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Comparing children's GPS tracks with geospatial proxies for exposure to junk food

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ABSTRACT

Various geospatial techniques have been employed to estimate children's exposure to environmental cardiometabolic risk factors, including junk food. But many studies uncritically rely on exposure proxies which differ greatly from actual exposure. Misrepresentation of exposure by researchers could lead to poor decisions and ineffective policymaking. This study conducts a GIS-based analysis of GPS tracks—'activity spaces'—and 21 proxies for activity spaces (e.g. buffers, container approaches) for a sample of 526 children (ages 9–14) in London, Ontario, Canada. These measures are combined with a validated food environment database (including fast food and convenience stores) to create a series of junk food exposure estimates and quantify the errors resulting from use of different proxy methods. Results indicate that exposure proxies consistently underestimate exposure to junk foods by as much as 68%. This underestimation is important to policy development because children are exposed to more junk food than estimated using typical methods.

1. Background

A range of geospatial techniques have been used to estimate children's exposure to environmental cardiometabolic risk factors, including junk food. Many of these studies rely on assumptions, however, which inadequately represent the environments to which children are truly exposed. The conclusions drawn by these studies may be erroneous, which can have negative implications for policy development if policymakers uncritically utilize the research findings. The key objective of this paper is therefore to demonstrate the bias created by using improper methods to estimate exposure to junk food. GIS analysis is used to visualize and quantify the errors present in a range of geospatial techniques for estimating junk food exposure, as well as contrast these results with validated GPS tracks representing true exposure.

1.1. Defining exposure

Within the health geography literature, methodological techniques for estimating exposure to cardiometabolic risk factors (e.g. junk food environments, opportunities for physical activity) and quantifying the effects of 'place' have been in a state of refinement for much of the past two decades. Studies initially focused on density of junk food outlets in home (Maddock, 2004; Morland et al., 2006) or school environments (Zenk and Powell, 2008; Gilliland, 2010) or both (Gilliland et al., 2012; He et al., 2012a,b), but results have been mixed and most do not adequately represent the contribution of environmental factors. Kearns and Moon (2002) indicated that "place, though

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undoubtedly a focal concept in the new geography of health, is neither unproblematic nor coherently applied" (p. 612). Even 10 years later, Kestens et al. (2012) recount that "in spatial epidemiology, the relationship between environmental exposures and individuals…is traditionally grounded to one reference location—most often, place of residence" (p. 2), suggesting that the literature has yet to transcend overly simplistic conceptions of exposure.

The need for transcendence is important because exposure proxies—such as buffers or containers surrounding home or school locations—ignore the well-known fact that human activity spaces are much more complex than single locations (Setton et al., 2011), an idea which Kestens et al. (2012) and Matthews (2011) refer to as 'spatial polygamy'. Further, the epidemiologic literature has long recognized the various components of personal exposure assessment, including environmental concentration, exposure concentration, and dose (Nuckols et al., 2004). To date, junk food exposure research has not fully explored the opportunities for quantifying exposure concentration or dose. Because junk food exposure papers continue to struggle with the first component—environmental concentration—in this paper we critique the use of proxies for estimating exposure to junk foods.

1.2. Bias in estimating exposure from misclassification of proxies

Recognizing the potential bias inherent in studies with simplistic methodologies, comparison studies have shown the effectiveness of various buffer types in estimating exposure to physical activity indicators. In one study, network buffers had more positive predictive associations with measuring the relationship between land use and propensity to walk for leisure (Oliver et al., 2007). Another study more comprehensively compared actual GPS tracks with circular, polygon network, line-based network, and variable-width buffers, as well as polygon, ellipse, and line buffers around recreational facilities (Boruff et al., 2012). Findings suggested that GPS measures have significant potential to revise the way exposure proxies of 'neighborhood' are conceptualized.

In methodological studies on measures of the built environment, authors lament that work continues to lean too heavily on exposure proxies of the built environment (Rainham et al., 2008). Oliver et al. suggest that "when making conclusions about the influence of the built environment…researchers need to carefully consider the methodology used to measure the built environment" (p. 10). Using buffers in exposure estimation has now been roundly criticized by spatial scientists (Boruff et al., 2012; Chaix et al., 2009; Rainham et al., 2010; Spielman and Yoo, 2009). And while researchers have cautioned against using GPS as the sole source of exposure data or expecting greater causal influences from GPS-derived daily activity paths solely because of a perception that these should be more accurate (Chaix et al., 2013; Nuckols et al., 2004), the use of GPS data to capture actual activity spaces is a significant improvement over the assumptions made in using buffers for analysis (Rainham et al., 2008).

