Social Science & Medicine 193 (2017) 41–50

Contents lists available at ScienceDirect

Social Science & Medicine

journal homepage: www.elsevier.com/locate/socscimed

Kids in space: Measuring children's residential neighborhoods and other destinations using activity space GPS and wearable camera data

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ARTICLE INFO

Article history:
Received 23 May 2017
Received in revised form
15 September 2017
Accepted 26 September 2017
Available online 28 September 2017

Keywords:
Activity spaces
Children
GPS
Wearable cameras
Urban
Everyday lives
children's destinations
Neighborhoods

ABSTRACT

Introduction: Defining the boundary of children's 'neighborhoods' has important implications for understanding the contextual influences on child health. Additionally, insight into activities that occur outside people's neighborhoods may indicate exposures that place-based studies cannot detect. This study aimed to 1) extend current neighborhood research, using data from wearable cameras and GPS devices that were worn over several days in an urban setting; 2) define the boundary of children's neighborhoods by using leisure time activity space data; and 3) determine the destinations visited by children in their leisure time, outside their neighborhoods.

Method: One hundred and fourteen children (mean age 12y) from Wellington, New Zealand wore wearable cameras and GPS recorders. Residential Euclidean buffers at incremental distances were paired with GPS data (thereby identifying time spent in different places) to explore alternative definitions of neighborhood boundaries. Children's neighborhood boundary was at 500 m. A newly developed software application was used to identify 'destinations' visited outside the neighborhood by specifying space-time parameters. Image data from wearable cameras were used to determine the type of destination.

Results: Children spent over half of their leisure time within 500 m of their homes. Children left their neighborhood predominantly to visit school (for leisure purposes), other residential locations (e.g. to visit friends) and food retail outlets (e.g. convenience stores, fast food outlets). Children spent more time at food retail outlets than at structured sport and in outdoor recreation locations combined.

Conclusion: Person-centered neighborhood definitions may serve to better represent children's everyday experiences and neighborhood exposures than previous methods based on place-based measures. As schools and other residential locations (friends and family) are important destinations outside the neighborhood, such destinations should be taken into account. The combination of image data and activity space GPS data provides a more robust approach to understanding children's neighborhoods and activity spaces.

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1. Introduction

There is mounting evidence of an association between neighborhood contextual characteristics and a range of health-related outcomes and behaviors (Kawachi and Berkman, 2003; Leventhal and Brooks-Gunn, 2000, 2003; Roosa et al., 2003). However, defining the spatial boundary of the 'neighborhood' has been a point of contention in health research (Boruff et al., 2012; Rainham et al., 2010; Spielman and Yoo, 2009). Often researchers have resorted to the use of pre-defined buffers, typically 200–1600 m, from a central point of interest (e.g., residential addresses, school) (Thornton et al., 2011). One of the challenges is that differences in buffer sizes and methodology (e.g., based on Euclidean versus network buffers) can significantly alter study results (Boruff et al.,

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https://doi.org/10.1016/j.socscimed.2017.09.046
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2012; Duncan et al., 2014; Spielman and Yoo, 2009; van Loon et al., 2014). They represent one form of the modifiable areal unit problem (MAUP) (Spielman and Yoo, 2009). The MAUP suggests that observed correlations and regression coefficients may change unpredictably as the scale of analysis changes (Fotheringham and Wong, 1991). Likewise, the most appropriate level for capturing neighborhood exposures of interest could be influenced by the sociodemographic characteristics of the study population (e.g., children versus elderly) (Kwan, 2012). For example, an individual's capacity and motivation to travel longer distances are likely to be affected by personal mobility, local land use and activity space (Kwan, 2012). Other factors include the extent to which that population relies on vehicular versus pedestrian transportation, the rurality of the setting, and the extent of urban sprawl (Madsen et al., 2014; Spielman and Yoo, 2009).

Another common method for defining neighborhoods is to assign individuals to the census tract (called Census Area Unit (larger administrative unit) and meshblock (smaller administrative unit) in NZ), postal code or other administrative boundary in which they live. These pre-defined boundaries have limitations including: not being meaningful to the individual, spatial spillovers for individuals residing near the border of the unit, and failure to account for the unique ways an individual interacts with their neighborhood (Perchoux et al., 2016; Vallée et al., 2014). Yet a third, emerging approach is to use activity space GPS data from observational studies to define each participant's neighborhood (Klinker et al., 2015; Loebach and Gilliland, 2016; Oliver et al., 2015). Activity space GPS data requires participants to collect primary spatial data using GPS devices. Primary spatial data collected by participants provides robust measures on participants' mobility patterns and activity spaces, particularly in relation to where they are spending their time.

Children typically have more restricted mobility (e.g. they cannot drive) and are more reliant on their local environment than adults (Loebach and Gilliland, 2016). Despite this, the literature on the spatial boundaries of children's neighborhoods is inconsistent. Studies investigating children's neighborhoods have mirrored buffer sizes utilized in adult populations (Bringolf-Isler et al., 2008; Larsen et al., 2009; Oliver et al., 2015; Villanueva et al., 2011; Wong et al., 2011). These studies have been conducted in developed countries (primarily urban settings) with readily available car transportation. Many studies also lacked validation of their definition of neighborhood, potentially resulting in misclassification of neighborhood exposures. Measurements that are more objective are required to validate the assumptions inherent in pre-defined buffer sizes.

