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# Objective measurement of children's physical activity geographies: A systematic search and scoping review

Melody Smith [a,*], Jianqiang Cui [b], Erika Ikeda [c], Suzanne Mavoa [d], Kamyar Hasanzadeh [e], Jinfeng Zhao [a], Tiina E. Rinne (nee Laatikainen)[f], Niamh Donnellan [g], Marketta Kyttä [e]

[a] School of Nursing, The University of Auckland, Auckland, New Zealand
[b] School of Environment and Science, Griffith University, Brisbane, Australia
[c] Centre for Diet & Activity Research (CEDAR), MRC Epidemiology Unit, University of Cambridge, Cambridge, UK
[d] Melbourne School of Population and Global Health, University of Melbourne, Melbourne, Australia
[e] Department of Built Environment, Aalto University, Espoo, Finland
[f] Active Life Lab, South-Eastern Finland University of Applied Sciences, Mikkeli, Finland
[g] School of Nursing, University of Auckland, Auckland, New Zealand

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ABSTRACT

This study aimed to systematically identify, map out, and describe geographical information systems (GIS)-based approaches that have been employed to measure children's neighborhood geographies for physical activity behaviors. Forty studies were included, most were conducted in the USA. Heterogeneity in GIS methods and measures was found. The majority of studies estimated children's environments using Euclidean or network buffers ranging from 100 m to 5 km. No singular approach to measuring children's physical activity geographies was identified as optimal. Geographic diversity in studies as well as increased use of measures of actual neighborhood exposure are needed. Improved consistency and transparency in reporting research methods is urgently required.

## 1. Background

Neighborhood environments are associated with children's health-promoting physical activity (PA) behaviors, including active travel (e.g., walking or cycling to destinations), independent mobility (active travel and outdoor play that are not supervised by adults), and time spent in moderate-to-vigorous PA (MVPA) (Ding et al., 2011; Davison and Lawson, 2006; Ferreira et al., 2007; Oliveira et al., 2014; Richter et al., 2000; Smith et al., 2017). A 2016 overview of measurement of children's geographies for PA revealed increasing use of geographic systems (GIS) to measure settings of importance for children (alongside other measures such as audits, wearable cameras, and surveys) (Oliver et al., 2016a). At this time, exploring environmental associates of children's active travel was a key area of focus in GIS research, with measures generally calculated around a child's residence or route to school. The review highlighted the need to also consider the area around schools in this context, and reiterated previous recognition of the importance of specificity and child-specific measurement approaches. Activity spaces were also raised as a useful approach to "provide a more accurate picture of children's movement in the local neighborhood" (p. 5). Homes, schools, public open spaces, and streetscapes were recognized as important PA locations. When considering PA promotion, children's "PA neighborhoods" or "PA geographies" could thus be contextualized as those environments that are in the home vicinity, along the route to school, or in the school vicinity, all important geographic PA settings in a child's local neighborhood. In this review, we use these terms interchangeably to encapsulate these local places of importance to children's PA promotion.

It should be noted that in health geography literature, the concept of neighborhood is intuitively appealing, yet operationally very challenging to measure. Neighborhoods in research are traditionally operationalized as census-defined or other administrative boundaries (Roux, 2001). However, more recently researchers have argued that such definitions are ill-fitting solutions which do not adequately capture the true

* Corresponding author. Private Bag 92006, Auckland, 1142, New Zealand.
*E-mail addresses:* melody.smith@auckland.ac.nz (M. Smith), jj.cui@griffith.edu.au (J. Cui), erika.ikeda@mrc-epid.cam.ac.uk (E. Ikeda), suzanne.mavoa@unimelb.edu.au (S. Mavoa), Kamyar.hasanzadeh@aalto.fi (K. Hasanzadeh), jinfeng.zhao@auckland.ac.nz (J. Zhao), tiina.e.rinne@aalto.fi (T.E. Rinne), n.donnellan@auckland.ac.nz (N. Donnellan), Marketta.kytta@aalto.fi (M. Kyttä).

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extents of neighborhoods as experienced by the residents (Perchoux et al., 2013). Therefore, a number of studies have used data collected through methods such as global positioning systems (GPS) or public participation GIS (PPGIS) to map self-identified or actualized neighborhoods for individuals (e.g. (Robinson and Oreskovic, 2013; Hasanzadeh et al., 2017). Therefore, the term neighborhood in this paper is used to refer to the local space concentrated around an individual's place of residence (which can also include schools) regardless of the method that is used for mapping it.

### *1.1. Advances in health geography*

Two areas of advancement are relevant in the context of this research field. Firstly, the use of GIS has become commonplace. Early work in this area focused on 'walkability' to characterize an individual's neighborhood (Leslie et al., 2007; Van Dyck et al., 2009). For the most part, this involved using GIS and spatial data to generate measures of residential density, land use mix, street connectivity, and retail floor-area ratio within an arbitrary neighborhood buffer around the individual's home address, census area unit, or other administrative boundary. Advances are being made in terms of understanding other key factors that might contribute to walkability of a neighborhood (e.g., through reducing distance between destinations, increasing availability of relevant destinations, or making an environment safer, more pleasant, and more enjoyable to walk in). Researchers are also continuing to grapple with how best to delineate neighborhoods and environments that are appropriate and meaningful for understanding children's PA.

One area that has received much attention in literature examining environmental measures (and delineation) in health geography research is the modifiable areal unit problem (MAUP). The MAUP is composed of two related problems: scale effect and zoning effect (Openshaw, 1984). The former indicates that study areas at different scales/sizes such as census area units or regional boundaries will lead to different statistical results even using the same data. While the latter indicates that areas at the same or similar scale but drawn with different criteria (i.e., with alternative boundaries) will result in different statistical results with different sensitivity and specificity (Dark and Bram, 2007; Mitra and Buliung, 2012). Thus, the MAUP is a key challenge for researchers because neighborhood effects on health are partly determined by the way neighborhoods are defined (Haynes et al., 2007). One compromise is to delineate areas using a set of zone design criteria that are customized to match the requirements of different kinds of analyses (Manley et al., 2014). The MAUP can also be mitigated by using buffers around individual locations (e.g., home addresses) but this is not always possible (e.g., due to privacy or lack of granularity in the primary data collected). In addition, buffered areas derived from different approaches (e.g., crow-fly buffer or network buffer) may cause zoning effect, while buffered areas derived from different radii may cause scale effect (Mavoa et al., 2019). The Uncertain Geographic Context Problem (UGCoP) is an additional limitation in area-based measures where spatial and temporal uncertainty exists – that is, the researcher-defined area may deviate from the true geographic context of interest (Kwan, 2012). For example, different individuals may have different "activity spaces" (i.e., areas where they spend time and are active) so a fixed buffer around a single location is unlikely to reflect the real environmental exposure of every individual when attempting to understand any environment-activity relationships (Dark and Bram, 2007; Mitra and Buliung, 2012; Haynes et al., 2007). Using individual-based methods of delineating actual exposure such as activity spaces can reduce the impact of these issues (Hasanzadeh et al., 2018).

There has been an upsurge in researchers and practitioners recognizing the value of working with individuals and individual data to improve spatial certainty. One increasingly common approach is the use of GPS data to objectively assess actual exposure (Hurvitz et al., 2014). These GPS data can provide information on where people are (via location coordinates), time spent at a location, and speed of travel. Further information on outdoor locations and mode of travel can also be derived. An important strength of GPS data is that it can contextualize other information, whereby individual factors can be linked to location information by combining it with other technologies (e.g. accelerometers, heart rate monitors, wearable cameras) (Oliver et al., 2010, 2013; Fjørtoft et al., 2009) or other data based on date and time. GPS and accelerometer data have been linked to assess PA location in an intervention to teach overweight and obese youth aged 10–16 years how to be active in their local built environments (Oreskovic et al., 2015). In a study with adolescent "citizen scientists", detailed environmental audits were obtained through simultaneous use of GPS (to determine walking route/location of additional data), photography, audio narratives, and survey responses (Winter et al., 2016). Children's travel diary data have successfully been linked to GPS data using automated sequence alignment (Mavoa et al., 2011). These examples demonstrate the varied and powerful contribution that GPS can make to gaining an accurate portrayal of experienced environments when combined with other measures. GPS methods do have limitations, such as dwell time impacting accuracy in detecting trip end times, signal drop-out (e.g., in urban canyons or inside buildings), issues with battery life, and a reliance on participants wearing the units (Oliver et al., 2010).

Another increasingly popular approach to improve spatial representation is the use of PPGIS. Similar to GPS approaches, PPGIS also allows assessment of where people spend time in their neighborhood, albeit with self-report locations as opposed to objectively assessed GPS locations. Compared to GPS, PPGIS more readily allows for collection of information such as how they get there, what they do there, and their general perceptions about neighborhood environments and characteristics (Brown and Kyttä, 2014; Kahila et al., 2009). This relatively new method has led to a plethora of new ideas and approaches for developing 'individual-centric' neighborhood delineations. Combining this community/individual voice by using individual-centric methods has substantial potential to lead to unique insights that are meaningful and relevant to the community of interest. These insights can be used for the development of appropriate recommendations for effective interventions for improving children's PA.

### *1.2. Research aim*

Given the rapid escalation of research in this field, the aim of this review is to map out and describe GIS-based approaches that have been employed to measure children's neighborhood geographies for understanding PA and related behaviors. This information is needed to provide researchers and practitioners with an up-to-date understanding of key approaches in the field, and to encourage consistency and transparency in reporting research methods.

## 2. Methods

### *2.1. Methodological taxonomy*

The taxonomy used for this research design took into account a range of review definitions and characteristics (Mays et al., 2001; Arksey and O'Malley, 2005; Grant and Booth, 2009), in light of the research aim and scope. Systematic review components (e.g., systematic article searching and screening using a-priori protocols and inclusion and exclusion criteria, article quality assessment) and elements to reduce or understand bias (e.g., protocol registration, duplication of article screening in a subset) are included. In this context, the review has characteristics of mapping, scoping, systematic searching, and systematized reviews. Thus we have taken the broad approach recommended by Colquohoun et al. (Colquhoun et al., 2014) and described this as a "scoping review." In addition, drawing from Grant and Booth (2009), we have included the term "systematic search" to the review description.

