipse	-May exclude some physical activity locations -Abstract representation of where people go (Sherman et al., 2005)
Daily Path Area	Buffers all GPS points into a single line or space. Buffer zone around path can be determined (i.e. 0.2 km, 0.5 km) to determine what is in	-Captures immediate vicinity around activity locations and travel routes (Zenk et al., 2011)	-Does not provide information about frequency in which different parts of the area were used (Rundle et al., 2016)

	immediate vicinity around the path (Zenk et al., 2011).	-Missing GPS data less of a concern	
Kernel Density Estimation	Smooths GPS points into a continuous surface and accounts for time element of an individual's behaviour, which results in greater exposure weight (Jankowska et al., 2015).	-Gives an element of distance decay rather than specific distance cut offs (Jankowska et al., 2015) -Weighted function provides a more realistic model of environmental exposure (Jankowska et al., 2015)	-Missing GPS data points may affect weighting

Creating a daily path for individuals was determined to be the most appropriate method for this research as it would allow a more accurate representation of an individual's daily movement without over or underestimating the space an individual used, as seen with using a minimum convex polygon or standard deviation ellipse. GPS points were converted into a line, using ArcMap's point to line tool. This allowed for visualisation of the daily path for each participant. Next, a 100 metre buffer was created around the daily path to create activity space (AS) (see Table 1 for example). One hundred metres was used to account for potential GPS errors (Paek et al., 2010, Donaire-Gonzalez et al., 2016). AS size was determined by calculating the area the 100 metre buffer covered and was reported in square kilometres (km^2) (Lee et al., 2016).

Self-drawn neighbourhoods

Participants were given instructions to complete a self-drawn neighbourhood (SDN) activity within Google My Maps. Participants entered their postcode and were asked to "*create a boundary of what you consider as your neighbourhood on the map*". This was left open for interpretation for the participant as to what 'neighbourhood' meant to them in order to provide a richer qualitative understanding of what adolescents perceive a neighbourhood to be. Participants' SDN were downloaded from Google My Maps and converted to a feature in ArcMap, allowing for visualisation and comparison (see Table 2 for example). SDNs size were than calculated by determining the area the SDN covered in square kilometres (km^2).

187 **Table 2**. Definitions of key terms

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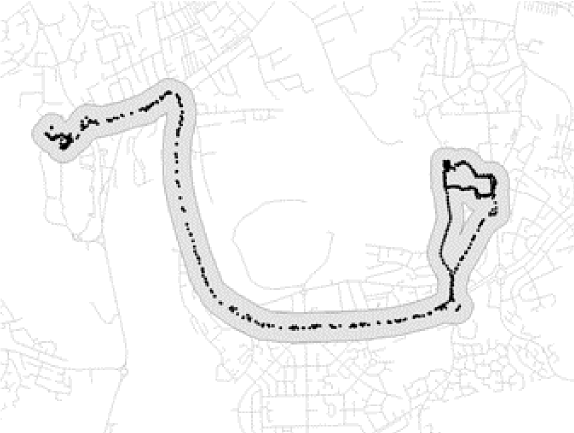
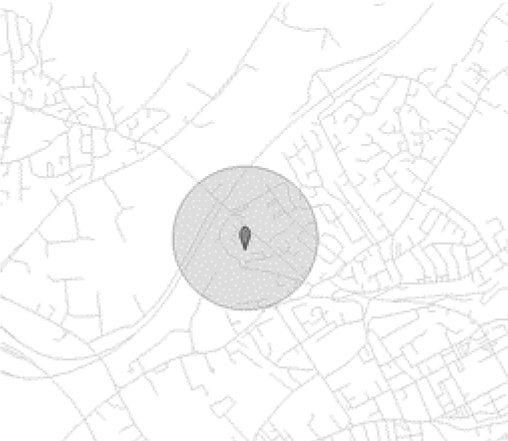
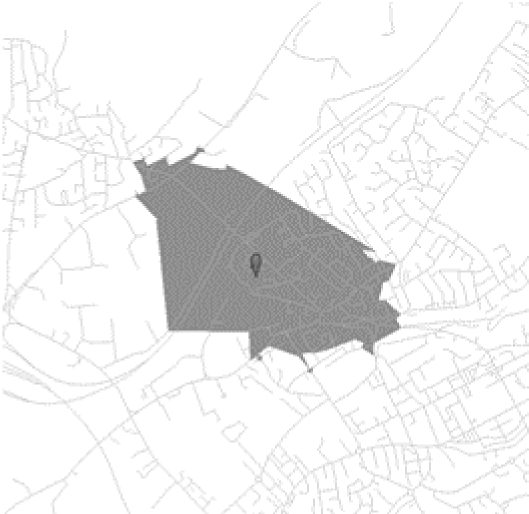
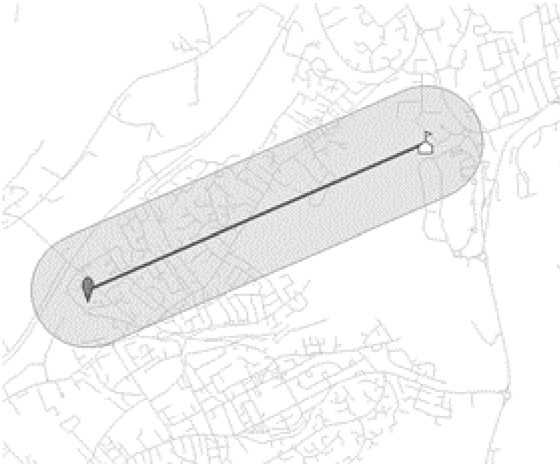
Term	Definition	Example
Activity Space (AS)	GPS data of everywhere an individual goes over the seven-day data collection period. 100 metre buffer around daily path Reflects an individual's mobility.	
Self-drawn Neighbourhoods (SDN)	Participants' self-drawn neighbourhoods, created through Google My Maps	
Radial Buffer	A circular buffer around the home or school	