GPS devices have been used to determine the spatial boundary of adults' neighborhoods to examine many neighborhood and health-related features. For example, studies have used GPS to explore cycling and physical activity behaviors (Boruff et al., 2012; Hurvitz et al., 2014; Madsen et al., 2014), and demonstrated GPS technology to be an effective tool for measuring and validating neighborhood buffers premised on assumptions about adult mobility patterns. To the authors' knowledge, only one study conducted in Auckland, New Zealand has attempted a similar procedure with children (Oliver et al., 2015). In this study, linked GPS data and accelerometer data informed population-specific neighborhood buffers. The authors generated Euclidean buffers at incremental distances from a minimum of 200 m to a maximum distance of 1600 m, concluding that a 1000 m residential Euclidean buffer was an optimal neighborhood size for analysis of physical activity in their study population. However, the authors did not describe the criteria used to make this decision. These analyses demonstrate the importance of validating population-specific definitions of the neighborhood.

Studies that only define residential neighborhoods have a limited scope. A more systematic approach would involve gaining an understanding of the reasons children travel outside their neighborhoods. Such an approach extends beyond the neighborhood and into children's other activity spaces. While not specifically investigating neighborhoods, one previous study used linked GPS activity space and accelerometer data to determine the setting of children's physical activity (Klinker et al., 2015). The linked data was combined with Geographic Information System (GIS) that contained geocoded amenities data. The study's main limitation was the reliance on existing information about local amenities that may be outdated or incomplete (Hoehner and Schootman, 2010). Further, the authors could not guarantee the participants entered the destination or exactly which type of destination it was. Rather, the GPS data was recorded near these locations. A different study of an adult sample used a data mining algorithm to detect groups of spatial data based on temporal and spatial parameters, called ST-DBSCAN (Brusilovskiy et al., 2016). The authors used ST-DBSCAN to identify time-space groupings of point data to identify the number of visits adults made to destinations. However, the authors could not identify what locations were visited within the activity space; rather, the study aimed to quantify the number of visits made by participants.

The use of wearable cameras may provide a more objective and direct confirmation of participant visits to destinations, which could be used in spatial analyses. Wearable cameras that automatically take pictures at regular intervals have been deployed to study health behaviors (Chambers et al., 2017; Kerr et al., 2013; Oliver et al., 2013). Such cameras provide an opportunity to collect objective observational data in a less invasive and more efficient and comprehensive manner than third-party observation (Signal et al., 2017). Further, wearable cameras obviate the need for self-reported measures that are subject to recall bias and have also proved a reliable validation tool for GPS data (Meseck et al., 2016). Wearable cameras may provide a robust method for understanding people's movement patterns if GPS data is also collected at the same time.

This study used wearable cameras and GPS devices to 1) define the boundary of children's neighborhoods; and 2) determine the destinations visited by children, outside their neighbourhoods.

2. Method

2.1. Study design

These analyses used data collected in a cross-sectional observational study of children's exposure to food and non-alcoholic marketing, called Kids'Cam. Study participants were children aged 11–13 (n = 168) in Wellington, New Zealand, who collected data over a four-day period. Data were collected between June 2014 and July 2015 to allow for seasonal difference. Participants were recruited from 16 schools in the Wellington region. Each child wore a wearable camera (Autographer http://www.autographer.com) and GPS unit (Qstarz BT-Q1300ST Sports Recorder) on a lanyard around their neck. The camera automatically captured a 136° image of the scene ahead approximately every seven seconds, and the GPS unit captured latitude and longitude every five seconds. Sociodemographic information (ethnicity, household deprivation (NZiDep2006) (Salmond et al., 2006)) was collected prior to the study period via survey. Participants' addresses were geocoded and linked with meshblock neighborhood level deprivation measures using NZDep2013 (Atkinson et al., 2014). Height and weight measurements for BMI were taken at the conclusion of the study. For more information on study design, sampling and data collection procedure, see (Signal et al., 2017).

2.2. Imputation of missing GPS data

From a total of 6,048,000 possible 5-s intervals from 7am to 9pm over the four-day study period, 3,869,438 5-s intervals of possible observation time were missing (64%). The study protocol required participants to turn off and remove their equipment in certain situations, including where the equipment could be damaged (e.g., playing sport, activities that may cause water damage), if requested by another party, or required to typically for privacy (e.g. at home, someone else's home, church, medical offices or some stores). Further, the denominator used to quantify 'missingness' included all time between 7am and 9pm and may not reflect the lived experiences of children (children often slept in longer than 7am and went to bed before 9pm). Therefore, the 64% missingness represents the proportion of total potential observation time and is likely to be a conservative estimation of data missingness.