### 2.2. Protocol

The review protocol was registered on the Open Science Framework on October 28, 2019 (https://osf.io/7wgur/). The Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) Checklist (Tricco et al., 2018) has been used to structure this review (Supplementary data S1).

### 2.3. Search methods

#### 2.3.1. Eligibility criteria

Studies were eligible at the searching stage if they were: (1) peer reviewed articles published in academic journals, (2) published in the English language, (3) conducted with human populations, and (4) published between January 1, 2006 (to align with the emergence of a growing body of literature using GIS in PA and child health research) and November 15, 2019.

#### 2.3.2. Information sources

Databases were identified by screening target journals and identifying indexing to ensure comprehensive coverage across health geography, applied geography, children's geographies, and PA/health promotion. The following databases were searched: GEOBASE, Scopus, PubMed (includes MEDLINE), and Social Sciences Citation Index.

#### 2.3.3. Search terms and strategy

Search terms were identified from MeSH terms, existing literature reviews, and the expertise of the research team. Terms were broad and fell under three categories: Method (e.g., GIS), Population (e.g., child), and Outcome (e.g., neighborhood). Categories, terms, and an example of the full electronic search strategy for PubMed is provided in the Supplementary data (S2 and S3).

#### 2.3.4. Selection of sources of evidence

Duplicate articles were removed. Thereafter, titles and abstracts of all articles retrieved were screened for inclusion by JC. Studies were eligible for inclusion at this stage if they: (1) used GIS to measure neighborhood environments (broadly conceptualized as environments around individual addresses, at the individual or neighborhood-area level), and (2) included child populations (defined as aged 5–13 years). Studies that included children aged 5–13 years as well as other age groups (e.g., adolescents) were included.

All study types were included providing they met other inclusion criteria. Studies were excluded if they: (1) did not include a GIS-based measure of the neighborhood environment, (2) did not include children, or (3) used area-level measures greater than the neighborhood scale (e.g., towns, cities, regions; if this information was stipulated in the title or abstract).

Duplicate screening was conducted independently by MS for a random 10% selection of all articles identified at the search stage. Differences between coding were resolved between the coders, and additional detail, descriptions, and instructions added to the screening instructions where necessary for clarification. Full text articles were then sourced for all "eligible" articles and those where it was not clear whether they met the inclusion and exclusion criteria. At the full-text screening stage, articles were included if they met the criteria above, and additionally: (1) described the methods used to generate the GIS-based measure of neighborhood environments, (2) included a PA (or related) outcome measure, or focused on the PA-environment relationship (3) provided descriptive information about the GIS-based measure (e.g., in graphical, narrative, or tabular format).

### 2.4. Data charting and synthesis

A study-specific data chart was developed, drawing from the environmental quality measures framework presented in Zhang et al. (Zhang et al., 2020) and the Spatial Lifecourse Epidemiology Reporting Standards (ISLE-ReST) statement (Jia et al., 2019). As well as descriptive characteristics of study country, participants, aim and results, GIS measurement-related variables were extracted as follows: exposure assessment (estimated, e.g., using a defined buffer around residential address; or actual, e.g., using GPS, child reports), environmental scale (e.g., ego-centric), buffer calculation type (e.g., road network), buffer radius, and variables calculated. As the focus of this study was on neighborhood built environments, information and results for social environmental variables used as covariates or independent variables (e.g., crime, socio-economic status) were not extracted unless their findings were related to the built environment results (e.g., through an interaction effect). Strengths and limitations related to neighborhood delineation and use of GIS, GPS, and PPGIS identified by authors of included studies and those identified by the researchers during the extraction process were also documented. These were then summarized to provide a broad overview of factors for researchers to consider when planning similar research. The identification of key strengths and limitations focused on areas where consistent issues were raised or identified across studies, where improvements in reporting would benefit the field, where risk to rigor of data was possible, or where factors were important to take into account when interpreting results.

JC undertook preliminary data extraction, and MS cross-checked all extracted data and populated the final data chart. Findings were described narratively with a focus on the range and prevalence of methods used, and findings of relevance when comparing particular methods.

### 2.5. Quality assessment

Individual study quality was assessed using the Mixed Methods Appraisal Tool (MMAT) (Hong et al., 2018). This tool was deemed optimal for the current research due to its flexibility in assessing varying research designs (i.e., qualitative, quantitative randomized controlled trial, quantitative non-randomised, quantitative descriptive, mixed methods). The tool focuses on five core criteria of evaluation relevant to each study design, and also assesses whether there are clear research questions and whether the collected data allow the researcher to address these questions. Evaluation criteria were tabulated and summary scores calculated following the MMAT protocol. Quality assessment was duplicated by MS for a random 10% subset of articles.

## 3. Results

### 3.1. Study characteristics

Of the 495 articles identified, 40 studies were included in this review (Fig. 1). Characteristics of articles and participants included are outlined in the Supplementary data (S4). A majority of articles were from USA (N = 15), followed by Aotearoa New Zealand (N = 5), Canada (N = 5), Australia (N = 3), The Netherlands (N = 3), and one article each from Norway, Mexico, Bangladesh, Switzerland, Germany, Finland, Israel, Belgium, and Scotland. Sample sizes ranged from 71 (Coughenour and Burns, 2016) to 21,146 (Nordbø et al., 2019), with a median size of 665 participants. Six articles had sample sizes over 6,000, all of which were from representative surveys (i.e., the Canadian Health Behavior in School Children Study (Laxer and Janssen, 2013; Mecredy et al., 2011), the US National Longitudinal Study of Adolescent Health (Boone-Heinonen and Gordon-Larsen, 2011; Boone-Heinonen et al., 2010a, 2010b), and the Norwegian Mother and Child Cohort Study (Nordbø et al., 2019)). Participant ages ranged from 2 to 94 years. Six articles were from the Teen Environment and Neighborhood study with US youth aged 12–16 years (Sallis et al., 2015, 2018; Carlson et al., 2014, 2015, 2017; Wang et al., 2017), three were from the US National Longitudinal Study of Adolescent Health with youth aged 11–22 years (Boone-Heinonen and Gordon-Larsen, 2011; Boone-Heinonen et al., 2010a, 2010b),

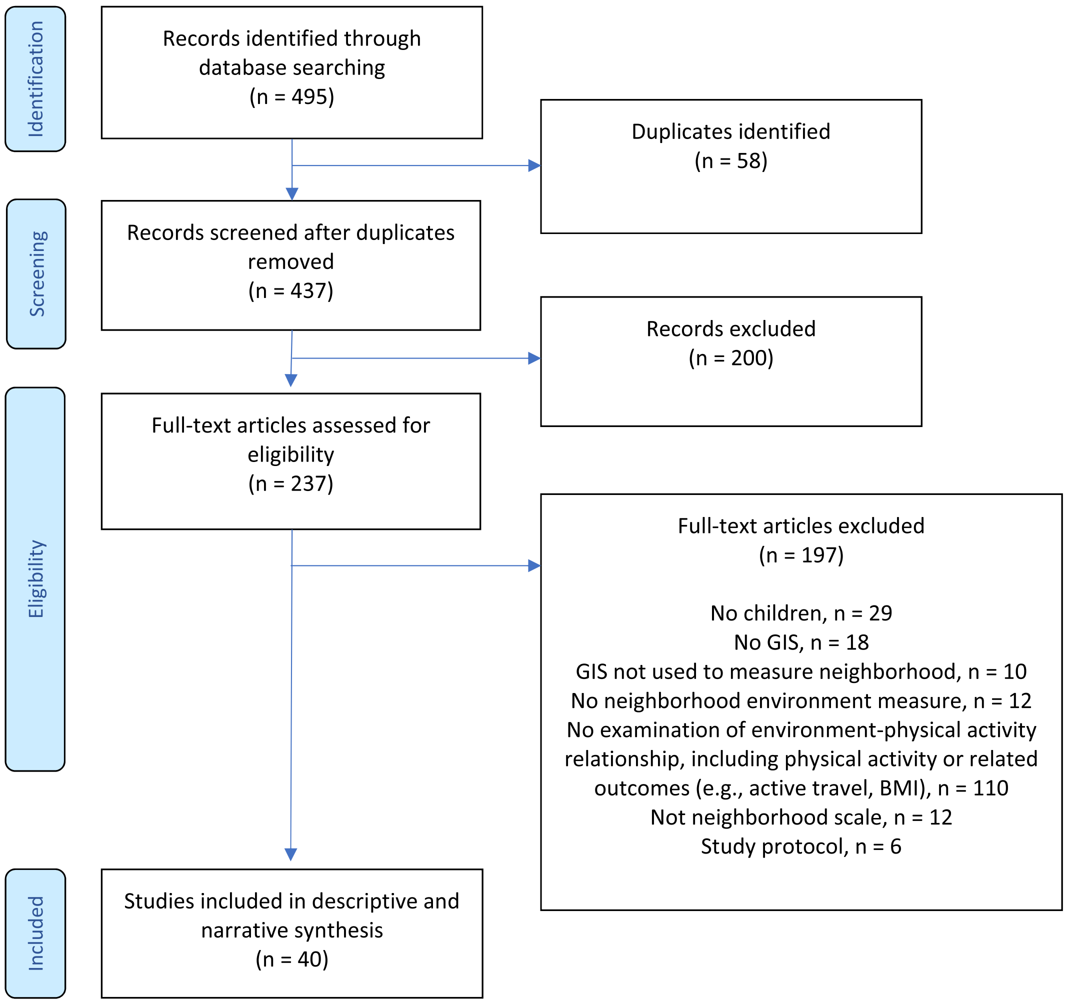


**Fig. 1.** Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram for articles identified, screened, and included in the review. Note: BMI = body mass index, GIS = geographic information systems.

two were from the Canadian Health Behavior in School-aged Children Survey with youth aged 11–15 years (Laxer and Janssen, 2013; Mecredy et al., 2011), and there were four individual studies with a range of youth aged 11–17 years from Canada (Tucker et al., 2009), Aotearoa New Zealand (Hinckson et al., 2017), Belgium (De Meester et al., 2012), and the US (Dalton et al., 2011).

