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Methodologies for Assessing Contextual Exposure to the Built Environment in Physical Activity Studies: A Systematic Review

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Abstract

Growing research has integrated Global Positioning Systems (GPS), Geographic Information Systems (GIS), and accelerometry in studying effects of built environment on physical activity outcomes. This systematic review aimed to summarize current geospatial methods of assessing contextual exposure to the built environment in these studies. Based on reviewing 79 eligible articles, methods were identified and grouped into three main categories based on similarities in their approaches as follows: domain-based (67% of studies), buffer-based (22%), and activity space-based (11%). Additionally, technical barriers and potential sources of uncertainties in each category were discussed and recommendations on methodological improvements were made.

Keywords

Geographic Information Systems (GIS); Global Positioning Systems (GPS); Accelerometer; Built Environment; Physical Activity; Exposure Assessment

1. Introduction

Insufficient physical inactivity is a major public health concern in the United States and worldwide (Katzmarzyk et al., 2016; Piercy et al., 2018) and can lead to serious health consequences such as obesity, diabetes, and cardiovascular disease (PAGAC, 2018). Socioecological models suggest that both individual characteristics and environmental exposures may influence health behaviors such as physical activity (Sallis et al., 2012).

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Supplemental Materials
Appendix 1. Summary of common study characteristics, data processing and integration considerations, and Methodological Considerations of RBECs Exposure Assessment for 79 studies reviewed. (See the attached Supplementary Table 1)

Declaration of Interests
None

While removing barriers at the individual level is a critical step, modifying the daily built environment in which people live and interact may drive the formation and long-term maintenance of physically active lifestyles (Ding and Gebel, 2012; Durand et al., 2011; Sallis et al., 2012).

Numerous studies have established associations between physical activity and a myriad of built environment characteristics – from single elements, such as parks, transit stops, and sidewalks, to composite measurements such as neighborhood walkability (Dunton et al. 2009; Brownson et al., 2010; Ferdinand et al., 2012). Previous research typically limits itself to relatively static, one-time exposure assessments of important domains such as residential, workplace, or school environments — even though interactions between built environment exposure and physical activity behavior occur dynamically and continuously across individuals' activity spaces (Chaix et al., 2013, 2012; James et al., 2016; Jankowska et al., 2015; Kwan, 2018). This usually introduces exposure misclassification or error into the assessment. For example, a study on effects of neighborhood parks on physical activity might only assess participants' accessibility to parks within residential neighborhoods; while all daily physical activity might actually be occurring in a park near the workplace.

To mitigate this issue, research has increasingly adopted real-time personal location monitoring technologies such as Global Positioning Systems (GPS) to understand the spatial and temporal variability in individuals' activity spaces, or locations where they spend time. Geographical coordinates of human movements generated by GPS are typically linked in space to geospatial data through Geographic Information Systems (GIS) and linked in time to physical activity data captured via accelerometry to study whether relevant built environment contexts (RBECs) are associated with concurrent or time-lagged physically activity outcomes (Chaix et al., 2012; James et al., 2016; Jankowska et al., 2015). In previous GPS-based physical activity studies, some reported GPS identified and assessed built environment domains considered to be important or frequently encountered in individuals' daily life, such as the park, school, home, or transport (Bürgi et al., 2015; Duncan et al., 2009; McCrorie et al., 2014; McMinn et al., 2014; Oreskovic et al., 2012). In addition, other studies reported epoch, trip, day-level or time-lagged associations between built environment characteristics such as neighborhood greenness, land use mix, population density, residential density, street network density, and walkability and physical activity outcomes (Burgoine et al., 2015; Chaix et al., 2016; Hurvitz et al., 2014b).

However, most or all of these studies follow a generalized scheme of data processing and analysis before reaching the statistical analysis phase where the association(s) between RBECs and physical activity outcomes is tested or investigated. These general stages can be summarized as follows: data preprocessing, data integration, and RBECs exposure assessment (See Figure 1). Some of the major tasks involved in data preprocessing include evaluation of missingness (and possibly imputation), outliers, and GPS accuracy. Data integration then focuses on linking or integrating GPS and accelerometry data in time. Considerations for aligning GPS and accelerometry data to produce a time-aligned GPS accelerometry (TAGA) point dataset have been addressed by previous literature reviews (Duncan et al., 2009; Krenn et al., 2011), which readers can refer to for more information. And lastly, the final stage involves linking the TAGA dataset in space with GIS data and applying a wide array of spatial averaging approaches based on the spatial extent of the GPS tracks per defined time period, domain or behavior and the duration of time spent per location (if employing a time-weighted spatial averaging technique) to generate exposure estimates for RBECs and link them with the physical activity outcomes in a final analytical dataset.

The analyst is usually required to make informed guesses or assumptions about the spatial and temporal extent of the built environment's contextual influence on the studied physical activity outcome since the truly relevant exposure cannot be directly measured or assessed (Kwan, 2018, 2012). Therefore, these calculated RBEC exposures are considered surrogates of true relevant built environment exposure and contain uncertainties. These uncertainties fall under what is usually described as the Uncertain Geographic Context Problem (UGCoP), since the truly causally-relevant environmental exposure is usually unknown and not directly measurable To tackle UGCoP, GPS-based studies typically choose a range of space and time parameters and apply different spatial averaging methods to derive RBECs geospatial exposure estimates that are hypothesized to affect physical activity based on their specific research question(s) (Kwan, 2012).

While the choice of the space and time parameters and statistical analysis approaches can vary greatly across the literature and can be very specific to the research question and outcome being investigated, we will not attempt to review this topic here. Rather, we point the reader to McCrorie et al. (McCrorie et al., 2014) for a thorough review of the literature findings on the topic of built environment exposure and the spatial and temporal extent of its impact on physical activity behavior.

In this manuscript, we aim to systematically review the different methods used to assess these RBECs exposure estimates in the physical activity and built environment literature employing GPS, GIS and accelerometry data. To accomplish this goal, the current literature review had three main aims. The first was to identify and categorize existing RBECs assessment methods from eligible articles. The second was to evaluate advantages and limitations of each method, and the third was to make methodological recommendations to mitigate identified challenges or gaps that can be applied in future studies.

2. Methods

2.1. Eligibility Criteria

This manuscript followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) checklist. Since the study is a methodological review, several recommended items in the PRISMA guidelines were not reported (see Supplementary File 1). This review was not prospectively registered. To be included in the review, a study had to meet three criteria. First, the article needed to be peer-reviewed and published in the English language with data on human participants. Second, the article needed to describe an empirical study, which excluded article types such as literature reviews, research methodologies, research protocols, and conceptual studies. Third, articles needed to collect data on both locations and intensities of physical activity, which could be measured separately by GPS and accelerometry devices or together via a single device. Lastly, studies needed to apply GIS in RBECs assessment, which eliminated articles that used other approaches such as interviews or web surveys.