Missing GPS data were imputed using a mixed imputation method. First, a Python script (see supporting information) automatically assigned coordinates to 5-s intervals with missing GPS data, using rules specified for two conditions with information from data gap bookends. Bookends were the points either side of a gap of missing GPS data. There were two criteria for a location for the first condition: Rule A) known bookend coordinates for these gaps must be less than 100 m apart [spatial constraint]; and Rule B) contiguous data gaps must be < 5 min [temporal constraint] (Fig. 1, condition A). These rules were selected due to the likelihood that very little movement (<100 m) within a short time period (<5 min) would result in less spatial mobility during gaps of missing data. If both criteria were met, the missing 5-s intervals were assigned identical coordinates to the bookend prior to the data gap. For the second condition, missing data were imputed when the distance between bookends was >100 m (Rule C) [spatial constraint] and the

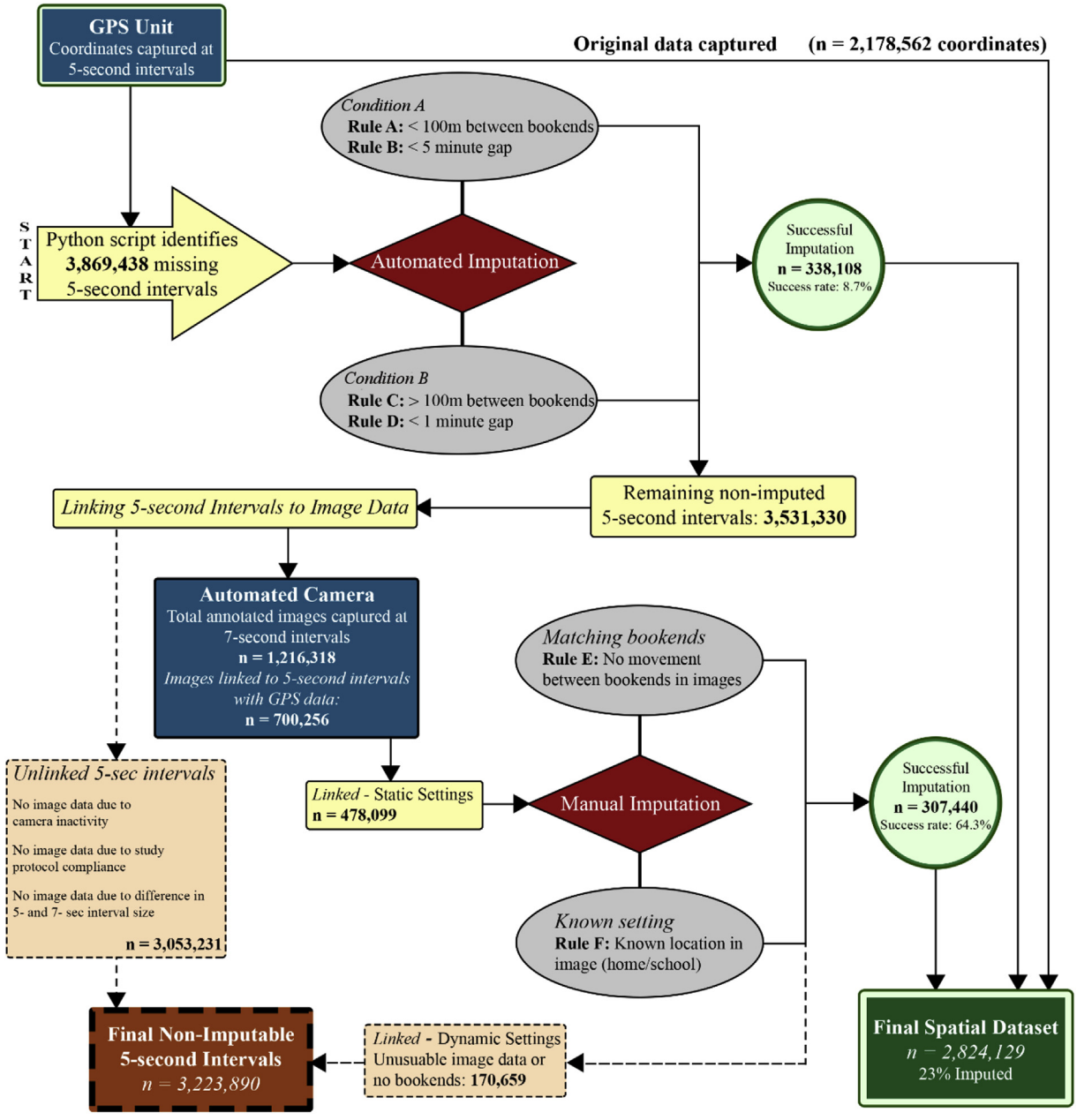


Fig. 1. Imputation method flow diagram.

gap in data was <1 min (Rule D) [temporal constraint] (Fig. 1, condition B). If both Rules C and D were met, then coordinates for missing intervals were assigned based on the last valid bookend before the data gap. The spatial accuracy of the imputation was considered to be hindered for gaps >1 min, particularly if participants were moving quickly (>100 m/minute), such as in a car, when it was not possible to be certain of the route taken or if stops were made.