Almost all articles (N = 36) were from cross-sectional studies. The remaining four were an intervention introducing neighborhood PA spaces (Mölenberg et al., 2019), an article measuring change in PA behaviors over time in relation to built environment features (Carver et al., 2010), and two articles from the US National Longitudinal Study of Adolescent Health investigating effects of time-varying built environment variables on MVPA (Boone-Heinonen and Gordon-Larsen, 2011; Boone-Heinonen et al., 2010a). Study quality as assessed using the MMAT was moderate to high across all studies (scores ranging from 3 to 5 of a possible score of 1 and 5), with the exception of one study which scored 2 (see Supplementary information). For the most part, scores were reduced due to unclear or missing information on study methods, reducing the ability to discern whether studies met quality assessment criteria. In the case of quantitative studies, lack of clarity on representativeness was also prevalent.

Physical activity was the outcome of interest in 38 articles, including active travel to school and other destinations or for leisure (N = 16), overall/total PA or exercise (N = 7), MVPA (N = 6), outdoor/neighborhood/setting-specific play (N = 6), leisure-time PA (N = 5), independent mobility (N = 3), or time spent in PA locations (reported or via GPS, N = 2). Body mass index (BMI) was also examined in relation to environmental variables in two articles as the outcome of interest (Burgoine et al., 2015; Carroll-Scott et al., 2013). One article compared built environment characteristics derived from GIS-estimated shortest route to school and child-reported route to school between school travel modes (and other variables) (Dessing et al., 2016), and another examined the accuracy of children's spatial mapping of their home-to-school route using child-drawn sketches versus child mapped routes on maps and compared accuracy between differing school travel modes (Moran et al., 2017). Accelerometry was used to measure PA objectively in 12 articles including one where GPS was combined with accelerometry to estimate travel mode (Carlson et al., 2015). The remaining six articles that used GPS measured routes to school (N = 3) (Burgoine et al., 2015; Dessing et al., 2016; Helbich et al., 2016), time spent in neighborhood locations (N = 2) (Carlson et al., 2017; Olsen et al., 2019), or used GPS data to determine residential location (in a subsample of one article) (Boone-Heinonen et al., 2010a).

### 3.2. *GIS methods used to delineate children's neighborhood environments*

A range of GIS methods were employed to delineate and describe children's PA geographies (Table 1, Fig. 2). Home neighborhoods, school neighborhoods, and school routes were conceptualized as environments of importance for children. The majority of articles used estimates of children's home and/or school neighborhood environments (i.e., delineating areas that children could spend time in, for example by

**Table 1**
Descriptive information for GIS methods used in studies included in this review.

| Study | Exposure[a] | | Area applied to measure environmental exposure | | | | Buffer calculation | | | | Distance to locations | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Lead author (year) [reference] | Estimated | Actual | Individual/egocentric buffered area: Home | Individual/egocentric buffered area: School | Individual/egocentric buffered area: Route | Aggregated administrative area/other (specify) | Euclidean[b] | Network[c] | Network – pedestrian[d] | Buffer distance | Distance calculated[e] | Destinations for shortest distance |
| Boone-Heinonen and Gordon-Larsen (2011) (Boone-Heinonen and Gordon-Larsen, 2011) | ●[1] | | ● | | | Census tract (socio-economic environment) | ● | | | 1 km, 3 km | | |
| Boone-Heinonen et al. (2010a) (Boone-Heinonen et al., 2010a) | ●[2] | | ● | | | Census tract (socio-economic environment) | ● | | | 1 km, 3 km | | |
| Boone-Heinonen et al. (2010b) (Boone-Heinonen et al., 2010b) | ●[3] | | ● | | | Census tract (socio-economic environment) | ● | | | 1, 3, 5, and 8 km | | |
| Bringolf-Isler et al. (2010) (Bringolf-Isler et al., 2010) | ●[4] | | ● | | | | ● | | | 100 m, 200 m, 500 m (street density measure); 9ha (population and building density); 25ha (green space) | | |
| Buck et al. (2015) (Buck et al., 2015) | ●[5] | | ● | | | Simple intensity and kernel intensity measures were used to assess three point characteristics such as intersections, public transit stations, and public open spaces | | ● | | 500 m, 750 m, 1 km, 1.25 km, 1.5 km, 2 km | | |
| Burgoine et al. (2015) (Burgoine et al., 2015) | ●[6]○[7] | ●[6] | ○ | ○ | ● | Inverse distance weighting - all discrete food outlets and PA location points contribute to exposure, with the inverse distance (1/distance) between point facilities (i) and homes or schools (j) then weighted according to a suggested distance decay parameter (k) of 2 | | ○● | | 100 m (routes); 800 m (home and school neighborhoods); 6 km (inverse distance weighting) | | |
| Cain et al. (2014) (Cain et al., 2014) | ●[8] | | ● | | | Census blocks | | ● | | N/A | | |
| Carlson et al. (2017) (Carlson et al., 2017) | ●[9] | ●[9] | ● | ● | | | ● | ● | | 15 m (school parcel); 50 m (home setting); 1 km (neighborhood variables) | | |
| Carlson et al. (2015) (Carlson et al., 2015) | ●[10] | | ● | | | | | ● | | 1 km | | |
| Carlson et al. (2014) (Carlson et al., 2014) | ●[11] | | ● | ● | | | | ● | | 1 km | ● | School |
| Carroll-Scott et al. (2013) (Carroll-Scott et al., 2013) | ●[12] | | | | | Census tracts | | ● | | Used a 20 m buffer around census tract boundaries for calculation of retailers variable (to capture retailers on opposite sides of a street) | ● | Grocery store; Convenience store; Fast food restaurant; Park |
| Carver et al. (2010) (Carver et al., 2010) | ●[13] | | ● | | | | ● | | | 800 m | | |
| Carver et al. (2015) (Carver et al., 2015) | ●[14] | | ● | | | | | | ● | 800 m, 5 km | | |
| Coughenour and Burns (2016) (Coughenour and Burns, 2016) | ●[15] | | ● | | | | ● | | | 1 mile | | |

(*continued on next page*)

**Table 1** (*continued*)

| Study | Exposure[a] | | Area applied to measure environmental exposure | | | | Buffer calculation | | | | Distance to locations | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Lead author (year) [reference] | Estimated | Actual | Individual/egocentric buffered area | | | Aggregated administrative area/other (specify) | Euclidean[b] | Network[c] | Network – pedestrian[d] | Buffer distance | Distance calculated[e] | Destinations for shortest distance |
| | | | Home | School | Route | | | | | | | |
| Dalton et al. (2011) (Dalton et al., 2011) | ●[16] | | | ● | | | ● | | | 1 km | ● | Home |
| De Meester et al. (2012) (De Meester et al., 2012) | ●[17] | | | | | Adjacent statistical sectors (smallest administrative entities for which statistical data are available) with comparable walkability and with SES in the same decile defined a neighborhood. | | ● | | N/A | | |
| Dessing et al. (2016) (Dessing et al., 2016) | ●[18] | ●[18] | | | ● | | | ● | | 25 m | ● | School |
| DeWeese et al. (2018) (DeWeese et al., 2018) | ●[19] | | ● | | | Census block group (socio-economic environment) | | ● | | 0.25 mile | | |
| Helbich et al. (2016) (Helbich et al., 2016) | | ●[20] | | | ● | | | ● | | 100 m | ● | School (actual route); Nearest major road/ highway (Euclidean) |
| Hinckson et al. (2017) (Hinckson et al., 2017) | ●[21] | | ● | | | | | | ● | 250 m, 500 m, 1 km, 2 km | | |
| Ikeda et al. (2019) (Ikeda et al., 2019) | | ●[22] | | | ● | | | ● | | 160 m (80 m either side of the centerline) | ● | School |
| Islam et al. (2014) (Islam et al., 2014) | ●[23] | | ● | | | | ● | | | 150 m | | |
| Jauregui et al. (2016) (Jauregui et al., 2016) | ●[24] | | | ● | | | ● | | | 400 m, 800 m | | |
| Kyttä et al. (2012) (Kyttä et al., 2012) | ●[25a] | ●[25b] | ● | | | Public participation GIS, with children marking destinations of importance to them | ● | | | 500 m | ● | All child-defined places of importance using public participation GIS data |
| Laxer and Janssen (2013) (Laxer and Janssen, 2013) | ●[26] | | | ● | | | ● | | | 1 km | | |
| McGrath et al. (2016) (McGrath et al., 2016) | ●[27] | | ● | | | | | ● | | 800 m | ● | School |
| Mecredy et al. (2011) (Mecredy et al., 2011) | ●[28] | | | ● | | | ● | | | 5 km | | |
| Mitchell et al. (2016) (Mitchell et al., 2016) | ●[29] | | ● | | | | ● | ● for shortest distance | | 500 m, 800 m | ● | Schools; Recreation centers |
| Mölenberg et al. (2019) (Mölenberg et al., 2019) | ●[30] | | ● | | | | ● | | | 600 m | ● | New dedicated PA space (the intervention) |
| Moran et al. (2017) (Moran et al., 2017) | | ●[31] | | | ● | | | | ● | 25 m | | |
| Nordbø et al. (2019) (Nordbø et al., 2019) | ●[32] | | ● | | | | ● | | | 800 m, 5 km | | |
| Oliver et al. (2014) (Oliver et al., 2014) | ●[33] | | | | | Meshblock (for walkability calculation) | | ● | | N/A | ● | School |
| | ●[34] | ○[35] | ● | | | | ●○ | | | | ○ | |

(*continued on next page*)