Network Buffer	A buffer based on street distance around the home or school	
Straight Line Ellipse	A straight line drawn from home to school, buffered at various distances	
Network Line Ellipse	Shortest street network route from home to school, buffered at various distances	

ANALYSIS

Each buffer was compared to determine how they reflect AS. Within ArcGIS, the tabulate intersection tool was used to calculate the area and percentage of intersecting features (e.g.

the percentage of AS within the buffer). The percentage of AS within all buffer types and sizes, were calculated (Figure 1a). Additionally, the percentage of the unused buffer space was also determined in order to determine extraneous captured space (Figure 1b). Similarly, using the tabulate intersection tool, AS was compared to SDNs to determine how much AS was within SDN, and the amount of unused SDN.

All buffers were also used to assess the amount of time that was spent within the buffers. This weights results, as it takes into account time spent at locations, rather than with activity space which just assess space accessed. Similarly to above, the count of GPS points within all buffers was determined by multiplying the number of points by length of epoch (i.e. 30 GPS points x 15 sec epoch= 450 seconds/60= 7.5 minutes). This provided the total amount of minutes spent in within each buffer. The average percent of time (i.e. based on individuals total time (mins) within each buffer divided by total time (mins)) captured by the various buffer types and sizes was then determined.

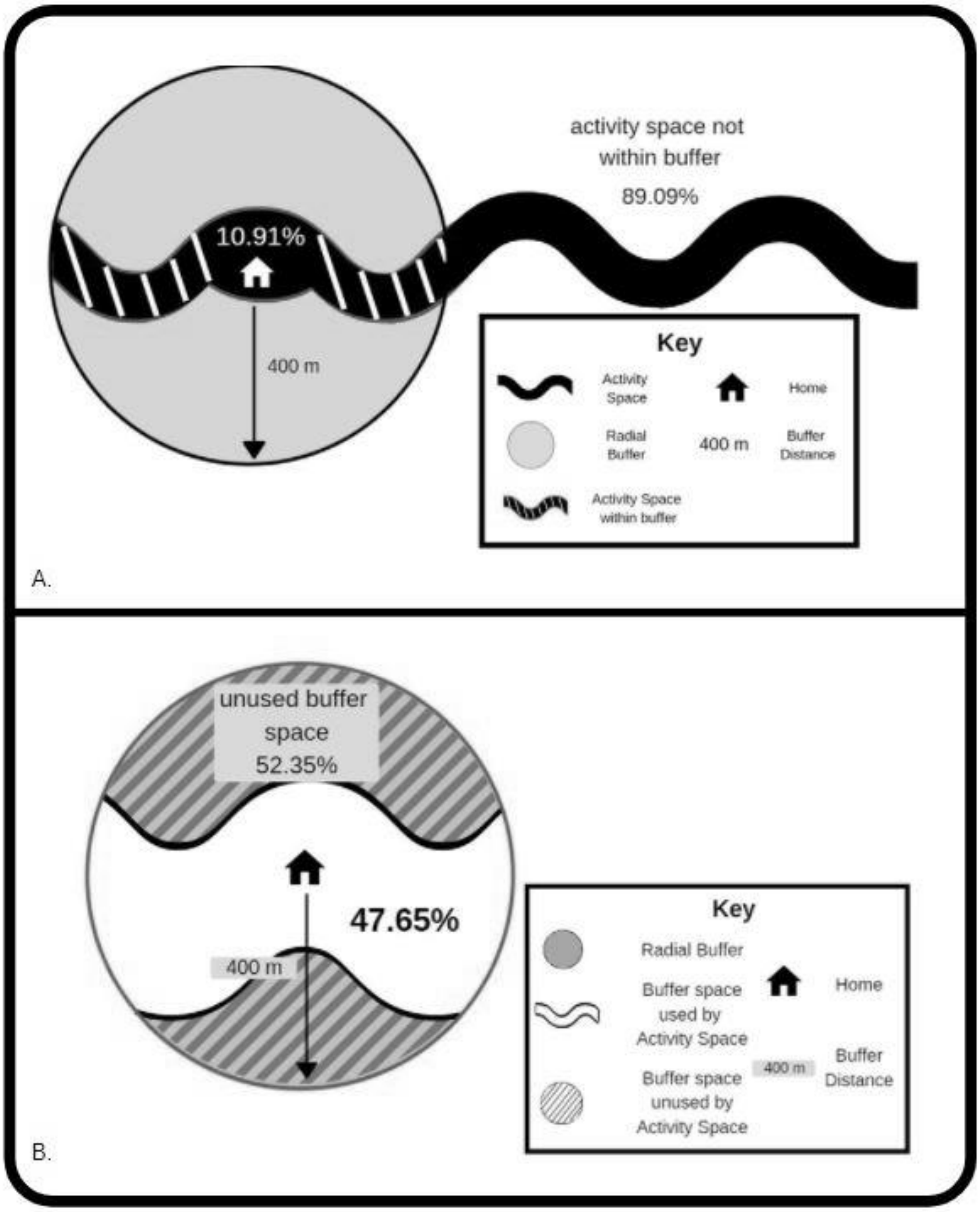