Following the automated imputation, a manual method used imagery from the wearable cameras to confirm the spatial accuracy of the data. To impute these coordinates, annotations for images were examined, and if the setting remained the same for the known bookend coordinates, each 5-s interval was assigned identical coordinates (Rule E). Alternatively, if the setting was a known location (e.g., school or home) based on images, coordinates were assigned based on the known location of the setting even when bookends were absent (Rule F). In total, 645,548 of the missing 5-s intervals were imputed using these methods, contributing 23% of the final spatial dataset and reducing total data missingness from 64% (95% CI 61.1 to 66.9) to 53.3% (95%CI 50.0, 56.7) (Supplementary Table 1).

2.3. Leisure time definition

The full Kids'Cam dataset contained approximately 2.9 million GPS points and 1.3 million images. For the current study, we were only interested in children's leisure time, defined as all non-school (all time except weekdays between 9am and 3pm, the Ministry of Education defined school hours) waking time. Thus, all image and GPS data between 9am and 3pm on weekdays (school time) were removed from subsequent analyses. Time spent at school outside 9am-3pm on weekdays were considered leisure time spent in a school setting. In addition to school time, we removed all data before 7am and after 9pm from the analyses as we considered these the temporal extremities for children's waking day and such data was very rare, <1% of data. For all analyses, each GPS point represented five seconds and each image represented seven seconds of observation time (average capture rates). The dataset used for the subsequent analysis included 1.9 million GPS points (2576 observation hours) and 700,000 images (1351 observation hours).

2.4. Methods used to define children's neighborhoods using time and space

First, participants' addresses were geocoded using R 3.2.4 (R Institute, Vienna, ggmap). Using ArcGIS 10.4 (Esri, Redlands), multiple separate network and Euclidean buffers (based on those used in previous research) were created around each participant's home location, at the following distances,: 200 m (Bringolf-Isler et al., 2008), 500 m (Larsen et al., 2009), 750 m (Villanueva et al., 2011) 1000 m (Oliver et al., 2015), 1250 m and 1600 m (Villanueva et al., 2011). Participant GPS data were spatially joined to the incremental Euclidean and network buffers. The proportion of time spent within each buffer size, out of all observation time, was calculated. The buffer size used to define children's neighborhood boundary was selected if the following two criteria were met: 1) the buffer with the largest absolute percentage increase in leisure time spent from one buffer to the next; and 2) the buffer in which greater than 50% of leisure time was spent. The 50% threshold has been used in one previous study using population specific buffers (Oliver et al., 2015).



Fig. 2. Validation of destinations using image data setting tags (A), ArcGIS (B) and *Google Street View* (C).

2.5. Content analysis of image data

Customized computer software developed by Dublin City University enabled tags to be assigned to image data. The software used a three-tiered coding framework, of which the first level was setting. The other two levels could be used to code for any environmental exposure variable but for this analysis only the setting level and associated codes were used. As part of the larger Kids'Cam study, every image received a setting tag following the study's coding framework (Signal et al., 2017). Setting categories included: home, school, community venues, sports venues, food retail, other retail, and outdoor recreation settings.

2.6. Identifying destinations visited outside the defined neighborhood

To identify destinations that each child visited outside of their residential neighborhood, a novel application based on ST-DBSCAN was used to identify space-time groupings of GPS data (hereafter destination). The space-time parameters used to define a destination in this study were: a minimum number of 120 GPS points (density parameter) separated by no more than 100 m (spatial parameter) and occurring over at least 10 min (temporal parameter). These parameters were selected based on both another study of activity spaces (Brusilovskiy et al., 2016) as well as a sensitivity analysis. Space-time point groupings related to transit were not considered destinations and were removed from the analysis.

Destinations were validated by a researcher on a sub-sample of 15 participants, using 20 visits with at least three visits to each destination type: home, school, community venue, food retail, sport and outdoor recreation settings. First, the setting from the camera data for each destination was recorded (Fig. 2, Panel A). Next, the latitude and longitude coordinates were extracted from the destination in ArcGIS (Fig. 2, Panel B). Image setting codes for each destination were compared to the setting at the latitude and longitude coordinates extracted from ArcGIS using *Google Street View* (Fig. 2, Panel C). For example, Fig. 2 shows a visit to a residential location (other than their primary home address) as shown by camera image coding ('Home') (Panel A), the GPS coordinates are extracted in ArcGIS (Panel B) and confirmed in *Google Street View* (Panel C). There was 100% concordance between the image codes from the wearable cameras and the type of location observed in *Google Street View*.

2.7. Statistical analysis

All statistical analyses were conducted in Stata v14 (StataCorp, College Station, TX). All analyses accounted for the complex sampling design used in the Kids'Cam study (which had a stratified sample, with clustering of children within sampled schools), with inferential statistics calculated using Stata's svy prefix commands and associated weighting options. The mean time spent within Euclidean and network buffers was calculated using Poisson regression models, using the total duration of available data per child as the offset term (i.e. providing person-time for the analysis). Both time spent at, and the number of visits to destinations outside the defined neighborhood buffers were calculated using negative binomial regression models, again using total duration of available data per child as the offset term. Time spent at destinations is reported as rates per hour of GPS data, while the number of visits to destinations are reported as rates per 10 h of GPS data. Ten hours represented a typical day, so this metric was used to help present the data in a meaningful way. Each GPS point was treated as representing five seconds of exposure time, due to data capture settings on the GPS unit.