2.2. Search Strategy

Based on aforementioned eligibility criteria, an initial list of terms was solicited from all co-authors to be broad and relevant to this field of research while at the same time not being too limited to one specific feature of the built environment (e.g. parks, land uses). Then authors went through several iterations and decided on this final list of terms that was deemed broad enough to cover a wider set of articles related to this topic, and not limited to one specific exposure or feature. Final search terms were determined as a list of the following keywords: (GPS OR “global positioning system”) AND (GIS OR “geographic information system” OR environment OR exposure OR “activity space”) AND (“physical activity”) and a search across five databases: Web of Science, Scopus, PubMed, PsycINFO, and SPORTDiscus was performed on July 16th, 2018. The searches limited the “Document Type” to “Article” and “Language” to “English.”

2.3. Selection Process

Articles (*N*=689) from the initial database search and additional articles (*N*=6) from searches of reference lists (i.e., citations at the end of articles and in supplementary tables) literature review articles (Duncan et al., 2009; Krenn et al., 2011; McCrorie et al., 2014) that focused on the same topic went through multiple steps of eligibility screening, which was conducted by two authors (see Figure 2 for the Preferred Reporting Items for Systematic Reviews and Meta-Analyses [PRISMA] diagram). Differences in article inclusion were resolved by discussion. To start, duplicated articles were removed from five databases (*N*=309). Then, the remaining titles and abstracts of all articles (*N*=386) were screened according to eligibility criteria and unqualified ones were excluded (*N*=236). Filtered articles (*N*=185) from the first screening entered the second screening process, during which the full texts of those articles were examined to manually determine their eligibility, and ineligible ones were removed (*N*=106). Articles that passed both screenings were included in the final pool of articles (*N*=79).

2.4. Data Extraction

After the study selection, three major types of data were extracted by the first author (see Appendix 1). A second author duplicated extraction from a random sample of 25% of articles. Any differences were resolved by discussion, and areas of mismatch were considered in the other 75% of articles. The first section included common study characteristics: study location, age of the sample, race/ethnicity of the sample, sample size, study design, and the research question. The second section included key parameters of GPS and accelerometry data preprocessing and integration before the RBECs assessment (see Figure 1): GPS device used, accelerometry device used, data collection period, and software or algorithm used to align GPS and accelerometry data, as well as intended built environment variable(s) and intended physical activity outcome variable(s) for the RBECs assessment stage. Lastly, the third section included information relevant to the RBECs assessment stage (see Figure 1), including the steps in which spatial operations were performed, parameter configurations (e.g., buffer) of these operations, and other notable operations relating to the RBECs exposure assessment.

2.5. Analytical Methods

The first aim was achieved by documenting detailed steps and associated parameters of spatial operations applied by previous studies to assess RBECs metrics, as well as looking into levels of integration information from GPS (mobility), GIS (built environment characteristics), and accelerometry (behavior) and research questions asked. The second aim, then, was achieved by evaluating technical barriers to implement each method, measurement uncertainties and biases associated with each method during the assessment process. The last goal was realized by linking findings and evaluations back to some major exposure-health study considerations (e.g., missingness of data, exposure measurement error, study biases, etc.) introduced during the RBECs assessment process.

3. Results

3.1. General Descriptions of Studies

For study locations, aside from a Brazilian study, 78 of 79 studies were conducted in Western countries, with 41 studies in North America, 31 in Europe, and 6 in Australia/New Zealand, and 1 in Asia. As for study population, 45 of 79 articles studied children and adolescents (≤18 years old), and 33 articles studied adults with 5 of those specifically targeting elderly adults (≥65 years old). Regarding sample size, samples ranged from 2 to 2,064 participants (*Median=148, Interquartile Range=247*).

Shifting to the data collection, the majority of studies (76 of 79 articles; 95%) used separate devices for capturing location and physical activity, while only three studies collected both through mobile phone applications. The Actigraph GT3X and GT3X+ (Actigraph, Pensacola, FL) were the most common accelerometers (44 articles; 56%) while QStar BT-1000X and 1000XT (Qstarz, Taipei, Taiwan) were the most common devices for GPS tracking (43 articles; 54%). In terms of the period of data collection, more than two-thirds (59 articles; 75%) of studies collected data for longer than 7 days (*Median*=7; *Interquartile Range*=1).

3.2. Choices of Built Environment Exposure and Physical Activity Outcomes

Of the 79 studies, 31 of them (40%) chose a single built environment context (e.g., park) or extent (e.g., home neighborhoods) as the exposure of interest. These single contexts and extents included home neighborhoods (15 articles; 19%), parks and green spaces (8 articles; 10%), schools (5 articles; 6%), catchment areas of public transit stations (1 article; 1%), snowfall countermeasure structure (1 article; 1%), and a district under urban renewal (1 article; 1%). In addition, 32 studies (39%) selected multiple built environment contexts or extents as the exposures of interest, such as life domains (e.g., home, school, leisure, and transport) or land uses (e.g., recreational, commercial, institutional). Additionally, 18 studies (21%) used built environment characteristics measurements (e.g., greenspace coverage, walkability, land use mix) within GPS point buffers, GPS trip buffers, and activity space polygons as the exposure of interest.

As for physical activity outcomes of interest, the majority of studies (60 of 79 articles; 76%) used epoch-level (e.g., minute) or bout-level (e.g., a continuous period of physical activity of a defined duration at certain intensities) moderate-to-vigorous physical activity (MVPA) as the outcome of interest with the commonly used cut-off points of sedentary (≤100 counts per min) and MVPA(≥2,296 counts per min) for children and sedentary (≤150 counts per min) and MVPA (≥1,952 counts per min) for adults (Evenson et al., 2008; Freedson et al., 1998). The epoch-level or bout-level outcomes were then usually aggregated during the analytical stage by person and domain as summed numbers (e.g., home MVPA: 30mins, school MVPA: 120 mins). Among the 60 studies, 36 of them focused on MVPA as the only outcome, while 24 used multiple physical activity outcomes including light physical activity, vigorous physical activity, and sedentary behavior. Other than MVPA, 13 studies used total daily number of walking trips, five studies used total daily movement counts, and one study used daily energy expenditure as the outcome.

3.3. Methods of Estimating or Assessing Exposure to RBECs

The studies we reviewed used various methods to calculate their estimates of RBECs exposure, including different ways of defining the shape and extent of the spatial footprint or activity polygon of interest (e.g., along identified trips or lines, around important domains based on actual locations visited or using circular or other types of buffers) and different spatial averaging techniques depending on their specific research questions. Below, we categorize and describe these methods based on whether they consider behaviors, domains, and temporal sequences of events to define the spatial polygons of interest, and whether they calculate purely spatial averages (with equal weights in space) or time-weighted spatial averages (with higher weights assigned to locations where participants spent more time) in calculating RBEC exposures. We labelled these three major categories as “domain-based”, “buffer-based,” and “activity space-based.” Glossary of technical terms/expressions used in the article, including concepts, data, and methods, along with use cases are available in Table 1.