**Table 1** (*continued*)

| Study | Exposure[a] | | Area applied to measure environmental exposure | | | | Buffer calculation | | | | Distance to locations | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Lead author (year) [reference] | Estimated | Actual | Individual/egocentric buffered area | | | Aggregated administrative area/other (specify) | Euclidean[b] | Network[c] | Network – pedestrian[d] | Buffer distance | Distance calculated[e] | Destinations for shortest distance |
| | | | Home | School | Route | | | | | | | |
| Olsen et al. (2019) (Olsen et al., 2019) | | | | | | ○ (Grid cells (25m2), identified from GPS points of participants) | | | | 25 m (2 grid for GPS data points); 800 m (traditional neighborhood comparison) | | Grid cells (controlled for distance to home) |
| Sallis et al. (2015) (Sallis et al., 2015) | ●[36] | | ● | | | Census blocks | | ● | | | | |
| Sallis et al. (2018) (Sallis et al., 2018) | ●[37] | | ● | | | Census blocks | | ● | | | | |
| Smith et al. (2019) (Smith et al., 2019) | ●[38] | | ● | | | | | | ● | 800 m | | |
| Tucker et al. (2009) (Tucker et al., 2009) | ●[39] | | ● | ● | | Postal code | ● | | | 500 m (home); 1.6 km (school) | | |
| van Loon et al. (2014) (van Loon et al., 2014) | ●[40] | | ● | | | | | ● | | 200 m, 400 m, 800 m, 1.6 km | ● | School; Park; Other recreational area |
| Villanueva et al. (2012) (Villanueva et al., 2012) | ●[41] | ● | ●[42] | ●[43] | | Activity space (minimum convex polygon) using children's home and marked destinations visited | | | ● | 2 km (school walkability); 800 m (destinations); 800 m, 1600 m (comparison with activity space) | | |
| Wang et al. (2017) (Wang et al., 2017) | ●[44] | | ● | | | | | ● | | 1 km | | |

[1-44]Detail for GIS characteristics calculated are provided in Table 2.
[a] GIS variables calculated. GIS = geographic information system, GPS = global positioning system, N/A = not applicable, PA = physical activity, SES = socio-economic status.
[b] Assumed unless network specified.
[c] Assumed street network unless specified otherwise.
[d] Pedestrian or cyclist network, used when motorways excluded, or trails etc. included.
[e] Shortest distance unless specified.

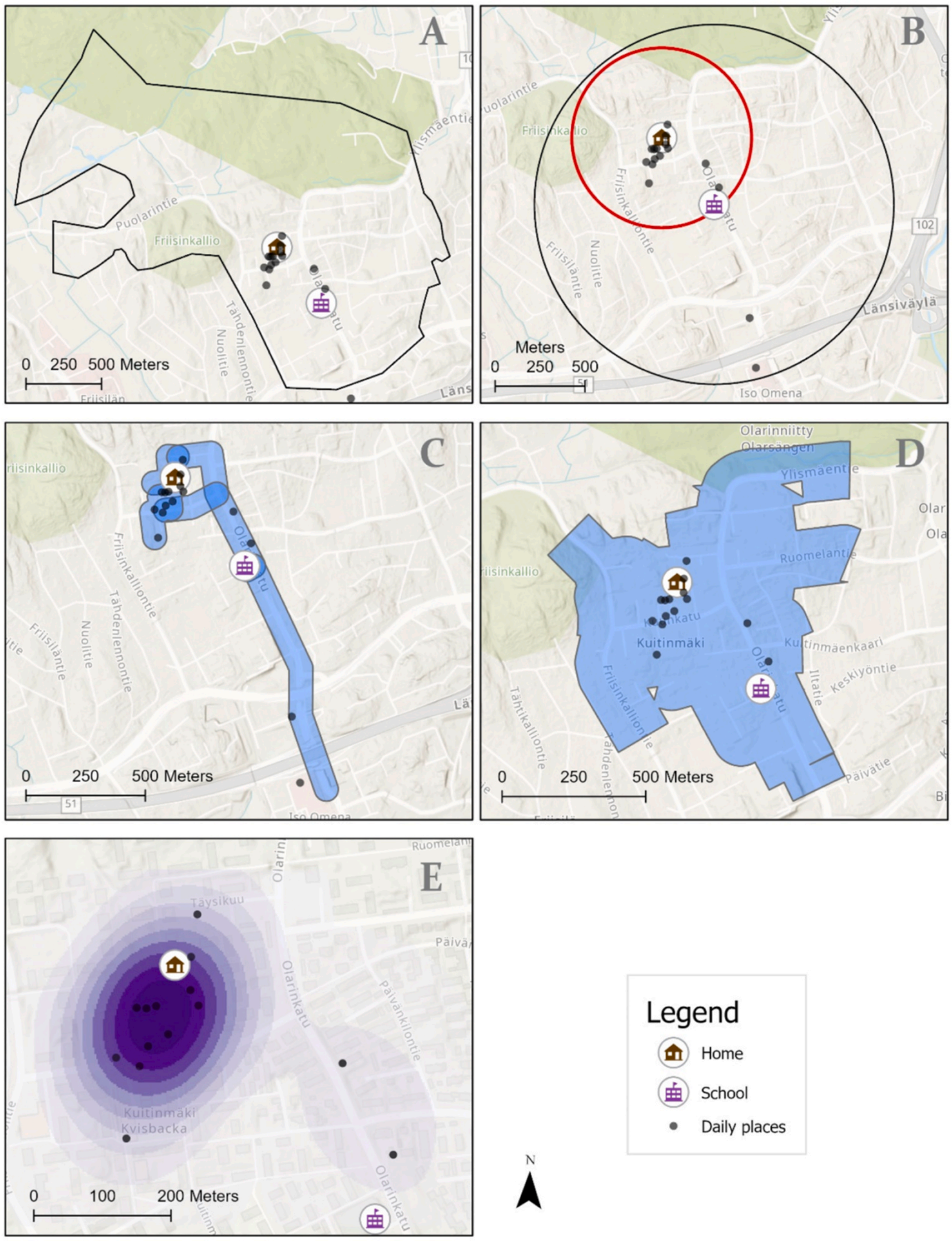


**Fig. 2.** Illustrative example of methods employed to measure built environment characteristics in articles included in this review. A: Administrative boundaries B: Home and school based circular buffers (500 and 1000 m radius respectively) C: Route buffer D: Home based network distance buffer E: Kernel density.

creating a buffer around a home address). Other methods used to delineate environments varied from child drawings of school routes (i.e., self-reported actual exposure) to GPS-defined time measured in neighborhood settings.

Alternative approaches such as kernel density (Buck et al., 2015), inverse distance weighting (Burgoine et al., 2015), and convex polygons generated from child maps (Villanueva et al., 2012) were used in three articles. Built environment GIS variables varied widely, with many focusing on walkability, and some examining alternative variables such as vertical urban morphology and new measures of ease of mobility (Helbich et al., 2016). Thirty-one articles used estimated environmental measures only, six used a combination of estimated and actual exposure, and three used actual exposures only. An overview of key strengths and limitations of GIS methods of the included studies is outlined in Table 3.

#### 3.2.1. *Articles examining actual exposure*

GPS or child-mapped routes to school were used in five articles to measure routes to school, and GIS subsequently used to generate environmental characteristics along routes (Burgoine et al., 2015; Dessing et al., 2016; Moran et al., 2017; Helbich et al., 2016; Ikeda et al., 2019). Moran et al. (2017) reported that compared with drawing their route on a map, children's sketched routes were more accurate for those residing in "traditional" neighborhoods (i.e., high density, street connectivity, land use mix, commercial land use) compared with children living in suburban neighborhoods (i.e., low density, high land use segregation, culs de sac and green open space). Route accuracy was also greater in children living in neighborhoods with greater walkability, residential density, street connectivity and percentage of retail area. Route accuracy was negatively related to route length, and percentage of route green space for the full sample, but not among those who were driven to school most of the week. Dessing et al. (2016) compared built