Figure 1. Panel A: A Diagram depicting 10.91% of activity space within 400 m home radial buffer compared to 89.09% of activity space occurring outside of buffer radius. Panel B: Diagram depicting 47.65% of 400 m home radial buffer is used by activity space, 52.35% of buffer space is not used by activity space

RESULTS

DESCRIPTIVE STATISTICS

This study had a relatively high participant burden and asked participants to complete multiple tasks and comply over a weeklong time period, resulting in only 44 participants providing GPS data. This loss to follow-up is likely due to low compliance (e.g. not turning GPS device on or logging into the GPS app). Additionally, four participants were excluded (2 participants only had weekend days available, 1 participant only had data at the home and school, and 1 participant had continuous large gaps in data that made daily path illogical/not feasible/accurate (see Supplemental Figure 1 and 2 for example). Therefore, 40 participants were included in the final sample. Participants averaged 3.36 days meeting the inclusion criteria, averaging 10.46 hours of wear time per day. Thirty-three participants had both completed SDNs and AS. Study sample characteristics are provided in Table 3.

Table 3. Study sample characteristics

Characteristic	Frequency
Gender	
Female	26 (65.0)
Male	14 (35.0)
Age[1]	16.12±1.20
Ethnicity	
White British	31 (77.5)
All other ethnic backgrounds	9 (22.5)
Area Level Deprivation	
1 (most deprived)	11 (27.5)
2	10 (25.0)
3	4 (10.0)
4	9 (22.5)
5 (least deprived)	6 (15.0)
Activity Space Size[1] (km^2) (n=40)	6.99±7.72
Self-Drawn Neighbourhood Size[1] (km^2) (n=33)	2.70±7.53

Data are presented as n (%) unless stated otherwise. [1]Mean ±SD

The average size of each buffer type and buffer size are reported in Table 4.