1.3. Measuring the built environment

Leal and Chaix (2011) quantify the concerns that many studies are using insufficient methods for estimating exposure by noting that 90% of built environment studies considered only the subject's residence in estimating exposure. Nearly three-quarters of these studies use some kind of administrative boundary (e.g. census tract), but only one calculated exposure around both the home and school. Inagami et al. (2007) likewise showed that, when neglecting to consider exposure beyond residential location, the relationship between exposure and self-reported health was underrepresented. Thus by including more sophisticated, objective measures of exposure, we can more accurately estimate the relationship between exposure and health. Yet because a range of proxy techniques continue to be employed, quantifying the bias arising from misclassification due to inadequate measurement techniques is critically important.

GPS tracking has been used to estimate exposure to physical activity opportunities (Almanza et al., 2012; Lachowycz et al., 2012; Rodríguez et al., 2012) and the food environment (Christian, 2012; Zenk et al., 2011). In one study, exposure to fast food was correlated with higher consumption of fat (Zenk et al., 2011). Two earlier studies also showed that GPS tracking is more accurate in quantifying activity spaces than estimations by parents or participant self-report (Elgethun et al., 2006; Burdette et al., 2004). Accurate tracking via wearable devices is therefore important to increase certainty in spatial analysis and provide accurate assessments of exposure. Given the bias found in misclassified exposure proxies of the built environment, and the use of GPS tracking as a baseline for accurate measurement, our objective is to quantify the errors in using a range of commonly employed techniques for estimating exposure when compared to GPS tracks. And while inroads are being made toward making this bias explicit (Shearer et al., 2014), we build on recent work by addressing differences in bias by travel mode and for a broader range of exposure proxies which continue to be used in spatial epidemiology and public health research.

2. Methods

2.1. The spatial temporal environment & activity monitoring (STEAM) project

Data was taken from the previously completed STEAM Project, which compiled demographic and spatial data (including home and school location) on 614 children (grades 4–8, or ages 9–13) in London, Ontario, Canada. STEAM's central aim is to assess how the physical (built and natural) environment influences children's activity patterns and food consumption habits. Data was collected over four years (2010–2013), and each child was surveyed twice (once in the spring, and again in the following fall season). Participating children represent 22 schools from a broad range of built and social environments.

Relevant data for this study include the child's geocoded home and school address, junk food sites (including fast food restaurants and convenience stores), and GPS tracks. Junk food sites were generated from the public health inspector database for the City of London and geocoded to their exact location (using principles of accuracy and inclusion as discussed in Healy and Gilliland, 2012, and Sadler et al., 2011). GPS tracks were generated by passive GPS devices which tracked children's movement every second along their trips to and from school, thus providing a validated measure of location for each child. We first screened out any tracks with less than 3 h of data on at least 2 weekdays, as defined by Loebach and Gilliland (2014) for another paper on the STEAM Project. Due to data quality and tracking issues, we used tracks for 526 children to conduct further spatial analysis. From our GPS tracking, we created activity space polygons (i.e. the viewsheds through which every child passed during tracking). Zenk et al. (2011) derived "daily path areas" by buffering points at half a mile. We posit that this is too large an area for an individual to see in an urban context, and have instead used 100 m (~328 feet) to represent a viewshed. While others have used 50 m as a buffer threshold (Larsen et al., 2012), the distance from adjacent sidewalks to strip mall storefronts is often greater than 50 m. As well, even in urban areas the distance from one side of a sidewalk to a setback storefront can exceed 50 m. We thus likewise suggest that 100 m is thus better suited to representing the full scope of a child's point of view in suburban and urban locations.