Decisions to use Poisson or negative binomial models for the count data regression analyses were based on model fit tests and signs of overdispersion. Time spent within buffers was best approximated by a Poisson distribution, while time spent at destinations and number of destinations were best approximated by a negative binomial distribution due to overdispersion.

3. Results

3.1. Participating children

In total, 168 children participated in the Kids'Cam study. Data from 18 children were excluded from these analyses due to missing GPS data and/or image data. Another 35 children were excluded due to insufficient GPS data (<8 h of leisure time). A breakdown of GPS wear time is presented in Supplementary Table 2. One additional child was excluded because their residential address information was missing. The final sample for these analyses was 114 participants. The analytic sample had approximately equal numbers of boys and girls (51% male) and children by household deprivation. There were more New Zealand European children (43%) than Māori (36%) and Pacific children (21%) (Table 1). More children lived in highly deprived neighborhoods (41%) than those living in neighborhoods of moderate (29%) and low deprivation (30%). Most children were a healthy weight (63%), with fewer overweight (21%) and obese (15%). Children who were overweight were more likely to be excluded (p-value 0.047) than children of a healthy weight. There were no significant differences detected between children included and excluded by any sociodemographic characteristic other than BMI.

Table 1
Sociodemographic characteristics of Kids'Cam participants – both included and excluded in the current study.

Sociodemographic characteristics	Included (n = 114)	Excluded (n = 54)	P-Value[e]
Sex, n (%)			
Males	58 (50.9%)	33 (61.1%)	0.428
Females	56 (49.1%)	21 (38.9%)	
Age, range (mean)			
	11–14.5 (12.5)	11.6–13.3 (12.6)	0.105
Ethnicity, n (%)			
NZ European	49 (43.0%)	17 (31.5%)	0.178
Māori	41 (36.0%)	20 (37.0%)	
Pacific	24 (21.0%)	17 (31.5%)	
Household deprivation[a] n (%)			
High	37 (32.5%)	13 (24.1%)	0.722
Medium	39 (34.2%)	19 (35.2%)	
Low	34 (29.8%)	19 (35.2%)	
Missing[b]	4 (3.5%)	3 (5.6%)	
Neighborhood deprivation[c] n (%)			
High	47 (41.2%)	12 (22.2%)	0.255
Moderate	33 (29.0%)	16 (29.6%)	
Low	34 (29.8%)	20 (37.0%)	
Missing	0 (0%)	6 (11.1%)	
Weight status, n			
Healthy/underweight	72 (63.2%)	25 (46.3%)	**0.047**
Overweight	24 (21.1%)	21 (28.9%)	
Obese	17 (14.9%)	8 (14.8%)	
Missing[d]	1 (0.8%)	0 (0%)	

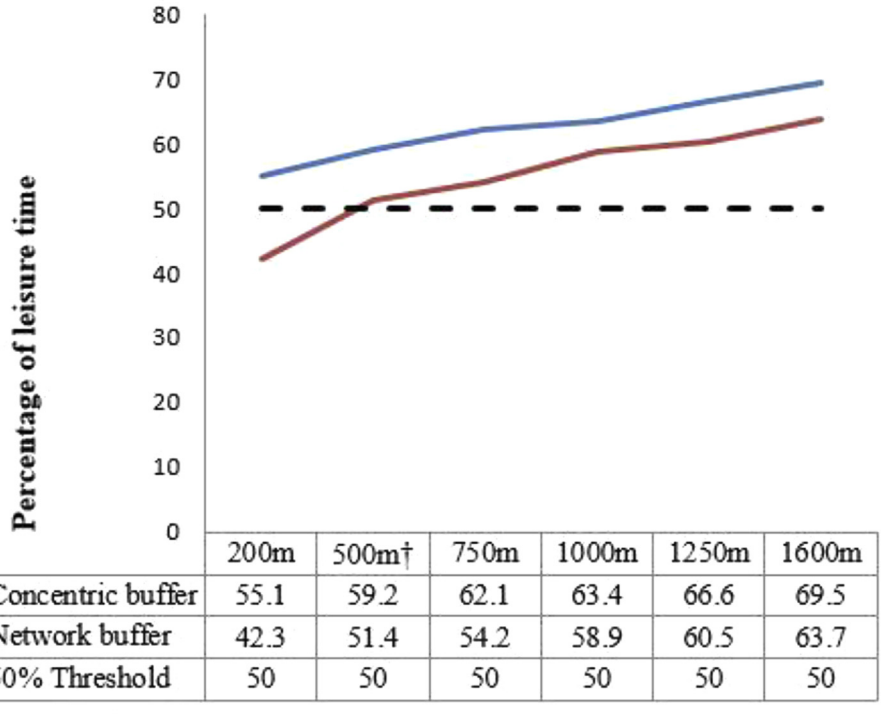
Statistically significant differences at the 0.05 level are bolded.
[a] Household deprivation was measured using NZiDep questionnair (Salmond et al., 2006) filled out at beginning of study by participants' parents.
[b] NZiDep missing for six participants (questionaire not completed).
[c] Neighborhood deprivation was measured using NZDep2013 (Salmond et al., 2006) based on participants' home addresses supplied by participant's parents.
[d] BMI missing for one participant as child declined to be measured.
[e] P-Value calculated using Pearson Chi-squared tests. Excluded category included those children excluded for insufficient GPS data (n = 36) and no GPS data collected (n = 18).