3.3.1. Domain-based RBECs Assessment Methods—The domain-based RBECs assessment methods include Visual Inspection, Spatial Join, and Hierarchical Domain Assignment (see Table 2 for detailed description). They all focus on assigning time-aligned GPS accelerometry (TAGA) point data with built environment contextual domains (i.e., locations that provide physical activity behavior opportunities such as home, school, park, transport), if GIS polygon geometries or visuals of satellite images that represent these domains intersect with TAGA point geometries. Therefore, the domain-based method was used by previous studies to describe how much physical activity occurred in each domain and if there was a specific domain that was associated with more or less physical activity than others.

The Visual Inspection method was often implemented by earlier studies (6 of 79; 8%) when GIS data (i.e., points, lines, polygons, classified aerial images) that represented built environment features were lacking. To perform the method, the TAGA point data has to be overlaid on built environment features that are manually identified from satellite imagery or online mapping services (e.g., Google Map). Then each TAGA point will be assigned built environment domains that it intersects with. With the increase of GIS data availability and the proliferation of GIS software, a high percentage of recent studies (32 of 79; 42%) have applied the Spatial Join method. Unlike Visual Inspection method, Spatial Join links each TAGA point data with its intersecting built environment GIS layer in space (e.g., commercial, residential, or other land uses) using spatial join operations provided by GIS software.

Additionally, 13 of 79 studies applied the Hierarchical Domain Assignment method. The method differs from the Spatial Join method by two preprocessing steps. Firstly, a trip identification algorithm is applied to separate the trip domain (e.g., in-vehicle) from the event domain (i.e., visits). Then, the GIS software is used to sub-classify the event domain to sub-domains (e.g., home, school) in a user-defined order that may be subjective (e.g., home to school to park) via repetitive spatial join operations. Also, based on domains of interests, both Spatial Join and Hierarchical Domain Assignment methods might demand extra processing steps to process built environment data inputs (e.g., generation of home domain by buffering around home address points).

3.3.2. Buffer-based RBECs Exposure Assessment Methods—Buffer-based RBECs assessment methods include Point Buffer and Trip Buffer (see Table 2). Instead of focusing on built environment contextual domains that provide physical activity opportunities, buffer-based methods assess built environment characteristic by using the buffer operation to delineate the hypothesized spatial extent of built environment contextual influence on physical activity and averaging desired built environment characteristics within the extent (see Figure 3). Depending on built environment characteristics of interest, sometimes additional spatial analysis is required to process raw built environment GIS data inputs (e.g., calculates walkability from land use data).

Point Buffer (17 of 79 studies; 22%) assesses RBECs exposure by measuring desired built environment characteristics within the buffer of each TAGA point. In terms of the Trip Buffer method, it was applied (3 of 79; 4%) when the goal was to examine whether the averaged RBECs exposure (e.g., total areas of green spaces) during trips of interests (e.g., home/school commutes) influenced the choices of trip modes (e.g., walking). Similar to Hierarchical Domain Assignment, Trip Buffer also utilizes GPS, GIS, and accelerometry information to perform trip identification and to extract trips of interests (e.g., home-school commutes). After then, trip paths are generated and buffered by connecting TAGA points by chronological sequences, and averaged built environment characteristics within those buffers are computed.

3.3.3. Activity Space-based RBECs Assessment Methods—The activity space-based RBECs assessment methods include Direct Path Area, Minimum Convex Hull, Standard Deviation Ellipse, and Kernel Density Estimation (see Table 2). Instead of focusing on point or path-based RBECs assessment in the first two categories, the activity space-based methods assess RBECs at a temporal unit of interest and spatial scale of activity spaces recorded by GPS. Among the three activity space-based methods, Direct Path Area aims at capturing the immediate RBECs along trips (Sherman et al., 2005; Zenk et al., 2018) by connecting TAGA point data into paths or lines based on the chronological sequence of coordinates and buffering these paths by a pre-selected buffer radius. The Minimum Convex Hull method delineates the extent of roaming areas regardless of chronological sequence of events or trips (i.e., areas where humans frequent in daily lives). This is achieved by identifying the minimum polygon geometries that contain all GPS points during a defined period of time. The Standard Deviation Ellipse method (2 of 79; 3%) identifies the geographic centroid of TAGA point data in space within roaming areas of participants (Rainham et al., 2010; Zenk et al., 2018, 2011), which is achieved by generating ellipsoid geometries that contain user-selected (typically 2 standard deviation or 68%) percentages of points.

Lastly, the Kernel Density Estimation method generates a surface or raster of weights based on the density of points in space or duration of time spent in a location and multiplies that with the spatial built environment feature of interest to create a time-weighted spatial average of the RBECs exposure. Of all previously described approaches, this is the only one that takes duration of time spent into account in the spatial averaging to calculate RBECs exposure (e.g., features of locations where participants spent the most time contribute the most to the overall average RBECs exposure estimate). Among all reviewed studies, two used the Kernel Density Estimation method to identify activity hotspots (i.e., space and time clusters) first, applied web-surveys to extract trip origins and destinations, and created buffers around both locations to assess averaged built environment characteristics within the buffer Chaix et al. 2016; Duncan et al. 2016. The steps of RBECs exposure assessment for activity space-based methods are visualized in Figure 3.

3.4. Choices of Distance Parameters in Buffer Operations

Buffer was a spatial operation that was applied by 51 of 79 (65%) reviewed articles. The operation served three main purposes in assessing RBECs of physical activity. First, methods under the domain-based category such as Spatial Join or Hierarchical Domain Assignment applied the buffer operation to delineate hypothesized spatial extents of certain built environment domains (e.g., home) from point locations (e.g., home addresses). The radius of the buffer operation under this purpose typically ranged from 400 to 1600 m, with 800 m as the most common choice since it represented 10–15 mins walking distances from homes (James et al., 2014). In terms of buffer types, 41(85%) studies used Euclidean-distance (i.e., straight-lines) buffers while 10 (15%) studies applied network-distance buffer (i.e., areas one could reach when walking along at a distance of street networks from the home location). In addition, Spatial Join and Hierarchical Domain Assignment also applied the buffer operation to GIS layers that contain polygon geometries of built environment domains (e.g., home, school) to account for GPS device accuracy and minimize the misclassification error (Klinker et al., 2015; Lawrence et al., 2017; Rodríguez et al., 2005). The buffer radius ranged from 5 to 150 m, with 10 m as the most popular choice (Alberico et al., 2017; Burgi and de Bruin, 2016; Evenson et al., 2013; Oreskovic et al., 2012; Rodríguez et al., 2012; Troped et al., 2010). Finally, the buffer operation was also applied by Point Buffer, Trip Buffer, and Direct Path Area methods to delineate spatial extents of point, trip, and, activity space-based built environment contextual influences on physical activities (Houston, 2014; Rodríguez et al., 2012), with buffer radii ranging from 10 to 100 m. Main reasons offered for the choice of these radius values included their similarity to common sizes of urban parcels (Dessing et al., 2016; Krenn et al., 2014) and their ability to capture immediate built environment vicinities along daily movement (Boruff et al., 2012; Helbich et al., 2016; Oliver et al., 2007).