**Table 2**
Key geographic characteristics calculated in studies included in this review.

| Lead author [reference] | Key geographic characteristics calculated* |
|---|---|
| Boone-Heinonen and Gordon-Larsen (2011) (Boone-Heinonen and Gordon-Larsen, 2011) | [1]Measures calculated at both time points. Street connectivity (ratio of observed to maximum possible route alternatives between nodes (intersections), 1 km buffer). Paid PA facilities (N/10,000 population, e.g., dance studios, basketball instruction, martial arts, athletic club, gymnasium, tennis club, basketball club, physical fitness facilities, bicycle rental, public golf courses, 3 km). Public PA facilities (N/10,000 population, 3 km). Landscape diversity (Simpson's diversity index, 1 km). Population density (N; calculated by averaging census block-group population counts, weighted according to the proportion of block-group area captured, 3 km). Area-level SES (median household income from census tract data in 1990 and 2000). |
| Boone-Heinonen et al. (2010a) (Boone-Heinonen et al., 2010a) | [2]Measures calculated at both time points. To account for slight inaccuracies in geocoded locations and inconsequential moves, residential relocation (mover vs. non-movers) was defined as > 1/4 mile Euclidean distance between waves 1 and 3 residential locations. Street connectivity (ratio of observed to maximum possible route alternatives between nodes (intersections), 1 km buffer). Paid PA facilities (N/10,000 population, e.g., dance studios, basketball instruction, martial arts, athletic club, gymnasium, tennis club, basketball club, physical fitness facilities, bicycle rental, public golf courses, 3 km). Public PA facilities (N/10,000 population, 3 km). Landscape diversity (Simpson's diversity index, 1 km). Population density (N; calculated by averaging census block-group population counts, weighted according to the proportion of block-group area captured, 3 km). Area-level SES (median household income from census tract data in 1990 and 2000). |
| Boone-Heinonen et al. (2010b) (Boone-Heinonen et al., 2010b) | [3]PA facility counts (N and N weighted by the inverse distance from residential address (facilities between 1 and 8 km; facilities within 1 km received weights of 1)). Two street connectivity measures, 'link:node' ratio and intersection density (3 or more-way intersections/km$^2$). Area-level SES (median household income from census tract data in 1990 and 2000). |
| Bringolf-Isler et al. (2010) (Bringolf-Isler et al., 2010) | [4]Population and building density (N of inhabitants and buildings within 9 ha (ha)). Street density (total length of each type of street segment within varying buffers). Green space (N ha out of a square buffer of 25ha around residence; ha assigned green space if land use at center was park/woods/ agriculture). |
| Buck et al. (2015) (Buck et al., 2015) | [5]Intersections (N). Public transit stations (N). Public open spaces (playgrounds, parks, public green spaces) (N). |
| Burgoine et al. (2015) (Burgoine et al., 2015) | [6]Route to school (●) - Takeaway food outlets (N). All food outlets (N). PA facilities (N). Green space (area/route length). Proportion of major roads (% of route that is on major road). Effective walkable area (ratio of length of route to Euclidean distance to school). Land use mix (sum of squares of % of each land use type along route). [7]Home and school neighborhoods (○) - Takeaway food outlets (inverse distance weighting (IDW) sum of distance to all outlets). All food outlets (IDW sum of distance to all outlets). PA facilities (IDW sum of distance to all outlets). Green space (% of area). Proportion of major roads (length of major roads/total length of roads). Effective walkable area (ratio of street network area/Euclidean radius area). Connected node ratio of junctions to junctions and culs-de-sac. Land use mix (sum of squares of % of each land use in neighborhood). |
| Cain et al. (2014) (Cain et al., 2014) | [8]Walkability (index of residential density, intersection density, land use mix, retail floor area ratio) used as adjustment factor in analyses. |
| Carlson et al. (2017) (Carlson et al., 2017) | [9]Time in each of the following locations: home (50 m Euclidean buffer); home neighborhood (1 km street network buffer, excluding home Euclidean buffer); school (15 m around school parcel); school neighborhood (1 km street network buffer, excluding school parcel buffer); and all other locations. |
| Carlson et al. (2015) (Carlson et al., 2015) | [10]Net residential density (housing units per residential parcel). Intersection density (intersections per square km). Retail density (N of retail parcels; e.g., shopping centers, stores, banks). Walkability (index of residential density, intersection density, land use mix, retail floor area ratio). Entertainment density (N of entertainment parcels [non PA-related]; e.g., theaters, museums, social clubs). |
| Carlson et al. (2014) (Carlson et al., 2014) | [11]Residential density (housing units/ residential parcel). Street connectivity (intersections/km$^2$). Retail floor area ratio (building ft$^2$/parcel ft$^2$). Mixed use (including residential, retail, food and entertainment and office land use types). Cul-de-sac density (N of cul-de-sacs/km$^2$). N parks per km$^2$. |
| Carroll-Scott et al. (2013) (Carroll-Scott et al., 2013) | [12]Grocery stores (N). Convenience stores (N). Fast food restaurants (N). Parks (N; % of area). |
| Carver et al. (2010) (Carver et al., 2010) | [13]Local/residential roads (maximum speed of 50 km/h) (length; ratio to total length of all roads). Intersection density. Residing on a cul-de-sac (yes/no). Walking tracks (L). Speed humps (N). Gates/barriers on roads (N). Slow points, chicanes, sections of road narrowing (N). Traffic/pedestrian lights (N). |
| Carver et al. (2015) (Carver et al., 2015) | [14]Bike paths (N). Sports/recreational facilities (basketball court; netball court; tennis court; soccer field; sports center; skateboard/BMX park; swimming pool) (N). Accessible parks (had to at least partially overlap with the buffer area) (N; total area). Post offices (used as a proxy for shops) (P/A). Bike paths and shared walking/cycling paths (length). |
| Coughenour and Burns (2016) (Coughenour and Burns, 2016) | [15]Parks (N). Trailheads (N). Pay-for use PA facilities (N). Grocery stores (N). Fast food outlets (N). |
| Dalton et al. (2011) (Dalton et al., 2011) | [16]Residential density (N of housing units per acre of developed land). Intersection density (N of intersections with three or more legs per acre of developed land). |
| De Meester et al. (2012) (De Meester et al., 2012) | [17]Walkability index (high/low; land use mix, residential density, intersection density). |
| Dessing et al. (2016) (Dessing et al., 2016) | [18]Land use (4 category entropy index). Street type (%; residential, pedestrian path, separate bicycle path, arterial roads with a bicycle lane). Residential density (N of residents/km$^2$). Traffic variables (junctions, traffic accidents, zebra crossings, street lights, traffic lights, speed bumps; all N/km). Water along route (average %/km, e.g., ponds, rivers lakes). Greenness along route (average %/km, e.g., bushes, grass plots, woods). Trees (N). |
| DeWeese et al. (2018) (DeWeese et al., 2018) | [19]Supermarket (P/A). Small grocery store (P/A). Convenience store (P/A). Fast food restaurant (P/A). Park (P/A). PA facility (P/A). Residential density (N of dwellings, high/low using median). Intersection density (N of intersections with 3 or more legs, high/low using median). Median household income used |

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**Table 2** (*continued*)

| Lead author [reference] | Key geographic characteristics calculated* |
|---|---|
| | as adjustment factor (at block-level as well as individual level). Participants categorized into groups using latent class analyses. |
| Helbich et al. (2016) (Helbich et al., 2016) | [20]Culs-de-sac (%). 3-way intersections (%). 4-way intersections (%). Proportion of >4-way intersections (%). Shannon land-use diversity index (median (SD)). Shannon building usage mix (median (SD), IQR). Building-roughness index (normalized, median (SD), IQR, reflects height differences between a building and its neighbors). Closeness index (median (SD), IQR, describes the nearness/farness by measuring how difficult it is to go from location *i* to all other locations on the street network). Betweenness index (median (SD), IQR, quantifies which street segment will be busiest to move from location *i* to all other locations along the shortest path). Street density (median (SD), IQR). Major road/highway (P/A, Euclidean distance to nearest). Cycling path (% of length relative to overall street length). Distance to school (derived from GPS). Green space (% woods, grasslands, parks). |
| Hinckson et al. (2017) (Hinckson et al., 2017) | [21]Residential density (N/km$^2$). Street intersection density (N/km$^2$). Culs-de-sac (N/km$^2$). Transit stops (N/km$^2$). Parks (N). Land use mix (entropy index). |
| Ikeda et al. (2019) (Ikeda et al., 2019) | [22]Distance to school. Active Mobility Environment was a first-order factor (latent variable), collectively assessed by four observed variables: residential density (ratio of residential dwellings to the residential land area); street connectivity (ratio of number of intersections with three or more intersecting streets to the land area); high traffic exposure (length; weighted by an inverse softGIS route distance, using road classification as a proxy for traffic volume); and low traffic exposure (length; weighted by an inverse softGIS route distance, using road classification as a proxy for traffic volume). |
| Islam et al. (2014) (Islam et al., 2014) | [23]Total building footprint area (sum of footprint areas of all buildings within a buffer area). Gross building floor area (total of footprint areas of all buildings within the buffer area, multiplied by the respective number of floor levels). Street intersection density (N of >2 leg intersections). Street pattern (overall pattern in buffer, either: colony internal (restricted zone of government housing), spontaneous, or gridiron (master planned)). |
| Jauregui et al. (2016) (Jauregui et al., 2016) | [24]Street connectivity (>2-way intersection). Residential density (households/km$^2$). Area-level SES. Walkability index: street connectivity, residential density (GIS), and land use and commercial mix (generated from a pedestrian environment scan). |
| Kyttä et al. (2012) (Kyttä et al., 2012) | [25a]Residential density (housing units per hectare). Green space (proportion of fields, forests, parks, and water area). Child population (proportion of birth to 15-year-olds within the buffer, calculated from city centroid data).[25b]Child-marked destinations of importance using public participation GIS methods. |
| Laxer and Janssen (2013) (Laxer and Janssen, 2013) | [26]Intersection density (N/km$^2$). Average block length (km). Street connectivity (% of intersections >2-way). Low speed roads (% ≤ 50 km/h). Sidewalks (% roads covered by sidewalks). Mixed land use (% residential). Walkability scale developed using principal component analysis including land-use mix, low speed roads, intersection density, and sidewalk coverage. Parks and other public green space (including national parks, provincial parks, territorial parks, and municipal parks/sports fields, % of area). Open wooded areas (% of area). Culs-de-sac ((N of intersections-N of true intersections)/land area). Presence of yards at home (sum of scores (max 60) from 15 observation points plotted in each 1 km buffer in an evenly spaced grid (approximately 500 m apart in the *X* and *Y* directions from the buffer's center) within Google Earth Streetview, a 36- degree panoramic view was taken at each of the 15 points to measure the proportion of houses and other buildings that had a yard in front). |
| McGrath et al. (2016) (McGrath et al., 2016) | [27]Recreational amenity index: green space, beaches, and sports facilities (N). Food outlets (P/A of supermarkets, petrol stations, bakeries, greengrocers, butchers, fishmongers, convenience stores, and fast food stores). Walkability index: retail floor area ratio (retail building footprint area by the total retail parcel area); road intersection density (N of > 2-way intersections/neighborhood area); dwelling density (N of occupied private dwellings/residential land area); and land-use mix (entropy index). |
| Mecredy et al. (2011) (Mecredy et al., 2011) | [28]Composite street connectivity scale using: intersection density (N of nodes/total land area); average block length (mean length of blocks in the area, calculated as sum of the link length per area/N of nodes per area); connected node ratio (N of street intersections divided by N of intersections plus cul-de-sacs, calculated as N of real nodes/total N of nodes). |
| Mitchell et al. (2016) (Mitchell et al., 2016) | [29]Open space parks (N/km$^2$ with no built recreational amenities). Parks with at least one sports field (N/km$^2$ with at least one sports field (defined as tennis courts, soccer fields, baseball diamonds, or football fields)). Parks with at least one playground (N/km$^2$ with at least one playground). Parks with both at least one sports field and playground (N/km$^2$ with at least one sports field and at least one playground). Distance to the nearest school (km). Distance to the nearest recreational site (km). Land use mix (entropy score). Multi-use path space (km$^2$). Intersection count (N of >2-way intersections/km$^2$). |
| Mölenberg et al. (2019) (Mölenberg et al., 2019) | [30]New dedicated PA space (the intervention, P/A in buffer, distance to space). |
| Moran et al. (2017) (Moran et al., 2017) | [31]Walkability index (land use mix/entropy index, residential density, intersection density, retail floor area ratio). Residential density (N of households/km$^2$). Intersection density (N of intersections/km2). Retail area (%; including shops, grocery stores, malls). Public institute area (%; including community centers, recreation facilities). Green open space area (%; including parks, playgrounds). |
| Nordbø et al. (2019) (Nordbø et al., 2019) | [32]Population density (N of residents/km$^2$, 800 m buffer only). PA facilities/amenities (N of schools, libraries, churches, cinemas, indoor pools, shopping malls, community centers). Playgrounds/sports fields (N). Schools (P/A). Green space (% area of forests, marshland, parks, golf courses; 800 m buffer only). Parks (P/A). |
| Oliver et al. (2014) (Oliver et al., 2014) | [33]Distance to school. Neighborhood walkability measure for self-selection variable was calculated using: retail floor area ratio (retail building footprint area by the total retail parcel area), road intersection density (N of > 2-way intersections/neighborhood area), dwelling density (N of occupied private dwellings/residential land area), and land-use mix (entropy index). |