2.2. Comparative method

To quantify the bias created by using non-GPS based techniques, we contrast the results seen from GPS tracking with a range of proxy techniques, including: circular and network buffers around home and school at 500, 800, 1000, and 1600 m (16 measures), container of home and school census tracts and dissemination areas (4 measures), and assumed network path to school (1 measure). Circular buffers were created around each individual's home or school location, while network buffers used the road network to compute the equivalent distance travelled along a street from each individual's home or school location. Container metrics consisted of assigning each individual to the census unit in which their home or school was found. As we also collected data on mode of travel to school, we report on the aforementioned measures for sub-groups of children (including those who travel actively, by car, by bus, mixed but dominated by active travel, and mixed but dominated by passive travel).[1] Fig. 1 represents the spatial dimensions of all 22 junk food exposure estimates for one child. The lack of overlap between the objectively derived track and the various estimates is indicative of the high degree of error found when evaluated for all 526 children.

3. Results

3.1. Proxy estimates vs. GPS tracking for measuring exposure

Table 1 shows the mean values for the various spatial measures, as well as the Pearson's R correlations and error measures to exposure measurements made using the actual path. Mean deviation is given to show how far the observed proxy mean was from the mean of actual paths. Percent error is calculated as: $|(T - E)/T|$, where T equals the actual value, E equals the error, and T minus E equals the net error. Percent difference is calculated with the assumption that the actual path is also an estimate, and computes the difference between the proxies and the actual path divided by the mean of the two estimates: $|E_1 - E_2|/((E_1 + E_2)/2)$.

The average child passed by 14.5 fast food restaurants and 10.8 convenience stores on their way to and from school. Overall, 19 of the 21 measures *under*estimated exposure to fast food when compared to actual GPS tracks, while 17 of 21 *under*estimated exposure to convenience stores. The average mean deviation between GPS and exposure proxies was 9.8 for fast food and 6.5 for convenience stores, meaning on average that these exposure proxies would yield errors of 68% and 61%, respectively. The average percent difference between them was 110% for fast food and 84% for convenience stores. The lowest error values in Table 1 are 1600 m network school buffers for fast food (36%) and 1000 m circular school buffers for convenience stores (9%). Using an assumed network path between home and school provided the highest Pearson's R correlations—0.52 for fast food and 0.56 for convenience stores.

3.2. Estimates by mode of travel to school

Table 2 breaks down the same estimates by mode and reports on mean values and Pearson's R correlations to determine whether any estimates would be better suited for particular modes of travel, especially since exposure is experienced differently depending on the mode of travel. Generally, the proxy-derived routes for children taking the bus were most closely correlated with the actual paths taken (on average, 0.45 for fast food and 0.39 for convenience stores), perhaps a result of the fact that buses take circuitous routes to school and would thus capture the approximate areas that the proxy measures would enclose. Yet these estimates are least valuable because children on buses have no autonomy to make their own food consumption decisions along the path to school.

Conversely, the estimated measures of exposure for children who actively travel or are driven to school have weak relationships with the validated GPS measure. Only a few measures were statistically significant with the GPS tracks, though this is not consistent across modes. The assumed path (0.45) and 800 m circular home buffers (0.42) were the highest estimates of fast food exposure for active travelers. Smaller associations were seen,

[1] 'Active' modes of travel include children walking or bicycling to school at least 60% of the time. 'Car' as a mode of travel includes children being driven to school at least 60% of the time. 'Bus' includes children taking a bus to school at least 60% of the time. 'Mixed – Active Dominant' includes children who walk or bike to school between 30% and 60% of the time. 'Mixed – Sedentary Dominant' includes children who are driven or bussed to school between 30% and 60% of the time and do not walk at least 30% of the time.