4. Discussion

Based on the hypothesized research questions, information extracted from GPS, GIS and accelerometry, and spatial averaging operations performed, this review categorized geospatial methods to assess or estimate exposure to RBECs into domain, buffer, and activity space-based categories. Of all methods, the domain-based category was the most commonly applied in studies describing built environment contextual domains of physical activities. Whereas, buffer and activity space-based methods were being used more in recent studies exploring causal effects of exposure to built environment characteristics on physical activity behaviors. To further evaluate each method, we first discuss technical barriers and potential sources of uncertainties that may be introduced under three methodological categories. Then, we detail several potential future directions that can improve the accuracy of RBECs exposure estimation and reduce uncertainties in physical activity studies.

4.1. Technical Barriers

For three methods in the domain-based category, the Visual Inspection method is the most user-friendly and requires the least technical knowledge. The implementation of this method only requires the accessibility to a mapping tool (e.g., Google Earth) that is capable of overlaying TAGA point data on top of digital maps (e.g., Google Map, Google Satellite) and making edits of its attribute tables so that RBECs can be manually assigned. In comparison to Visual Inspection, the Spatial Join method has higher technical barriers since it requires knowledge and skills to implement spatial join operation in GIS software. Lastly, the Hierarchical Domain Assignment method operates under the logic of assigning RBECs to TAGA points with a user-defined order, which is most efficiently implemented in GIS databases (e.g., PostgreSQL + PostGIS). Although researchers have flexibility to arrange built environment contextual domains based on research questions asked and/or their relative importance to physical activity outcomes, the knowledge of programming language to query and analyze geodatabases can be a barrier for those with less programming experience.

In terms of buffer-based methods, understanding types of buffer operation (i.e., network or circular) is essential in implementing Point Buffer approaches. In addition to buffer operation, the Trip Buffer method also requires points to line operation in GIS software to connect TAGA points into trips in chronological sequences. Similarly, to implement the activity space-based approach, the researcher needs to know how to operate activity space generation tools in GIS software (e.g., minimum bounding geometry in ArcGIS). Additionally, since GPS datasets are often large in file size, RBECs exposure might take substantial processing time and computing powers depending on the complexity of methods applied (e.g., Kernel Density Estimation method could take much longer time to run than the Spatial Join method).

4.2. Potential Sources of Uncertainty in Assessing Exposure to RBECs

Other than technical barriers, the assumptions or choice of parameters made to calculate exposure to RBECs under each method can have varying degrees of uncertainty in assessing the truly relevant exposure relative to the outcome or research outcome at hand. Since the truly causally relevant built environment exposure for physical activities is unknown, GPS-based studies have applied assorted spatial averaging approaches to assess surrogate built environment exposure that might match true exposure (Chaix et al., 2013; Kwan, 2018, 2012).

When GIS data inputs were not available or of poor quality, the Visual Inspection method was used in some of the reviewed articles. Since it relies on manually identifying built environment characteristics from mapping products (e.g., aerial maps, Google Map), it is highly error-prone and low in efficiency and reproducibility. Additionally, built environment characteristics identified from aerial maps might be distorted during two-dimensional processing of three-dimensional objects, which might introduce additional uncertainties (e.g., a high-rise building might be distorted and the time-aligned GPS and accelerometry point that falls on the building might actually be on streets or vice versa).

Additionally, uncertainty might also be introduced when applying spatial operations to process built environment data inputs prior to assignment of RBECs to each physical activity outcome. For instance, the majority of methods rely on the buffer operation to generate spatial extents of exposure (e.g., generating home domain in Hierarchical Domain Assignment, generating point buffers in Point Buffer). Thus, the parameters (e.g., type, radius) chosen for the buffer operation affect the assessment results. Among reviewed studies, almost all applied a one-size buffer approach, which created an arbitrary cut-off (e.g., 100 m) and might not represent the truly causal RBECs that exert contextual influences on physical activity behavior.

Moreover, the buffer operation generates spatial extents of exposure by assuming equal weights in all spatial directions on a two-dimensional surface, which is usually not the case in the real world considering the interactions between the human and built environments are conducted in a network pattern and in three-dimensional space. For example, a pedestrian who walks on the sidewalks of streets might only be influenced by street façade characteristics and retailers on the same side of the street. In this case, the exposure (e.g., built environment characteristics along streets) is exerting contextual influence on PA outcomes (e.g., walking) in one direction (i.e., one side of a street) within three-dimensional places (i.e., vertical and horizontal street characteristics of buildings).

Furthermore, specifically for the Spatial Join method, uncertainty or error is introduced when polygons that represent two different built environment domains (e.g., home and school) intersect. When this happens, one TAGA data point will be assigned two domains and, as a result, labor-intensive and error-prone verification process is needed. In terms of the Hierarchical Domain Classification method, the hierarchy or subjective choice of priority/order of assigning points to domain might be biased to overestimate the RBECs exposure that is higher in the hierarchy and underestimate the exposure that is lower. For example, using this method to classify domains into home, school, and transit in this order might overestimate time at home and school and underestimate time in transit.

Despite the inherent temporal nature of the data, many reviewed studies have applied spatial averaging approaches that assess RBECs exposure by taking averages of built environment characteristics (e.g., walkability index score, park areas, fast food density) along point or line buffers (i.e., buffer-based) or within activity space polygons (i.e., activity space-based methods) during a defined period of time. The limited consideration of duration of contact or time in the reviewed articles could lead to spatiotemporal patterns or associations being missed by relying on simple spatial averages. By ignoring the temporal component, exposure to RBECs may be over- or under-estimated leading to more error or noise in the analysis and potentially lower statistical power to detect effects.

Finally, most reviewed studies were subject to the selective daily mobility bias. For example, a person that is highly knowledgeable about the health benefits of physical activity might choose to visit a park to exercise on their way from home to work Chaix et al. 2013. Under this scenario, the fact that they were exposed to parks during the day (as estimated by their activity-space-based RBEC exposure) might merely be a result of or byproduct of their intention to exercise. The conclusion that parks exposure is associated with exercise minutes during the day might be conflated or erroneous. Consequently, in these studies, RBECs exposure assessed (i.e., accessibilities to built environment resources for physical activities along activity spaces) were based on intended locations to perform physical activities (e.g., driven by self-efficacy) rather than places where people organize their daily activities (Chaix et al., 2013). As a result, analytical results between RBECs exposure and physical activity outcomes might be biased.