(*continued on next page*)

**Table 2** (*continued*)

| Lead author [reference] | Key geographic characteristics calculated* |
|---|---|
| Olsen et al. (2019) (Olsen et al., 2019) | [34]Grid cells (○) and[35]Home neighborhood (●) - Motorway or *A* (major) road (P/A). *B* or minor road (P/A). Railway stop (P/A). Bus stop (P/A). Food and/or drink retail (P/A). Primary school (P/A). Leisure center (P/A). Place of worship (P/A). Library (P/A). Derelict land (P/A). Private gardens (P/A). Playing field (P/A). Sports club (P/A). Woodland (P/A). Public park (P/A). Play park (P/A). Green verge (P/A). Other (P/A). Dense population (P/A). Urban (P/A). Income Scottish Index of Multiple Deprivation (quintiles of deprivation). Walkability score (defined using a composite 'walkability score' based on street/path connectivity, and dwelling density). |
| Sallis et al. (2015) (Sallis et al., 2015) | [36]Walkability index used as control variable, calculated from: net residential density; street connectivity; retail floor area ratio; and land use mix. |
| Sallis et al. (2018) (Sallis et al., 2018) | [37]Walkability index: net residential density; street connectivity; retail floor area ratio; and land use mix. |
| Smith et al. (2019) (Smith et al., 2019) | [38]Traffic speed exposure (ratio of high speed (>60 km/h), road length to low speed (<60 km/h), road length). Signalized crossings (N). Cycle paths (ratio of cycle path lengths to road lengths). Pedestrian network connectivity (PedShed: ratio of reachable pedestrian network area (network buffer area) to the maximum possible area (Euclidean buffer area)). |
| Tucker et al. (2009) (Tucker et al., 2009) | [39]Land use mix (entropy index). Recreation opportunities (N of publicly funded recreational facilities, including soccer fields, baseball diamonds, basketball courts, community centers, arenas, pools, tennis courts, playgrounds and wading pools). Level of park coverage (% of public parkland divided/total land area). |
| van Loon et al. (2014) (van Loon et al., 2014) | [40]Net commercial density. Net residential density. Land use mix. Intersection density in neighborhood and en-route to school (N of 4-way intersections). Cul-de-sac density. Proportion of low speed limit streets (>30 km/h). Parks (N). Population density of children. Child population (%). Distance to school, parks, other recreation sites. |
| Villanueva et al. (2012) (Villanueva et al., 2012) | [41]School neighborhood (2 km) - Walkability index: network connectivity and road traffic volume exposure. Home neighborhood (800 m) - Parks/greenspace (N). Utilitarian destinations (N). Recreation destinations (N).[42]Destinations[43]Walkability, SES |
| Wang et al. (2017) (Wang et al., 2017) | [44]Walkability index: net residential density; street connectivity; retail floor area ratio; land use mix. Parks (N). Recreation facilities (N). |

[1-44]Detail for other GIS methods employed are provided in Table 1.
GIS = geographic information system, GPS = global positioning system, IQR = interquartile range, L = length, N = number, PA = physical activity, P/A = presence or absence, SD = standard deviation, SES = socio-economic status.

environment characteristics derived from GIS-estimated shortest routes and GPS-derived routes to school. No significant differences were found for actual and estimated route distances, but characteristics of routes differed significantly, and different results were observed for walking and cycling trips. Burgoine et al. (2015) investigated associations between children's BMI and home, school and route environmental exposures measured using GPS-derived route to school and GIS-estimated home neighborhood. GPS data were collected over one week, but were only used for the route to school and not used to delineate home or school neighborhood.

In studies of home or school neighborhoods, one article used GPS to determine time spent in specified locations, but these data were not used

**Table 3**
Overview of key strengths and limitations related to neighborhood delineation and use of GIS, GPS, and PPGIS in articles included and examples of literature identified.

| Topic/issue | Strengths (with examples of studies) | Limitations (with examples of studies) |
|---|---|---|
| Neighborhood delineation | Multiple buffer distances explored (Boone-Heinonen et al., 2010a; Carlson et al., 2017; Buck et al., 2015; Carver et al., 2015; van Loon et al., 2014) Multiple neighborhood delineations explored (e.g., use of multiple buffer distances and both simple and kernel intensity approaches (Buck et al., 2015)), child-reported destinations of importance, objective GIS-estimated measures, and shortest distances to destinations (Kyttä et al., 2012), simultaneous consideration of activity spaces and traditional neighborhood buffer boundaries, school-specific walkability measure (Villanueva et al., 2012) | Inconsistent use of multiple buffer distances did not allow for comparability (Nordbø et al., 2019; Boone-Heinonen and Gordon-Larsen, 2011; Boone-Heinonen et al., 2010a, 2010b) Issues with studies examining both home and school environments (e.g., unclear how school and home neighborhoods were combined, and whether there was any consideration of overlap between home and school neighborhoods (Tucker et al., 2009)), some crossover (6%) in school buffers when using an 800 m buffer (Jauregui et al., 2016), and potential overlap and collinearity between home and school neighborhood exposures for children who lived close to school (Burgoine et al., 2015) Activity space calculation did not account for trip frequency and/or duration (Villanueva et al., 2012) Minimum convex polygons used for activity space calculation do not use pedestrian network measures (Villanueva et al., 2012) |
| Temporal alignment of data | GIS environmental measures calculated at each time point (Boone-Heinonen and Gordon-Larsen, 2011; Boone-Heinonen et al., 2010a) | Temporal mismatch between interview/survey/outcome data and GIS data (Nordbø et al., 2019; Boone-Heinonen and Gordon-Larsen, 2011; Boone-Heinonen et al., 2010a; Carroll-Scott et al., 2013) Longitudinal outcome data but GIS variables at baseline only (unclear if participants had moved) (Carver et al., 2010) |
| GIS databases | Verified food outlet type where necessary by phoning businesses and conducting store visits (Burgoine et al., 2015) | Limited access to detailed green space GIS data (Bringolf-Isler et al., 2010) Spatial differences between time points (e.g., shifts in census boundaries over study measurement periods (Boone-Heinonen and Gordon-Larsen, 2011; Boone-Heinonen et al., 2010a)) |
| GPS studies | Sensitive and accurate data collected on individual routes to school (Burgoine et al., | Although GPS used to measure time in locations, buffer distances were |

(continued on next page)

**Table 3** (*continued*)

| Topic/issue | Strengths (with examples of studies) | Limitations (with examples of studies) |
|---|---|---|
| | 2015; Dessing et al., 2016; Helbich et al., 2016) or neighborhood locations visited (and time spent in these) (Carlson et al., 2017; Olsen et al., 2019) | estimated rather than actual exposure (Carlson et al., 2015, 2017; Burgoine et al., 2015) Multi-destination tracks were not accounted for in analyses (Dessing et al., 2016) |
| Data analyses (relevant to GIS/ neighborhood environment measures) | Neighborhood exposure considered (e.g., length of residence in the neighborhood included as a covariate (Hinckson et al., 2017); child needed to have lived in the study area for at least 1 year in order to-participate (Moran et al., 2017; Islam et al., 2014), authors measured duration of residence in the-neighborhood, with approximately 70% having lived in the neighborhood for 5 years or more (DeWeese et al., 2018)) Neighborhood self-selection considered (Boone-Heinonen et al., 2010a; Oliver et al., 2014) Statistical adjustment for macrolevel walkability (Sallis et al., 2015; Cain et al., 2014) Stratification of analyses by socio-demographic factors ( Boone-Heinonen and Gordon-Larsen, 2011; Carver et al., 2010; Olsen et al., 2019; Buck et al., 2015; van Loon et al., 2014) | |
| Study design (relevant to GIS/ neighborhood environment measures) | Heterogeneity in environmental characteristics likely due to stratified recruitment of households ( Carlson et al., 2014, 2015, 2017) (albeit noting that in one study although stratified recruitment in higher and lower-socio-economic status neighborhoods occurred, education levels of parents were generally high, likely reflecting education levels of the university city (De Meester et al., 2012)) Environmental variability including low density, single family housing neighborhoods to mixed use and medium-high density neighborhoods characterized by a range of apartment type housing (van Loon et al., 2014) Inclusion of urban and rural areas (Carver et al., 2015) | |
| Specificity of measures/methods | Separate analyses conducted by transport mode (Dessing et al., 2016). Cyclist and pedestrian-specific variables calculated (but did not analyze separately by travel mode due to low cycling numbers) (Smith et al., 2019) Multiple addresses: Excluded children living in postseparation families to make certain that the child lived at the actual address used for the calculation (although this would have increased specificity it may introduce unanticipated bias through excluding a participant group) (Nordbø et al., 2019) Participants living further than 2 miles (Carlson et al., 2014) or 2 km (Villanueva et al., 2012) from their school were excluded (albeit this will produced biased results towards those living close to school) | Walkability index of the school neighborhood used as a proxy for neighborhood walkability (Laxer and Janssen, 2013; Villanueva et al., 2012) |

GIS = geographic information system, GPS = global positioning system.

to generate egocentric home or school neighborhood boundaries (Carlson et al., 2017). Olsen et al. (2019) used a combination of 25 $m^2$ grid cells identified from GPS points of participants and GIS-estimated home neighborhood to assess environmental characteristics associated with time spent in specific locations. Kyttä et al. (2012) generated measures for children's places of importance using PPGIS, but did not use these places to delineate neighborhood boundaries, instead using a 500 m network buffer. Over half (53%) of meaningful places marked by children were within 500 m from home. Villanueva et al. (2012) used actual exposure data to generate egocentric neighborhood delineations by making a minimum convex polygon from children's home and marked destinations visited (only for those reporting active travel to local destinations).