3.2. Defining children's neighborhood boundary: sensitivity analysis

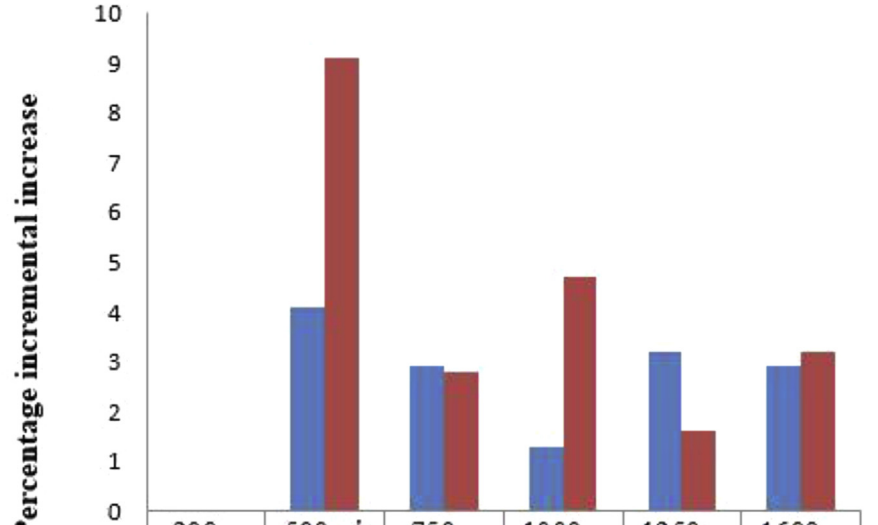
Fig. 3 shows the average time spent within each buffer size calculated using Poisson regression models. Children spent more than 50% of their leisure time within 500 m of their homes using both Euclidean (59.2% of total leisure time) and network (51.4% of total leisure time) buffers. The largest difference in percentage of leisure time occurred between the 200 m and 500 m buffers for both Euclidean (4.1% absolute increase) and network (9.1% absolute increase) buffers. Based on these criteria, 500 m was used to define children's neighborhood boundary for the subsequent analysis.

3.3. Destinations visited outside of the defined neighborhood

The specified space-time parameters used to define a



	200m	500m†	750m	1000m	1250m	1600m
Concentric buffer	55.1	59.2	62.1	63.4	66.6	69.5
Network buffer	42.3	51.4	54.2	58.9	60.5	63.7
50% Threshold	50	50	50	50	50	50



	200m	500m†	750m	1000m	1250m	1600m
Concentric buffer	0	4.1	2.9	1.3	3.2	2.9
Network buffer	0	9.1	2.8	4.7	1.6	3.2

†The 500m buffer was chosen as children's neighbourhood extent based on having the greatest percentage difference between mean values of adjacent buffer sizes and the point at which participants spent the majority of their time in both concentric and network buffers.

Fig. 3. Average percentage of leisure time spent within Euclidean and network buffers around participants' homes (mean, 95% CI, from Poisson regression) accounting for complex sampling strategy and observation time.

destination in this study were: a minimum number of 120 GPS points (density parameter), separated by no more than 100 m (spatial parameter) and occurring over at least 10 min (temporal parameter). Under these specified space-time parameters, there was an average of 9.9 (95%CI 8.5 to 11.3) destinations visited per child, containing 91.1% of the leisure time spent more than 500 m away from home. Fig. 4 presents four examples of destinations captured by the cameras; outdoor recreation, structured sport, food retail and other residential (clockwise from top left image).

The rates of children's leisure-time visits to destinations outside their neighborhood and time spent per visit are presented in Fig. 5. Children left their neighborhood most frequently to visit: school (as a leisure-time destination, as analysis did not include school times) (mean 2.4, 95%CI 1.9 to 3.0 visits per 10 h), other residential locations (other than their primary home address) (mean 1.9, 95%CI 1.4 to 2.7 visits per 10 h) and food retail outlets (mean 1.9, 95%CI 1.3 to 2.8 visits per 10 h). School, other residential locations and food retail outlets had more visits collectively (mean 6.2 visits per 10 h) than all other identifiable destinations combined (mean 3.2 visits per 10 h). Children made more visits to food retail outlets (mean 1.9 visits per 10 h) than structured sport and outdoor recreation locations collectively (mean 1.5 visits per 10 h). One reason for the frequency of unidentifiable destinations was due to there being nearly three times more GPS data collected than image data. There were no statistically significant differences in the destinations visited by season, except children were 1.8 times more likely to visit a food retail outlet in the winter terms than in the summer terms.