4.3. Future Directions

4.3.1. Novel Sources of GIS Data—To avoid having to use less sophisticated methods (e.g., Visual Inspection method), future studies are recommended to explore novel sources of GIS data that could potentially complement or increase spatial resolution and/or coverage of traditional data resources from governments or organizations. Particularly, they could explore the potential of utilizing crowd-sourced Volunteered Geographic Information data (e.g., OpenStreetMap). However, a caveat is that the accuracy of Volunteered Geographic Information might be of particular concern due to its lack of quality-control processes (Elwood et al., 2012) in comparison to traditional sources. Moreover, studies could also look into obtaining built environment GIS data by applying satellite image classification techniques (Lu and Weng, 2006). Recent innovations in machine learning have greatly improved the accuracy of classifying built environment features (e.g., land uses, tree canopies, buildings, streets) from satellite or street view imagery in complex urban environments (Li et al., 2014). For instance, recent studies have applied image pattern recognition in detecting street environment features such as pedestrians (Yin et al., 2015), tree canopies (Li et al., 2018; Lu et al., 2018), visual enclosures (Yin, 2017), and buildings (Li et al., 2018) from Google Street View images.

Furthermore, traditional residential neighborhood-based studies have indicated perceived built environment (e.g., walkability obtained from self-report survey) results might moderate or mediate associations between objectively measured (walkability measured by GIS) built environment characteristics and physical activity outcomes (Brownson et al., 2010; Hoehner et al., 2005). Similarly, studies that integrate GPS, GIS and accelerometry have yet to integrate assessments of perceived built environment characteristics into the RBECs exposure assessment process (Dunton, 2018; Hurvitz et al., 2014a; Kwan, 2018). Two reviewed studies under the Kernel Density Estimation category utilized survey or interview tools to obtain perceived neighborhood characteristics (e.g., safety) after applying detecting frequently-visited locations from TAGA point data (Chaix et al., 2016; Duncan et al., 2016). However, these methods typically focused on a limited number of frequently visited locations (e.g., home, school, work) and did not collect time-resolved RBECs data.

Alternatively, future studies could consider utilizing assessment tools such as Ecological Momentary Assessment. Context-sensitive Ecological Momentary Assessment applications can be installed on mobile devices and prompted at a pre-determined within-day temporal frequency (Dunton, 2018) or spatial extent when an entry is detected by GPS devices (Huang et al., 2016) to capture highly-temporally-resolved perceived RBECs data. Studies have already started using context-sensitive Ecological Momentary Assessment applications to investigate relationships between affect and walking (Hekler et al., 2012), greenness and stress (Mennis et al., 2018), and physical/social contexts and physical activity (Dunton et al. 2012). Similarly, perceived RBECs collected from context-sensitive Ecological Momentary Assessment can be linked to objectively measured RBECs data to investigate covariations of the objectively and subjectively measured RBECs and PA.

4.3.2. Methodological and Study Design Recommendations to Reduce Uncertainty—

Future studies should continue recognizing and seeking solutions to limit the UGCoP. Performing sensitivity analyses is one way to explicitly test and report on the influence of buffer choice on reported associations for example (Baek et al., 2015; Houston, 2014). One study (Houston, 2014) found that the association between RBECs exposure and the minute-level PA outcome varied by the buffer radius utilized to delineate the contextual neighborhood around each GPS point. Also, the same study discovered smaller buffer radii tended to exhibit stronger associations, but those associations varied by built environment characteristics examined.

Moreover, temporal variation can be introduced or preserved in assessing exposure to RBECs in terms of assigning higher weights to locations where individuals spent more time, or by applying time-decay functions similarly to space-decay functions. For example, the influence of certain built environment conditions (e.g., greenness) at locations that are more proximal in both space and time to where and when physical activity occurred can be weighted higher than characteristics further away in space and time (e.g., at the beginning versus the end of a trip, in space closer to the end of the trip or closer to where the person spent the most time).

An example of shifting towards time-weighted spatial averaging methods that integrate or jointly account for space and time in assessing RBECs exposure could be kernel density estimation. Current studies have only applied kernel density estimation to pre-select hotspots with intense spatial and temporal concentrations of TAGA point data (Chaix et al., 2016;

Duncan et al., 2016; Thierry et al., 2013) prior to buffer operation to access RBECs exposure around trip origins and destinations. However, future studies could also apply kernel density estimation to TAGA point data to generate an intensity-based activity space surface grid that accounts for both spatial clustering and temporal durations (Rainham et al., 2010; Silverman, 2018; Thierry et al., 2013). The surface can then be multiplied by any built environment GIS data to produce RBECs exposure surface for PA outcomes (Jankowska et al., 2017).

Finally, to tackle or mitigate selective mobility daily bias, one recommendation is to restrict RBECs exposure assessment around anchor points (e.g., daily life centers in which individuals spend a substantial period of time, associate material or symbolic meanings, organize their daily activities, or are obligate to go) such as residence, workplaces, and schools where spatial access to opportunities of physical activities are of critical importance (Chaix et al., 2013, 2012), similar to two reviewed studies (Chaix et al., 2016; Duncan et al., 2016). Additionally, studies should collect data on cognitive variables (e.g., attitudes, motivation) that influence physical activity behaviors. Both approaches will allow studies to rule out intra-personal factors that confound true associations between RBECs exposure and physical activity outcomes.

Future studies could also consider experimental, quasi-experimental or simulation study designs to mitigate the bias. Among reviewed studies, two were designed upon occurrences of natural experiments (i.e., the construction of light-rail station and the urban renewal project) and measured changes of physical activities before and after experiments (Huang et al., 2017, Anderson et al., 2017) while the other one (Zhu et al., 2013) simulated physical activity behaviors in an actual neighborhood based on historical physical activity data from residents. Similarly, future studies should take advantage of such opportunities should they arise to establish the temporal sequence of exposure and outcome. Furthermore, we highly recommend future studies report on how this bias was considered in their analytical approach and what remedies if any were used in addition to recognizing its presence. Lastly, since physical activity could also be a potential modifier between RBECs and other health outcomes such as obesity, future studies might consider testing physical activity as a modifier of RBECs and health-based outcomes.