### 3.2.2. *Articles estimating neighborhood exposure*

Twenty-three articles estimated the home neighborhood using individual participant addresses and Euclidean or network buffers only, four measured the school neighborhood environment only (Laxer and Janssen, 2013; Mecredy et al., 2011; Dalton et al., 2011; Jauregui et al., 2016), and five (Carlson et al., 2014, 2017; Tucker et al., 2009; Burgoine et al., 2015; Villanueva et al., 2012) generated measures for both the home and school neighborhood (albeit these were not always consistent). Area-level measures were used to define neighborhoods in six articles (e.g., Census tracts (Carroll-Scott et al., 2013), statistical sectors (De Meester et al., 2012), post code (Tucker et al., 2009), or meshblocks (Oliver et al., 2014)). Five articles estimated the route to school using GIS-estimated shortest route methods (Burgoine et al., 2015; Dessing et al., 2016; Moran et al., 2017; Helbich et al., 2016; Ikeda et al., 2019). The article of Burgoine et al. (2015) was the only to measure home neighborhood, school neighborhood, and school route.

Two articles used intensity measures that were not reliant on arbitrary neighborhood buffer delineations. Buck et al. (2015) applied both simple intensity and kernel intensity approaches to measure intersections, public transit stations, and public open spaces. Sex-specific and age-specific differences were observed, whereby MVPA was associated with availability of public open spaces in school-aged girls and pre-school children (but not school-aged boys), and for school-aged girls only significant associations were observed with public transit and higher street connectivity. Burgione et al. (Burgoine et al., 2015) used inverse distance weighting for neighborhood measures of food outlets and PA locations within 6 km from the home and school address (combined with walkability measures and exposure to green space using 800 m network buffers around home and school addresses). In the inverse distance weighting, all discrete outlets and PA location points contributed to neighborhood exposure.

### 3.3. Buffer distances used in neighborhood delineations

For home neighborhood delineations, buffer distances of between 100 m (Euclidean) (Bringolf-Isler et al., 2010) and 5 km (Euclidean, pedestrian network) (Nordbø et al., 2019; Carver et al., 2015) around the home were observed. This range for school neighborhoods was between 400 m (Jauregui et al., 2016) to 5 km (Mecredy et al., 2011) Euclidean buffers from the school. Sixteen articles used more than one neighborhood buffer distance. The most common buffer distances used were 800 m and 1 km (both N = 11 studies). One article measured time spent within the home parcel (using a 50 m Euclidean buffer), the school parcel (15 m buffer), and the home and school neighborhoods (1 km street network buffer excluding the home and school parcel, respectively) (Carlson et al., 2017). Five used multiple buffers that were inconsistent across variables (Nordbø et al., 2019; Boone-Heinonen and Gordon-Larsen, 2011; Boone-Heinonen et al., 2010a, 2010b; Tucker et al., 2009), and two used multiple buffer distances that were inconsistent due to use of differing methods. For example, Olsen et al. (2019) developed 25 $m^2$ grid cells based on GPS data points, and estimated children's home neighborhoods using an 800 m Euclidean buffer. Results showed that children often used specific amenities outside the 800 m buffer, even if these amenities were also available close to home. Burgoine et al. (2015) stipulated an 800 m network buffer to characterize home and school environments, and employed inverse distance weighting using a 6 km maximum distance threshold.

Less than a quarter of articles used at least some consistent measures, enabling comparison of the utility of differing buffer calculations. Most of the articles that enabled comparison included children aged between 6 and 14 years and all used estimated measures of neighborhoods. There was some indication that larger buffer sizes may capture activity neighborhoods better in this age group. For example, van Loon et al. (van Loon et al., 2014) reported that larger buffer sizes (i.e., 800 m, 1.6 km), and predominantly the largest buffer size (1.6 km), best explained the associations between MVPA and environments (compared with smaller street network buffer sizes of 200 m and 400 m). Buck et al. (2015) found stronger effects in environmental associations with MVPA when using larger network distances (~1–2 km). Villanueva et al. (2012) determined that the amount of neighborhood area overlap with GPS-derived activity spaces was greater when using 1.6 km street network buffers compared with an 800 m buffer. In a study of children's odds of cycling, significant results were only observed in the 5 km home neighborhood buffer (using a pedestrian network buffer including cycling infrastructure) and not for an 800 m buffer. Although Mitchell et al. (2016) found comparable results between 500 m and 800 m home neighborhood buffers (Euclidean) for children's MVPA, sex differences were observed, whereby the 800 m buffer only was important for females. Conversely when examining active school travel and school neighborhood walkability (Euclidean), Jauregui et al. (2016) observed a significant negative relationship at 400 m and no significant relationship was found for the 800 m buffer.

In age-stratified analyses, Bringolf-Isler et al. (2010) noted significant and comparable results in relationships between 100 m, 200 m, or 500 m home neighborhood environments (Euclidean) and vigorous outdoor play in children aged 6–10 years. For adolescents aged 13–14 years, no significant associations were observed at any of these buffer sizes. One article examined a range of distances from home (500 m, 750 m, 1 km, 1.25 km, 1.5 km, 2 km) with younger children aged 2–9 years (Buck et al., 2015). Findings showed consistent associations for MVPA and environmental characteristics between 750 m and 1.5 km for school-aged children, and between 500 m and 1 km for preschool-aged children in studies in this review, but only when using a kernel density approach, rather than simple network buffer. Conversely, the single study with adolescents (aged 12–18 years) that had comparable environmental variables (pedestrian network buffers around homes of 250 m, 500 m, 1 km, and 2 km) showed MVPA was only associated with residential density and number of parks within 2 km from home, and also when this was combined into an objective environmental index of activity-friendliness (Hinckson et al., 2017). For routes travelled, buffers of 25 m (Dessing et al., 2016; Moran et al., 2017), 100 m (Burgoine et al., 2015; Helbich et al., 2016), and 160 m (80 m either side of the centerline) (Ikeda et al., 2019) were used. No studies compared the utility of differing route buffer distances.

## 4. Discussion

The aim of this review was to map out and describe GIS-based approaches that have been employed to measure children's neighborhood geographies for understanding PA and related outcomes. Forty articles were included in this review, the GIS methods of which are explored and contextualized within the extant evidence base here. Studies were predominantly conducted in the USA and in non-rural neighborhoods. A plethora of GIS methods and variables were used in the literature identified, with the majority obtaining estimates of children's home environments using Euclidean or network buffers ranging from 100 m to 5 km. Reporting of methods was reporting of methods was inconsistent across studies and sometimes incomplete meaning not all data could be extracted.

Comparison of PA neighborhood buffer distances used suggested distances of around 800m-1.6 km may be optimal (dependent on context, type of environment being measured, and age group), with greater distances for older youth, and shorter distances for younger children. To some extent, the finding that larger distances performed better in identifying relationships is unsurprising. This is particularly relevant when considering destinations - as boundaries are increased, so too should the volume of possible relevant destinations. The trade-off of using larger buffer sizes is reduced specificity and subsequent impacts on utility for informing urban planning. Larger buffer sizes can also limit geographic variability between individuals living within the same area. Overall, findings reveal the value of measuring actual exposure, and where this is not possible, using multiple buffer sizes as well as stratification of analyses by socio-demographic characteristics (e.g., age) and behaviors (e.g., walking, cycling).

A small number of studies stratified by socio-demographic factors, and where this occurred, studies showed important differences in relationships between activity and environments by age group, sex, socioeconomic status, and geography (particularly with regard to urbanicity). Additionally, differing results were found by population groups by stages of the day (e.g., before school and after school) (Carver et al., 2010), and other studies supported the value of focusing on out of school hours (Mitchell et al., 2016). These differences signal the importance of considering how children's relationships with their neighborhood can differ within-individual (e.g., over time, in different contexts), within population groups or neighborhood environments, and between population groups or geographic contexts. Consistent approaches to measuring environments by spatial (e.g., school neighborhood, home neighborhood, routes; rural, urban; etc.) and temporal (e.g., time of day) factors are needed to understand the relationship between environments and children's PA behaviors.

These issues also speak to the need for conceptual matching of dependent and independent variables for improved specificity in this field (Giles-Corti et al., 2009). For example, while pedestrian network buffer calculations conceptually align with understanding active travel, these buffers were only used in a small number of articles. There is a need to understand associates of walking and cycling behaviors better through (1) examining these behaviors independently, and (2) measuring specific infrastructure hypothesized to support the behaviors (e.g., cycle lane size, proportion of footpaths). Where PA is the outcome of interest, multiple approaches may be required that measure characteristics within home and school "neighborhoods", as well as characteristics along routes of importance (e.g., between home and school).