In terms of time spent per visit, children spent the most time at the following destinations: other residential locations (mean 14.4, 95%CI 10.1–20.7 min/hour), school (mean 10.3, 95%CI 7.8 to 13.6), and food retail outlets (mean 8.5, 95%CI 6.1–11.5 min/hour). Nearly a quarter (mean = 14.4 min/hour) of the leisure time spent outside of the neighborhood occurred at another residential location. Similar to the number of visits, the collective time spent at other residential locations, school (for leisure) and community venues is greater (mean 33.3 min/hour) than all other venues combined (mean 16.6 min/hour).

4. Discussion

Our results showed the 500 m residential Euclidean and network buffers represent an appropriate boundary to define children's neighborhoods, based on our criteria. These criteria included children spending over 50% of their time within this buffer, and the largest absolute increase in the percentage of time spent from adjacent buffers. During leisure time, children left their neighborhood most frequently to visit and spend time at other residential locations, school and food retail outlets. Interestingly, children visited and spent more time at food retail outlets than at structured sport and in outdoor recreation locations collectively. Per visit, children spent more time at other residential addresses compared to other destinations. These results reinforce the use of activity space data from the specific population of interest (here, children) to define neighborhood boundaries (Oliver et al., 2015). Researchers with access to GPS activity space data should utilize a similar approach that accounts for where participants spend their time. In the absence of such data, our findings can help inform other researchers interested in children's neighborhoods and mobility patterns. Further, our study highlights not only how often and how long children spend outside their neighborhood, but also confirmed the visits to particular locations outside their neighborhoods using images from wearable cameras.

Our results also show that children are relatively constrained in their proximal residential environment, only spending around 40% of their leisure time outside the 500 m designation. The constrained nature of children's mobility, in this study, echoes existing neighborhood research (Bringolf-Isler et al., 2008; Larsen et al., 2009; Oliver et al., 2015; Villanueva et al., 2011). Therefore, we believe our results are generalizable to children in other developed countries and can be used to inform similar research, particularly given the similarlities in previous research findings. Importantly, however, researchers interested in neighborhood effects on children's health need also to consider venues commonly visited such as school, other residential addresses, food retail outlets, community venues and sports venues, which were outside the 500 m neighborhood buffer, to gain a comprehensive picture of children's broader exposures.

There are a number of methodological considerations investigated in this research. First, missing data was imputed using a mixed imputation method that combined the use of an automated process (Python script) and a manual process using image data. It is unlikely that the imputation method was biased towards any one



Fig. 4. Examples of settings coded in destination analysis (clockwise from top left panel); outdoor recreation, structured sport, food retail, other residential.

location (e.g. home v food retail outlet). Rather the imputation method was more likely to impute data while participants were relatively spatially and temporally constrained [traveling less than 100 m in 5 min]. Thus, it is likely that participants' trips to destinations [automobile transport] were less likely to be imputed than the destinations themselves. This has implications for research interested in children's trips to desintations, rather than the destinations themselves. Second, the use of specific and replicable criteria to define children's neighborhoods enabled a more systematic approach than other studies (Oliver et al., 2015). The use of population neighborhood definitions [based on replicable criteria] could enhance comparability between studies, as there is no universal neighborhood size; rather, studies could construct participants' neighborhoods based on how people spatially and temporally use the area around them. For example, a child in rural New Zealand is likely to spend their time at different locations and