4.4. Strengths and Limitations

The main strengths of the study include its systematic nature, detailed documentation, categorization of the RBECs exposure assessment methods, and consideration of all data processing and analysis stages that are involved in integrating GPS, GIS and accelerometry to study the association between built environment exposure and physical activity outcomes. Notably, the classification of methods into domain, buffer, and activity space -based RBECs exposure assessment methods provides a methodological blueprint for future research to select the most appropriate method based on the similarities of the research questions, availability and quality of data inputs, and spatial averaging approaches desired. Further, this review links the RBECs exposure assessment methods and their implications on exposure assessment uncertainties and biases that affect the overarching field. In terms of the weaknesses of this study, this review only included studies that were written in English, but there may be other studies written in non-English languages that offer insights on other possible methodological categories. Moreover, this review did not assess study quality due to the disparities in study designs and research questions.

5. Conclusions

This is the first review that systematically summarized methodologies for assessing RBECs exposure of physical activity outcomes. After reviewing a total of 79 articles, three RBECs exposure assessment categories: domain-, buffer-, and activity space-based emerged, with each method category aiming to clarify specific aspects of the relationship between built environment exposures and physical activity outcomes in space and time. Technical barriers and exposure assessment uncertainties and biases were highlighted for consideration in future research and recommendations for future work were made.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

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Highlights

- First review on integrating GPS, GIS and accelerometry to measure built environment
- Domain, buffer and activity-space based methods are most commonly used
- Most approaches are limited in considering temporal dimension
- Future study designs should attempt to mitigate selective daily mobility biases

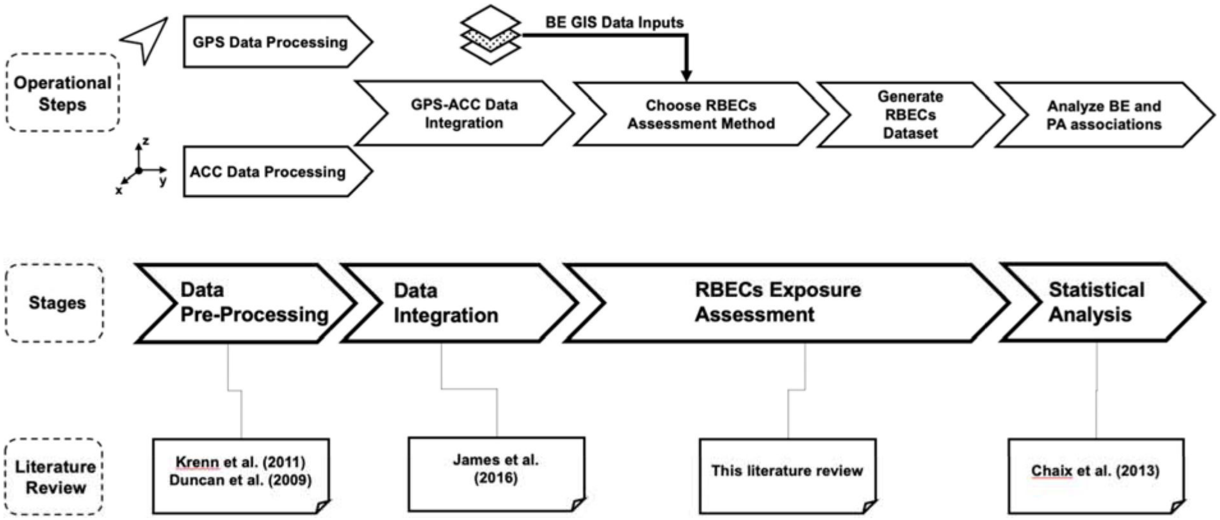

Figure 1.

Three common preparation stages prior to the statistical analysis stage that examine associations between built environment exposure and physical activity outcome for studies that integrate GPS, GIS and accelerometry. Operational steps refer to the activities that are completed during each stage. Literature review refers to previous literature reviews that have been conducted for each stage, with the current review focusing on RBECs exposure assessment.

Notes. ACC=accelerometry; GIS=Geographic Information Systems; GPS=Global Positioning Systems; BE = Built Environment; PA = Physical Activity; RBECs = relevant built environment contexts.

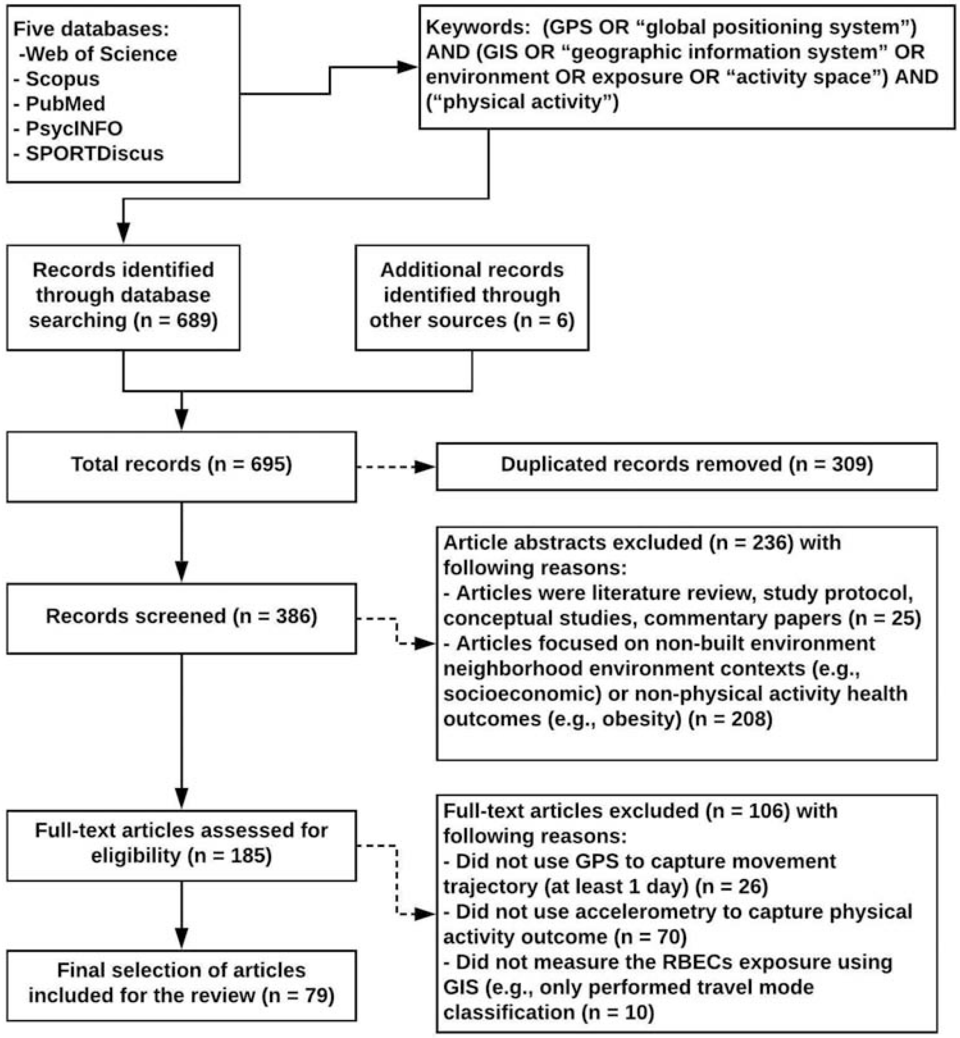

Figure 2.