Table 4. Mean spatial coverage by buffer type and distance

Buffer Distance	Buffer Type Radial	 Home (Network)	 School (Network)	 Ellipse (Straight Line)	 Ellipse (Network Line)
400 m	0.50	0.13 (0.06, 0.22)	0.11 (0.09, 0.18)	3.48 (1.05, 7.13)	3.98 (0.42, 8.44)
800 m	2.01	0.64 (0.26, 1.01)	0.59 (0.55, 0.84)	7.7 (1.21, 15.27)	8.93 (1.42, 17.73)
1 km	3.14	1.06 (0.52, 1.67)	1.02 (0.98, 1.28)	10.60 (4.51, 19.71)	12.11 (4.77, 22.74)
1.6 km (1 mile)	8.04	3.12 (1.69, 4.71)	3.15 (3.10, 3.46)	19.97 (10.23, 34.55)	22.15 (10.63, 39.23)
3 km	28.27	12.99 (8.64, 17.58)	12.77 (12.54, 14.08)	50.62 (32.36, 77.96)	54.15 (33.09, 86.03)

Results are presented as km^2. Mean value (min, max)

CAPTURED ACTIVITY SPACE

The percentage of AS within the radial, network and ellipse buffers around the home and school are presented in Table 5. Results demonstrate that network buffers captured notably less activity space than the radial and ellipse buffers when compared to the other types of buffers at equivalent distances. For example, at a 400m distance, network buffers encompassed 3-5% of AS, while radial buffers captured 10-11% and ellipse buffers captured 36-47%. Radial buffers contained more AS than network buffers around both the home and school, however, even at 3 kilometres, radial buffers captured less than two-thirds of AS (3 km home radial 65.14%, 3 km school radial 62.25% of AS). Overall, ellipse buffers encompassed notably more AS than network and radial buffers, at all distances, with 3 kilometre ellipse buffers capturing 87% of AS.

Table 5. Percentage of activity space within the radial, network and ellipse buffers (400m, 800m, 1km, 1.6km and 3km) around the home and school

Buffer Distance	Buffer Type Home (Radial)	 Home (Network)	 School (Radial)	 School (Network)	 Ellipse (Straight Line)	 Ellipse (Network Line)
400 m	10.91 (1.74, 38.03)	4.79 (0.51, 24.56)	11.25 (1.46, 58.51)	3.53 (0.42, 14.71)	36.44 (7.54, 96.67)	47.17 (11.32, 99.49)
800 m	21.3 (4.56, 84.19)	12.62 (2.65, 39.23)	23.06 (2.04, 7.58)	13.41 (1.58, 59.73)	55.49 (18.14, 100)	60.09 (18.08, 100)

1 km	26.71 (5.89, 98.43	16.62 (4.01, 50.90)	27.36 (3.19, 100)	18.41 (2.31, 78.92)	62.21 (19.3, 100)	64.88 (19.25, 100)
1.6 km (1 mile)	40.43 (9.98, 100)	28.41 (7.55, 92.55)	38.74 (5.48, 100)	29.24 (3.91, 100)	75.28 (23.00, 100)	75.82 (22.94, 100)
3 km	65.14 (18.8, 100)	50.08 (16.39, 100)	62.25 (10.05, 100)	48.32 (7.93, 100)	87.18 (31.66, 100)	87.98 (31.61, 100)

Mean value (minimum value, maximum value)

UNUSED BUFFER SPACE

The percentage of each buffer that was unused is reported (Table 6). All types of 400m buffers had the least amount of unused space, while 3km buffers had the greatest amount of unused space. For example, a 400m home radial buffer had 52.45% of unused space, while at 3 kilometres had 93.88% of unused space. Network buffers, when compared to the other types of buffers at equivalent buffer distances, had the least amount of unused space at all distances, however at a 3km, more than 89% of the buffer was unused. Ellipse buffers had the greatest amount of unused space, with a 400m buffer distance having 70% of unused buffer space.

Table 6. Percentage of unused space buffers captured for radial, network and ellipse buffers (400m, 800m, 1km, 1.6km and 3km)