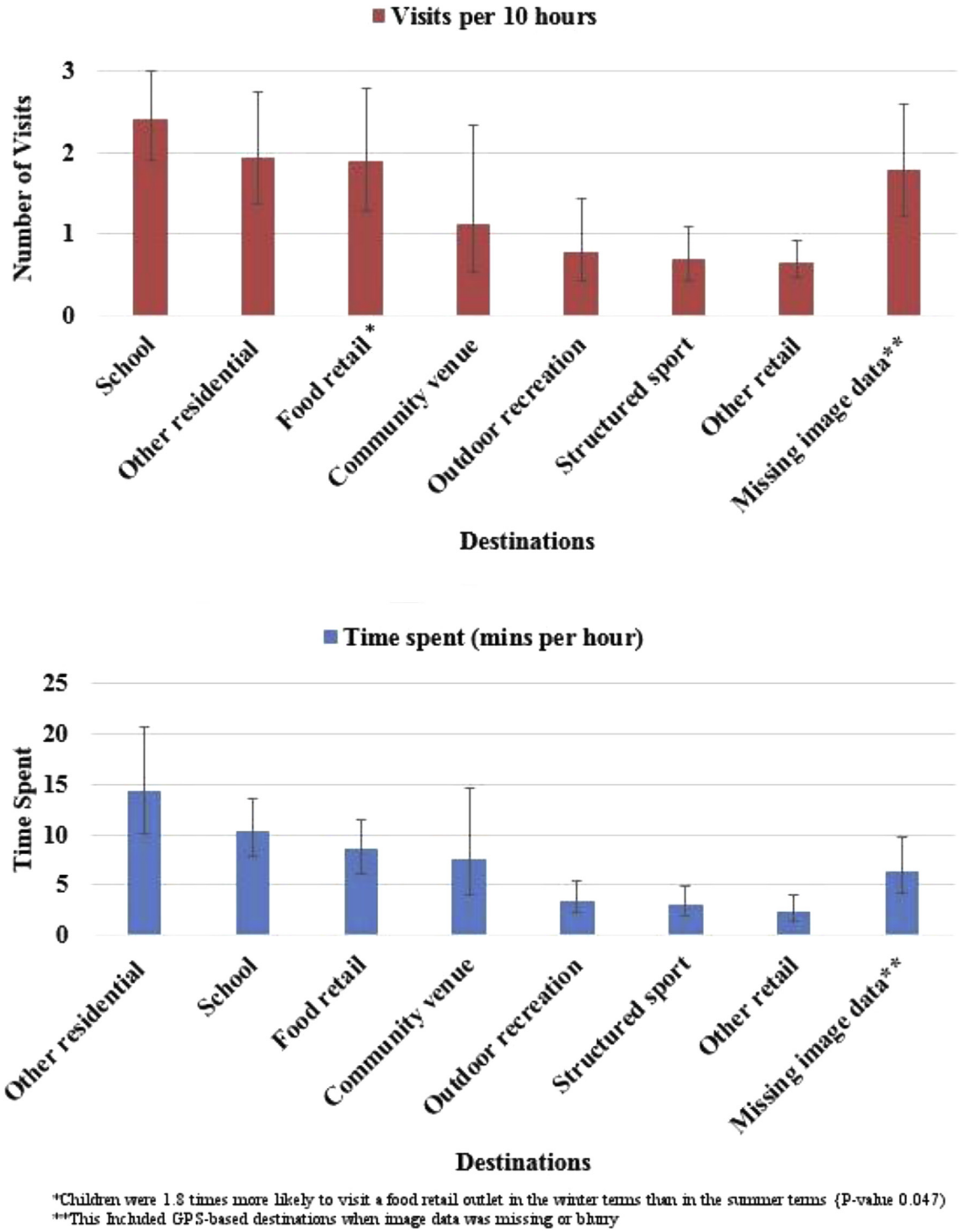


Fig. 5. Mean rate of visits to destination (per 10 h) and mean time spent at destinations (minutes) outside their neighborhood (per hour, with 95% CI, from negative binomial regression) accounting for complex sampling strategy and observation time.

have different mobility patterns than a child in urban New Zealand. Thus, the focus should shift away from universal concepts of neighborhood size, and focus on how and where people spend their time. Finally, this study utilized a novel methodological approach – combining GPS with image data – which allowed us to capture children's reasons for leaving their neighborhood. Wearable cameras provide a robust method to confirm children's actual location when used in combination with GPS data, which is likely to be more reliable than using spatial data alone.

Our study had some limitations. Some children were excluded from the initial sample, as they did not collect any GPS data (10.7%) or had insufficient such data (21.4%). Moreover, our analytical sample included more children living in high deprivation neighborhoods or who were overweight, compared to excluded participants. It is possible that wealthy children may have more opportunities to be mobile, and greater means of being mobile, than less well-off children, and therefore be more likely to venture beyond their neighborhood boundary. Therefore, our findings may slightly overestimate the time spent within 500 m of home. However, this could be offset by our sample having a smaller proportion of overweight children than children of healthy weight, who may be less mobile (e.g., traveling by bicycle or on foot). Another limitation was the missing or blurry image data, which did not allow for destination confirmation. However, it is unlikely that this type of missing data are biased toward any one setting, as missing image data appear to occur at random. There were moderate levels of GPS data missingness in the Kids'Cam study (53.3% overall, 25.8% in the current sub-sample), based on a systematic review of studies using GPS technology that reported data loss ranged between 3 and 92% (Krenn et al., 2011). Further, our definition of data missingness included all time between 7am and 9pm, which is likely to overestimate missing data due to children's days starting after 7am and finishing before 9pm. Finally, the image coding categories are relatively broad; future studies could incorporate a more complex coding schedule to determine whose residential address (e.g. friend, relative, etc) or what community venue is being visited, or the outcome of the trip (e.g. brought milk). Nonetheless, the categories used in this analysis are sufficient to answer this study's research questions.

Children in this study spent the majority of their leisure time within 500 m of their home. The main reasons for children leaving their neighborhood were to visit school, other residential locations and food retail outlets. Population-specific neighborhood size definitions should be critically examined, using clear and replicable criteria such as those outlined in our study. The combination of GPS activity space data and images from wearable cameras, and the use of a novel software application provided a robust method to confirm destinations visited. Our methodology could be extended in the future to validate neighborhood exposures for different population sub-groups.

Acknowledgments

The Kids'Cam project was funded by a programme grant from the Health Research Council of New Zealand (HRC programme grant #13/724), Science Foundation Ireland grant 12/RC/2289 and a University of Otago, Wellington Research Equipment Grant. We would like to thank Chris Lowrie for his contribution to the creation of the Python script used for GPS data imputation. We thank the children, parents and caregivers, and schools who let us into their lives. We also thank Ryan Gage and the 2015 Fourth Year medical students who assisted with the image coding, especially Saskia Campbell, Ryan Cullen and Richard Kennedy. The authors also wish to acknowledge Amanda Rzotkiewicz for her helpful edits and creation of the figures.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.socscimed.2017.09.046.

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