Preferred Reporting Items for Systematic Reviews and Meta-Analyses [PRISMA] diagram

Notes. GPS=Global Positioning Systems; GIS=Geographic Information Systems; RBECs=relevant built environment contexts.

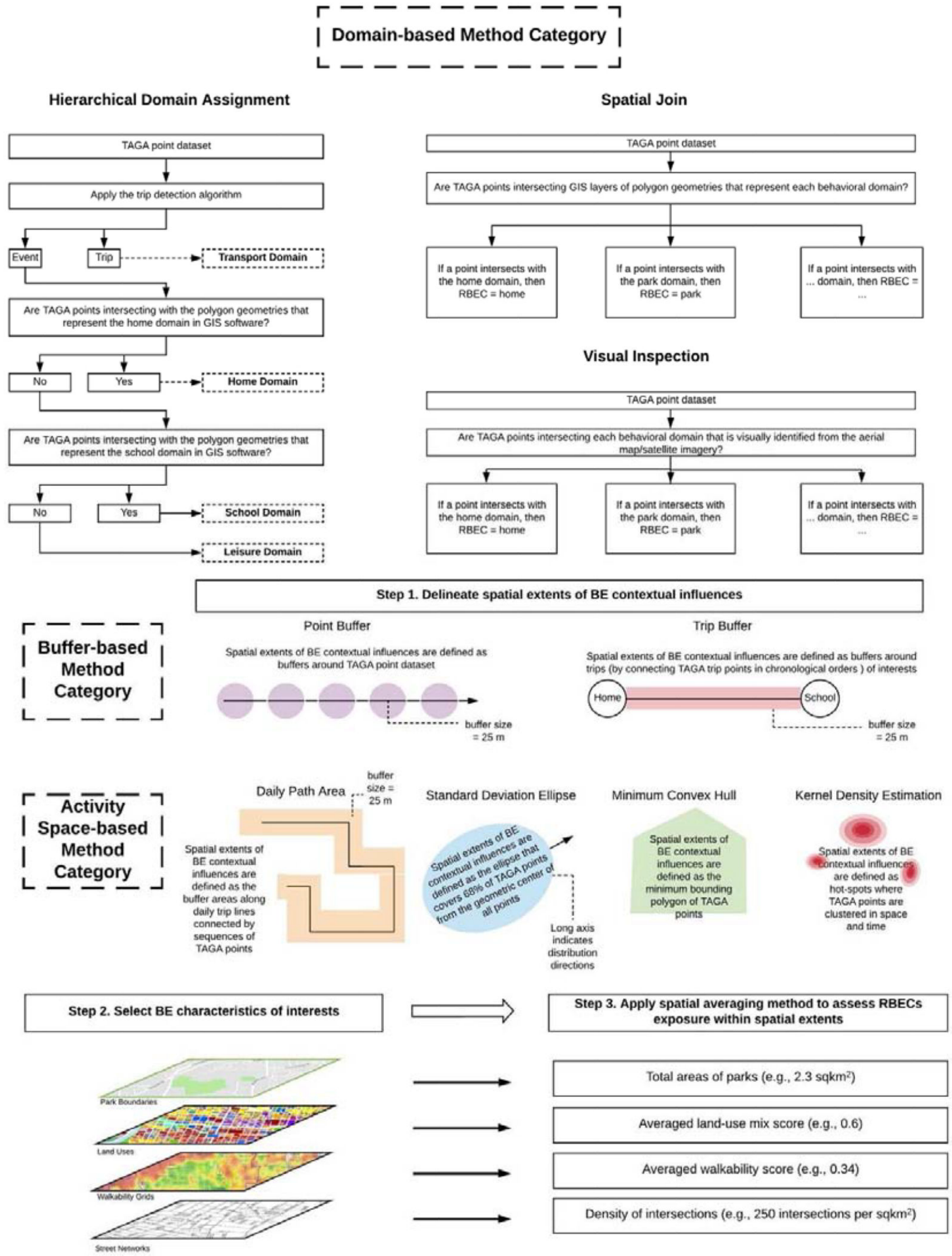

Figure 3.

Schematic drawings showing domain-based, buffer-based, and activity space-based RBECs assessment methods: including steps of spatial averaging operations and examples of measurements of BE characteristics.

Notes. BE=Built Environment, PA=Physical Activity, RBECs = Relevant Built Environment Contexts, TAGA point data = time-aligned GPS accelerometry point data

Table 1.

Glossary of technical terms/expressions used in the article, including concepts, data, and methods, along with use cases.