	Buffer Type					
Buffer Distance	Home (Radial)	Home (Network)	School (Radial)	School (Network)	Ellipse (Straight Line)	Ellipse (Network Line)
400 m	52.35 (12.46, 78.1)	21.78 (0, 81.81)	57.72 (20.46, 80.68)	34.07 (0, 96.09)	70.97 (36.81, 92.56)	70.54 (39.27, 94.38)
800 m	75.50 (51.31, 89.67)	51.50 (16.41, 84.15)	78.40 (41.28, 90.92)	55.63 (7.29, 82.29)	80.92 (46.92, 93.71)	82.37 (59.40, 95.27)
1 km	79.95 (58.78, 91.49)	60.73 (23.71, 89.63)	83.11 (52.65, 92.42)	64.81 (12.74, 85.40)	83.88 (57.46, 94.46)	85.31 (66.53, 95.84)
1.6 km (1 mile)	87.30 (60.52, 95.06)	77.10 (40.97, 95.99)	89.51 (69.97, 95.16)	81.06 (21.08, 97.69)	89.22 (67.34, 95.67)	90.29 (72.21, 97.87)
3 km	93.78 (81.39, 98.43)	89.30 (64.26, 96.58)	94.38 (81.39, 98.43)	91.17 (74.1, 96.47)	94.76 (83.13, 98.63)	95.00 (84.51, 98.68)

Mean value (minimum value, maximum value)

COMPARISON OF BUFFERS

To compare each buffer, the percentage of AS captured within each buffer was plotted against the amount of unused space captured (Figure 2). The upper left quadrant on the figure would demonstrate the ideal buffer (high amount of activity space within the buffer, and low amount of unused space) whereas the lower right quadrant would represent an unsuitable buffer (low amount of activity space within the buffer, and high amount of unused space).

Figure 2 shows a positive trend where, as buffer size increases, the amount of space within increases and the amount of unused space also increases. Additionally, no buffer falls within the upper left quadrant, meaning that all buffers either demonstrate a low amount of space captured by the buffer, have a high amount of unused space, or both. Ellipse buffers at 800 metres and greater, and 3 km home and school radial buffers captured the most AS, but had the highest amount of unused space, meaning they fall within the upper right quadrant of the scatter plot. Home and school 400 metre network buffers were the only buffers within the lower left quadrant, meaning they had low amounts of AS within the buffer and low amounts of unused buffer space. All other buffers fell within the lower right quadrant, with moderate to high amounts of AS within the buffer and moderate to high amounts of unused buffer space. Overall, when considering both space within buffers and unused buffer space, no buffer was the ideal at capturing activity space.