Only one study in this review characterized children's environments using all three approaches (Burgoine et al., 2015). Care must be taken to ensure there is no overlap in areas, for example where home and school neighborhoods are simultaneously taken into account (particularly for children who live close to school). To overcome this issue, one study removed 20% of their sample who had overlap in their home and school neighborhood buffers (Carlson et al., 2017). Alternative approaches that do not exclude participants are warranted, for example, identifying, clipping and removing overlap (Egli et al., 2020). Temporal matching of GIS datasets with outcomes is also an area for improvement, with some studies having using historical datasets that were nearly a decade apart from the behavioral data being collected, and longitudinal studies using baseline addresses only to generate environmental measures for analyses.

Findings from one article suggested intensity measures (i.e., examining intensity of environmental characteristics within specified distances from a location) performed more consistently than using neighborhood buffers (Buck et al., 2015). However, intensity approaches remain only estimates of specific settings and overall neighborhood environments that children spend their time in. Moreover, while neighborhood buffer distances do not need to be specified, intensity methods such as kernel density estimation do require specification of bandwidth distances, which are still generally relatively arbitrary. Choice of destinations for examination must be carefully considered and may still only be estimates of actual exposure. For example, use of GPS and accelerometry (Badland et al., 2015) and PPGIS (Egli et al., 2020; Kyttä et al., 2018) in earlier research has highlighted unique patterns in children's neighborhood use, including identifying the importance of school settings, shopping destinations, and large, multipurpose outdoor settings.

Use of GPS to measure actual exposure can overcome some of these limitations (Hurvitz et al., 2014; Jankowska et al., 2015) and was employed in a number of articles to assess routes travelled thus improving precision in behavioral measurement (e.g., when combined with accelerometry as in Carlson et al. (2017)) and environmental exposure. Combination with accelerometry can also mitigate issues with non-activity/environmental exposure time being inaccurately coded (e.g., while in a stationary car). In articles included in this review, GPS was used in to identify places of importance to children within their neighborhood and where physical activities actually occurred (Carlson et al., 2017; Olsen et al., 2019). Multi-destination tracks (e.g., trip-chaining) were not considered in GPS-derived route studies (Dessing et al., 2016). Future studies should consider this issue in order to fully understand route characteristics and destinations of importance in relation to children's PA. For example, for the home-school trip, a route will look different if a child was picked up en-route (potentially requiring divergence from the home-school journey) compared with a direct home-school journey. GPS approaches themselves are not without limitations, including varying model validity (Duncan et al., 2013) issues with data quality, battery life, unit failure, signal drop out, increased participant burden through having to wear the unit, and participant non-compliance in free-living activities (Oliver et al., 2010). The resourcing required for units and data processing also means studies are generally limited to small sample sizes. No studies cited applying minimum GPS inclusion criteria or potential issues with bias in data inclusion, an important consideration considering the potential for inequitable exclusion of participants with increasingly stringent criteria (Mavoa et al., 2018). Disagreement was found in terms of whether constraining GPS paths to street networks for routes is appropriate or not. In comparisons of approaches, Burgoine et al. (2015) proposed snapping to the street network resulted in a more accurate estimation of the route travelled (but acknowledged this could also miss through-ways between street networks), while Dessing et al. (2016) reflected on the value of buffering 'raw' GPS signals of the route travelled to resemble the actual routes as closely as possible. Specification of shorter GPS sampling epochs is intrinsically related to this challenge, whereby shorter epochs may allow for greater spatial accuracy (negating the need to "snap" to the network), and overcome issues with signal drop-out (e.g., due to being in an urban jungle).

Several types of spatial data, such as GPS and PPGIS, provide the functionality to map activity spaces and define individualized neighborhood areas (Perchoux et al., 2013; Hasanzadeh et al., 2017, 2018). Individual activity spaces are increasingly gaining interest as spatial units in empirical research. Activity spaces have been recognized for their value in understanding relationships between human behavior and the built environment (Sherman et al., 2005). However, studies reviewed in this paper have rarely used such data to define children's neighborhood areas or their activity spaces. In one study, child-mapped destinations were used to generate individual activity space maps using minimum convex polygons (Olsen et al., 2019). However, there are limitations associated with minimum convex polygons, or the so-called "container" approaches in general. Such approaches do not use pedestrian network measures and hence do not adequately account for the variability of accessibility and exposure within their boundaries (Hasanzadeh et al., 2018). There is also a need to consider the varied exposure within these polygons, for example by taking into account the frequency of visitation to key destinations (Hasanzadeh et al., 2018).

Child-mapped destinations were used in one article to examine children's perceptions and use of neighborhood destinations (Kyttä et al., 2012), but these data were not used to generate a neighborhood area of interest. These approaches rely on children's ability to accurately recall and report destinations of importance. Evidence suggests that for younger children (i.e., aged 8–13 years) undertaking PPGIS surveys one-to-one researcher support may be necessary to ensure children are able to complete mapping activities (Oliver et al., 2016b). It is also possible that differences in accuracy of maps and routes will exist by geography (e.g., traditional vs. suburban neighborhood), and by usual mode of travel (Moran et al., 2017; Oliver et al., 2016b; Stewart et al., 2017). While involving children in determining neighborhood environment measures through mapping activities can be time consuming, and longer non-active routes may be more susceptible to self-report error (Stewart et al., 2017), these approaches can provide detailed insights in ways that estimated measures cannot. There is a need to advance these techniques and the evidence base through considering relative importance and role of key destinations in children's lives.

Ethical issues exist with regard to ensuring participant anonymity. In one study, spatial blurring of children's addresses was undertaken, and minor effects on assessment of urban measures was observed (Buck et al., 2015). This issue is not restricted to home addresses – in earlier work exploring neighborhood destinations, Egli et al. (2019) geomasked neighborhood destinations where children reported spending time when presenting maps of child marked locations, schools, and outdoor advertising. Improved reporting of consideration for protecting child participants and their anonymity is needed, alongside implications for interpreting research results.

A large body of GIS literature has explored measurement issues in environments and health research with a focus on mobility of adult or general populations, or access to health services. For example, Páez et al. (2012) highlighted important distinctions in accessibility measurement, reflecting on the utility of using measures of normative accessibility (how far is it reasonable to travel) and positive accessibility (how far people actually travel) in tandem using access to childcare as a useful case study. Langford et al. (2018) also examined issues related to access to formal childcare provision, calling for "a more integrated and consistent approach to collating data that enables both spatial and temporal patterns in provision to be elucidated" (p. 663). The review of Yi et al. (2019) summarized geospatial methods used to measure built environments in PA research using three main categories. Of the 79 articles, most used domain-based approaches (i.e., aligning GPS accelerometry with environmental context to identify levels of PA in particular domains), 22% used buffer-based methods, and 11% activity-space approaches. Numerous technical limitations were identified, including issues related to temporal dimension and selective daily mobility bias with specific regard to understanding the environment-activity relationship. A number of studies call for improved reporting of GIS methods in health geography research, with proposed reporting checklists including Geo-FERN for food environments (Wilkins et al., 2017), and the ISLE-ReST for use in spatial lifecourse epidemiology research (Jia et al., 2019). The quality assessment results in this research further demonstrate the need for improved clarity in reporting across all methods. Overall, the clear and consistent messages are that no one approach is optimal, careful consideration of the limitations of approaches is necessary, as is an understanding of the impacts that decision-making in GIS analyses can have on variable calculation and subsequent identification of relationships. Here, the focus on children as a population group and physical activity behaviors as an outcome provides a unique contribution to the predominantly adult-centric evidence base. Child-specific insights and recommendations have been provided regarding buffer distances, socio-demographic considerations, and pragmatic considerations about conducting mapping research with children.

Finally, the value of GPS and child-mapping methods to better elucidate children's physical activity geographies remains underexplored. In addition to specific suggestions for future research identified above, it will be useful to consider how Chaix's (Chaix, 2018) recommendations for future 'mobile sensing' research - development of theoretical models and a priori hypotheses, improved data collection/analysis, and development of interventions that take advantage of mobility data – apply (or not) to research with children.

### *4.1. Review strengths and limitations*

Strengths of the review are the systematic approach to identifying, screening, and including literature with random duplication across all activities, however a number of limitations should be considered. The review took a narrow approach to focusing on built environment aspects only, and in doing so did not include studies that focused on factors that fit more broadly under the social environment (e.g., crime, socioeconomic status). It is recognized that the relationship between the built environment and these factors is complex. For example, socioeconomic factors can drive environmental design and subsequently impact health outcomes in children, potentially exacerbating inequities (Egli et al., 2020). Considering these factors together requires an in-depth and comprehensive approach to understand the multiple relationships and pathways between factors, which was beyond the scope of this study.

Because the focus was on GIS analyses, the review has not reported on other environment-PA relationships observed in the literature included. In some cases, additional variables were important contributors to understanding the environment-PA relationship (e.g., perceived environmental features (Hinckson et al., 2017; Ikeda et al., 2019), weather (Helbich et al., 2016; Oliver et al., 2014), and environmental quality (Cain et al., 2014; Islam et al., 2014)), however these were not explored in the current review. Broader study design issues such as sample size, representativeness, seasonality, and reliability and validity of outcome measures have not been systematically examined in this review (but are reported briefly in this discussion). The heterogeneity in methods, combined with the fact most of the evidence arose from the USA, also limited any comparison in utility of GIS approaches by geographic context. Finally, while the value of including grey literature (Gebel et al., 2015) is acknowledged, this review was delimited to published academic literature only, primarily in the interest of maintaining feasibility. It is likely a number of relevant studies were missed through this decision, however the diversity in methods presented from literature sourced likely mean that methods currently employed in the field have been covered.

## 5. Conclusion

A heterogeneous body of literature was identified and reporting of methods was inconsistent. It is likely that no singular existing approach to measuring geographies for children's PA is optimal, and instead triangulation of a range of approaches is needed, with methods determined taking population, geography, and study context into consideration. Greater geographic diversity in international evidence is needed. Improved consistency and transparency in reporting research methods is urgently required to enable comparability across socio-demographic groups and geographic regions.

## Declaration of competing interest

The authors have no conflicts of interest to declare.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2020.102489.

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