Term	Explanation
Data pre-processing stage	A stage during which GPS and accelerometry data is pre-processed. Tasks in this stage usually include examining completeness, outliers and accuracy and performing missing data imputation (Duncan et al., 2009; Krenn et al., 2011).
Data integration stage	A stage during which pre-processed GPS and accelerometry data is integrated to produce TAGA point data. Tasks in this stage usually include aggregating (if temporal intervals of GPS and accelerometry data differ) and aligning GPS and accelerometry data by timestamps (James et al., 2016; Kerr et al., 2011).
RBECs exposure assessment stage	A stage during which TAGA point data is processed and integrated with BE GIS data to assess RBECs. Tasks in this stage usually include applying spatial linkage and averaging operations to 1) draw a polygon in space based on TAGA point data (only for buffer-based and activity space-based categories); 2) import and process BE GIS data; 3) calculate RBECs exposure estimates by integrating processed GIS data and TAGA point data (Chaix et al., 2013).
Analytical stage	A stage during which RBECs exposure estimates are analyzed directly or aggregated depending on the research question(s) and the statistical analysis to test the association between built environment and physical activity outcomes is conducted. Tasks in this stage usually include 1a) if domain-based method, aggregate RBECs assessment outputs by BE domains to study distribution patterns of PA outcomes or 1b) if buffer or activity space-based methods, perform statistical analysis to study associations between RBECs and PA outcomes (Chaix et al., 2013; McCrorie et al., 2014).
Domain-based approach	An approach that identifies domains first which could be places of special meaning to individuals (e.g., home, work) or behaviors (e.g., trips) and then assigns RBECs exposure by spatially joining and averaging built environment characteristics within the boundaries of those domain-based activity spaces. For example, Burgi et al. (Bürgi et al., 2016) identified 7 physical activity domains based on TAGA data, drew polygons in space around them, spatially joined them to GIS layers and calculated a spatial average of the built environment characteristics within those polygons as estimates of RBECs.
Spatial averaging approach	An approach that estimates RBECs exposure by spatially averaging built environment characteristics within line- or polygon-based activity spaces. For example, Zenk et al. (Zenk et al., 2018) generated activity space polygons by buffering daily travel paths and calculated spatial averages of BE characteristics within those activity space polygons (e.g., density of fast food outlets).
Time-weighted spatial averaging approach	An approach that estimates RBECs exposure by a) generating weights based on duration of time spent at each location and b) using these weights to calculate a time-weighted spatial average of the BE characteristic within line- or polygon-based activity spaces. For example, the Kernel Density Estimation method is a typical example of a time-weighted spatial averaging approach. Chaix et al. (Chaix et al., 2016) implemented a variation on kernel density estimation approach where they extracted activity hotspots or areas where participants spent the longest duration of time, based on spatial (i.e., densities of points within searching radius) and temporal (i.e., minimum durations of stay at a given location) properties of TAGA point data. Buffers were then generated around these hotspots and spatial averages of BE characteristics were calculated within these buffers.
TAGA point data	A dataset with each row entry contains columns of geographic coordinates collected by GPS and PA movements collected by accelerometry aligned at an epoch-level (e.g., 30-sec).
RBECs exposure assessment outputs	A database that contains both geometries and tabular data attached to each geometry with the calculated summary BE exposure metric which can then be linked to health outcomes.
Activity space	Set of spatial locations one visited during a specific period of time.
GIS Operations	
Radius buffer	Radius Buffer (also termed as crow-fly buffer or circular buffer) is a spatial operation that creates polygon geometries around point, line and polygon geometries based on a pre-selected radius distance.
Network buffer	Network Buffer (also termed as street buffer) is a spatial operation that creates polygon geometries around point based on pre-selected distances along street networks.
Spatial join	A spatial operation that assigns attributes of one GIS layer to another intersecting layer in space.
Kernel density estimation	An algorithm that extracts peaks of point data clusters within an extent that is identified by a search radius and generates raster surfaces where each pixel represents the density value.

Term	Explanation
Trip identification	An algorithm that identifies trip activities from TAGA point data (meaning a series of points with an origin and end) and further classifies trips into different modes (e.g., walk, run, bike, drive).

*GPS = Global Positioning Systems, GIS = Geographic Information Systems, PALMs = Physical Activity Location Measurement System, TAGA point data = time-aligned GPS accelerometry point data, RBECs = relevant built environment contexts.

Table 2.

Three categories of RBEC assessment method categories and methods under each category, as well as data inputs, GIS data processing, spatial/spatiotemporal operations, data outputs, and counts of each method that has been applied by reviewed studies.

Category	Method	Data Inputs	GIS Data Processing	Spatial Averaging Operations	Data Outputs	# of Studies
Domain-based Exposure Assessment	Visual Inspection	Aerial images, TAGA point data	N/A	Manually assign each point with the designated BE domains by visually identifying its spatial relationships with image pixels that represent BE domains (e.g., home, park)	A database with built environment contextual domains that link to epoch-level physical activity outcomes	6
	Spatial Join	BE GIS layers, TAGA point data	1. construct GIS layers for specific domains (e.g., home, school, park)	Perform spatial join operation to assign each TAGA point with designated BE domains (e.g., home, park) if the point falls into polygon geometries that represent those domains in GIS	The same as above	34
	Hierarchical Domain Assignment	The same as above	1. perform trip identification and trip mode classification on TAGA point with data processing software (e.g., PALMs[a]); 2. the same as step 1 above	In a hierarchical order (e.g., home > school > transport > leisure > others), perform spatial join operation as described in Spatial Join method.	The same as above	13
Buffer-based Exposure Assessment	Point Buffer	The same as above	1. buffer TAGA point data by a pre-determined radius distance	Measure desired BE characteristics (e.g., walkability) within each point buffer.	A database with spatially-averaged built environment characteristics that link to *epoch-level* physical activity outcomes	14
	Trip Buffer	The same as above	1. the same as step 1 of Hierarchical Domain Assignment; 2. connect TAGA points that represent trips of interest (e.g., home/school commutes) into lines and generate buffer polygons along lines in GIS software	Measure desired BE characteristics (e.g., walkability) within trip buffers in GIS.	A database with spatially-averaged built environment characteristics that link to *trip-level* physical activity outcomes	3
Activity Space-based Exposure Assessment	Direct Path Area	The same as above	1. connect temporally-integrated (e.g., 1 day) TAGA points as lines based on timestamp sequences and aggregate the epoch-level PA outcome by the same temporal unit with GIS software; 2. buffer each trajectory by a distance and merge all buffers to generate direct path area polygons in GIS;	Measure desired BE characteristics (e.g., walkability) within activity space polygons in GIS.	A database with spatially-averaged built environment characteristics that link to *day or any study period level* physical activity outcomes	5
	Minimum Convex Hull	The same as above	1. execute the "minimal bounding geometry" operation in GIS to temporally-integrated (e.g., 1 day) TAGA points to generate minimum convex hull polygons and aggregate the epoch-level PA outcome by the same temporal unit	The same as above.	The same as above	3

Category	Method	Data Inputs	GIS Data Processing	Spatial Averaging Operations	Data Outputs	# of Studies
	Standard Deviation Ellipse	The same as above	1. the same as the Minimum Convex Hull method above; however, in step 1, the "standard deviation ellipse" operation is executed to generate ellipse polygons[b]	The same as above.	The same as above	2
	Kernel Density Estimation	GPS and Accelerometry datasets, BE GIS layers	1. create radius buffers around hostpots detected for each participant and average built environment characteristics within the buffer as RBECs exposure	1. Derive a list of all visits over the period made to each detected location (i.e. space-and-time peaks from GPS data) with their start and end times by applying the kernel density estimation method; 2. Implement a web-survey to obtain trip origins and destinations based on locations detected.	A database with time-weighted spatially-averaged built environment characteristics that link to day or any study period level physical activity outcomes	2
				Total Counts		**79**[c]

Notes. BE=Built Environment, PA=Physical Activity, RBECs = Relevant Built Environment Contexts, TAGA point data = time-aligned GPS accelerometry point data

[a]Physical Activity and Location Measurement System (University of California San Diego, San Diego, CA, USA).

[b]A ellipse polygon generated from the "Standard Deviation Ellipse" starts from the geographic centroid of the GIS points and covers one-standard deviation (68% of points) from the center, with major and minor axes determined by directional distributions of those points.

[c]The Hirsh et al. (2016) applied all three Activity Space-based methods and the Zenk et al. (2011) applied two Activity Space-based methods; therefore, the Total Counts were subtracted by 3 when adding up all counts.