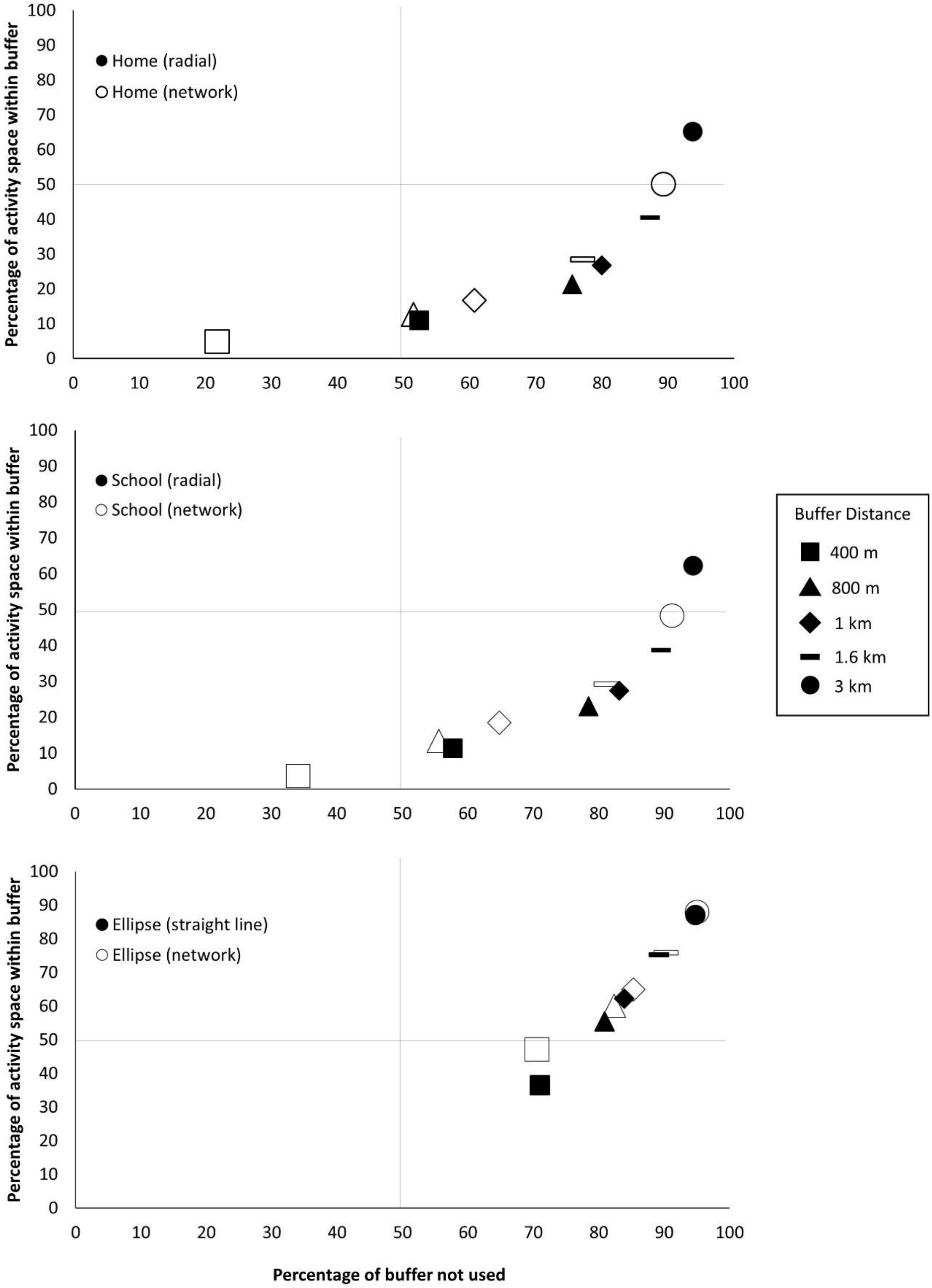


Figure 2. Comparison of buffers in capturing activity space and unused space.

PERCENTAGE OF GPS TIME

Table 7 reports the average percent of time captured by various buffer types and sizes. Results demonstrate that school buffers captured notably less time than the home and ellipse buffers when compared to the other types of buffers at equivalent distances. For example, at a 400m distance, school buffers encompassed 3-8% of time, while home buffers captured 70-76% and ellipse buffers captured 87%. Radial buffers contained more time than network buffers around both the home and school. Overall, ellipse buffers encompassed notably more time than network and radial buffers, at all distances, with 3 kilometre ellipse buffers capturing 96% of time.

Table 7. Percentage of GPS time buffers captured for radial, network and ellipse buffers (400m, 800m, 1km, 1.6km and 3km)

	Buffer Type					
Buffer Distance	Home (Radial)	Home (Network)	School (Radial)	School (Network)	Ellipse (Straight Line)	Ellipse (Network Line)
400 m	76.89 (19.37, 99.10)	70.46 (0, 96.64)	8.70 (0.18, 42.93)	3.05 (0.06, 42.82)	87.22 (26.93, 100)	87.72 (26.71, 100)
800 m	78.74 (22.22, 99.83)	76.41 (3.88, 99.15)	12.30 (0.25, 100)	7.62 (0.25, 43.06)	90.57 (29.03, 100)	90.08 (29.34, 100)
1 km	81.02 (22.64, 100)	78.37 (21.98, 99.29)	20.19 (2.95, 100)	13.25 (0.25, 92.91)	91.78 (29.77, 100)	91.69 (29.78, 100)
1.6 km (1 mile)	83.43 (27.28, 100)	79.50 (24.19, 99.88)	31.20 (1.86, 100)	21.40 (0.49, 100)	93.39 (32.52, 100)	93.62 (32.52, 100)
3 km	88.18 (36.23, 100)	84.72 (29.07, 100)	53.34 (2.68, 100)	39.65 (2.01, 100)	96.49 (74.78, 100)	96.71 (75.93, 100)

Mean value (minimum value, maximum value)

ACTIVITY SPACE AND SELF-DRAWN NEIGHBOURHOODS

The percent of AS within SDN and the amount of unused SDN was determined (Table 8). Self-drawn neighbourhoods on average captured 9.36% of activity spaces and 38.84% of self-drawn neighbourhoods were unused. This suggests approximately 40% of perceived environmental boundaries aren't accessed through daily movement (i.e. 40% of what participants drew for their environment, had no activity space).

Table 8. Amount of activity space within self-drawn neighbourhoods and amount of self-drawn neighbourhoods within activity space

Activity space within self-drawn neighbourhoods	Unused Self-drawn neighbourhood space
9.36 (0.50, 39.03)	38.84 (0, 84.73)

Mean value (minimum value, maximum value)

DISCUSSION

The most appropriate spatial context remains unclear for understanding the relationship between the environment, behaviour and health outcomes (Mavoa et al., 2019, James et al., 2014). Despite significant discussion and commentary, empirical evidence rarely considers the spatiotemporal dynamics of individual daily exposure, with noticeably little evidence in adolescence. To help this void, this exploratory study in a small sample of adolescents compared different potential methods of researcher- and participant-defined classifications of neighbourhood reflect an adolescent's actual activity space as measured by GPS.

This exploratory study provides evidence cautioning against the use of static neighbourhood definitions such as radial or network buffers and supports previous evidence which has suggested that static neighbourhood definitions do not fully represent the area a person interacts with (Kwan, 2012). In a small sample of adolescents, we highlight large variability in activity space and time captured. This finding is supported by previous research comparing GPS data to static measures (Holliday et al., 2017, Laatikainen et al., 2018). Adolescent females for instance, spend one-third of their awake time more than 1 km away from the home (Wiehe et al., 2008) while in older adults, only 35% of activity space was within 500 metres of the home (Laatikainen et al., 2018). This supports other evidence which has suggested a need within the field to move away from buffers to more dynamic definitions of exposure - without more dynamic definitions, the impact of the environment on behaviour will continue to be inaccurate (Hillsdon et al., 2015, Zhao et al., 2018). Furthermore, our study of adolescents demonstrates that accounting for both the home and school by using ellipse buffers, captured notably more adolescent's activity space than radial or network buffers. For instance, at 400 metres an ellipse buffer captured, at worst 36% of activity space but at 3 kilometres averaged 87% of activity space. This is in line with past research that highlight how researchers fall into the "residential trap" by ignoring non-residential locations and ignoring the fact that people live and spatially relate to multiple points, and thus misrepresent true environmental exposure

(Kestens et al., 2012, Perchoux, 2013, Cummins, 2007). Researchers need to be aware of, and acknowledge the significant limitations of only using the home location. Future research should consider accounting for multiple exposures, such as home and school or home and workplace, as this may have potential to improve the amount of actual behaviour captured and allow a better understanding of the relationship between environments and health outcomes.

While research continually comments on how buffer methods are too heterogeneous and are poor proxies for capturing behaviours, the fact that they encompass large amount of unused space is often ignored. Interestingly, although ellipse buffers encompassed the most space, they had notably higher amounts of unused space. Alternatively, network buffers, which had the lowest amount of space within, had the lowest proportion of unused activity space than other buffers at equivalent buffer distances. However, it is important to consider the size of the buffer types. Ellipse buffers are larger geographically (i.e. the area they cover is much larger). By creating a space that encompasses a large proportion of an individual's day (i.e. at home and school) it is logical that these buffers encompass the most space, but also have the highest proportion of unused space. On the other hand, network buffers are much smaller in size and therefore capture less space, but also reducing the amount of unused space. These results are supported by Holliday et al. (2017) who found high amounts of unused buffer space across 6 types of buffers when assessing MVPA space in adults (mean age 41.0) in the U.S. They found that the median amount of the buffer used was 40.0% for a 0.5 mile radial buffer and 44.1% for a 0.5 mile network buffer; 33.4% for a 1 mile radial buffer and 36.2% for a 1 mile network buffer; and 8.0% for a 5 mile radial buffer and 11.2% for a 5 mile network buffer. These findings demonstrate that researchers cannot simply just increase buffer size to encompass more of the exposure area of an individual, as this will lead to including large amounts of the environment that are not accessed by the individual and cause either an over/underestimation of the influence of the environment.

This study assessed buffers by measuring both space within and unused space, which demonstrated high unsuitability among all buffers. While these results are expected and confirm assumptions from previous studies which suggest buffers fail to accurately nor adequately measure daily life (Boruff, 2012, Kerr et al., 2011, Perchoux et al., 2013) this is the first time these assumptions have been quantified across multiple buffer types and distances in adolescents. This provides further support that future research needs to carefully consider the research questions of interest to ensure appropriate methods are employed and ensuring the balance of space within and unused space are adequate for the outcome of interest. This will have implications on studies seeking to understand how the environment influences behaviour and suggests future research should carefully consider the aim of the research to choose an appropriate method. For example, ellipse buffers would be more appropriate for research wishing to capture individual behaviour, whereas network buffers would be best for research wishing to minimise the amount of unused space within buffers. The most appropriate method will need to be determined by the research questions of the project and warrants careful consideration.

This study also extends current knowledge by demonstrating a discrepancy between actual activity spaces and self-drawn neighbourhoods. For instance, what adolescents defined as their self-drawn neighbourhood only captured 10% of their actual daily movement and 40% of their self-drawn neighbourhood was not actually used. This means, that although individuals self-defined their neighbourhood boundaries, they still included a large amount of space that they do not go to during their weekly sampling period. This contradicts previous assumptions that SDNs better capture behaviour, due to being individually defined (Robinson and Oreskovic, 2013). However, similar results have been found in previous research. Basta et al. (2010) found low correspondence (i.e. spatial overlap) between activity paths and hand drawn neighbourhoods in adolescents (aged 15-19). Similarly, Colabianchi et al. (2014) examined the spatial overlap between self-drawn neighbourhoods and physical activity behaviour in adolescents (aged 14-17) and found that the average proportion of individual physical activity locations within self-drawn neighbourhoods was 43%. This suggests that neighbourhood definitions are influenced by more than where individuals spend their time and it is likely that neighbourhood can be interpreted differently depending on the context or how the question has been asked (Baldock, 2012, Ma, 2015). These factors need to be better understood and warrant further investigation in future research. This will allow a better understanding of the lack of concordance between self-defined boundaries and objective behaviour which may enable researchers to identify potential leverage points to positively influence behaviour.

Overall, results from this study caution against the use of predefined buffer boundaries. Results clearly show the unsuitability among buffers and SDNs in assessing individual activity space. This means that when interpreting previous and current research that use these predefined boundaries, researchers need to be cautious when drawing conclusions from these studies. Despite these present results and other findings questioning the use of buffers (Jansen et al., 2018, Holliday et al., 2017, Laatikainen et al., 2018), these methods are still the most commonly used within the field and policies are being based on these inconsistent results. Future studies may need to consider using flexible geographical scales (Hillsdon et al., 2015) or using buffers that encompass more than one key location to an individual (Laatikainen et al., 2018, Kestens et al., 2018). By avoiding a one-size fits all approach and ensuring more than one key location is collected in data sets (e.g. home and school or home and workplace) it will allow a better representation of environmental influences on individual behaviour. These methods hold promise for future research and should be investigated further.

This exploratory study is limited by a lack of data on actual use of environmental facets such as physical activity facility or food outlets. Other important aspects of the environment such as quality, aesthetics or walkability were not captured (Handy, 2002, D'Haese et al., 2015, Ding et al., 2011). In light of the small sample size, the findings may not be generalisable to other settings or populations. While participation was open to all adolescents at the participating schools, there may have been self-selection bias that may have impacted results. Adolescents who were more active or had more mobility may have self-selected into the research and the sample may not be an accurate representation of adolescents. Until recently, standard practice was 7 days of GPS data was adequate to represent individual behaviour, however, a recent publication following data collection by Zenk et al. (2018) recommends 14 days of valid GPS data is needed to measure activity space. It should also be acknowledged that a weeklong timeframe only provides a snapshot of individual behaviour and may not fully capture routine behaviour. Therefore, future research should use longer monitoring timeframes. Additionally, adolescents may also self-select into areas therefore, activity spaces may in part be a reflection of neighbourhood self-selection bias. Adolescents have more independent mobility than children and thus have more control of areas they spend time, however, parental self-selection of home neighbourhood and/or school must also be noted (Hillman, 1990, Tranter, 2006, van Loon et al., 2014). Neighbourhood preference and self-selection could be important to account for in future analyses. Finally, there may be moderating effects we could not detect due to the small sample. For instance, socioeconomic status or age may be related to AS size (Boone-Heinonen et al., 2010, Giles-Corti and Donovan, 2002).

CONCLUSION

Our exploratory study of adolescents aimed to investigate uncertainty in the geographical context of adolescent movement by comparing researcher- and participant-defined definitions of neighbourhood reflect an adolescent’s activity space and time. Findings in this study help broaden understanding of adolescent activity spaces and in turn, can help inform future studies and policy concerned with developing healthy places. To further develop understanding of how aspects of the physical environment, (e.g. exposure to physical activity facilities or greenspace) relate to health outcomes, future research must move beyond static spatial measures and accurately capture individual exposure using GPS technology.

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