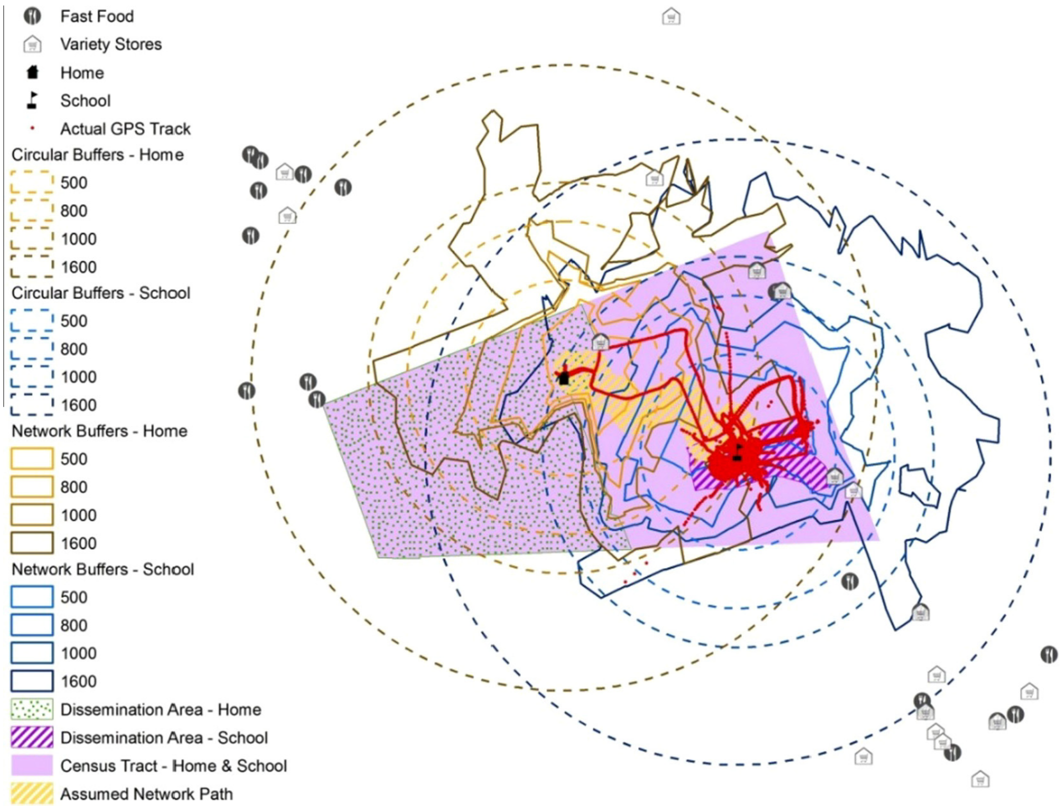

Fig. 1. Junk food exposure estimates for 21 exposure proxies and GPS-derived activity space.

Table 1
Mean values, Pearson's *R* correlation with actual path, mean deviation, indication of over- or underestimation, and percent error/difference of exposure to junk food sites (Fast Food = FF; Convenience Stores = CS).

Container type	Point of origin	Buffer size	Mean value		Correlation with actual path		Mean deviation		Percent error		Percent difference	
			FF	CS	FF	CS	FF	CS	FF (%)	CS (%)	FF (%)	CS (%)
Circular buffer	Home	500	1.5	1.8	0.20*	0.07	12.8	8.8	89	83	162	142
		800	4.4	4.7	0.14*	0.01	9.7	5.7	69	57	106	79
		1000	7.5	7.5	0.11*	−0.01	6.4	2.8	48	31	64	36
		1600	20.5	19.7	−0.02	−0.06	−7.2	−10.2	41	82	34	58
	School	500	1.8	2.6	0.04	0.11*	12.5	7.9	88	76	156	123
		800	5.0	8.3	0.22*	0.35*	9.5	1.2	66	23	98	27
		1000	7.8	11.8	0.21*	0.35*	7.3	−2.3	47	9	61	8
		1600	20.6	25.9	0.16*	0.41*	−6.9	−19.0	42	139	35	82
Network buffer	Home	500	0.6	0.7	0.21*	0.08	13.8	9.9	96	93	185	174
		800	1.6	1.9	0.19*	0.06	12.7	8.8	89	83	160	141
		1000	2.8	3.2	0.15*	0.00	11.6	7.4	81	71	136	110
		1600	9.1	9.4	0.02	−0.04	4.5	0.7	38	13	46	14
	School	500	0.8	1.3	0.10*	0.22*	13.5	9.1	95	88	180	157
		800	2.8	5.1	0.26*	0.35*	11.3	4.3	81	52	136	71
		1000	4.3	7.2	0.24*	0.36*	9.8	1.9	70	33	109	40
		1600	9.3	14.5	0.23*	0.36*	4.8	−5.9	36	34	44	29
Census tract		Home	6.9	5.6	0.12*	0.13*	7.5	4.5	53	49	72	64
		School	7.8	7.7	0.13*	0.41*	7.1	2.5	46	29	60	33
Dissemination area		Home	1.1	0.9	0.17*	0.12*	13.1	9.7	93	91	172	169
		School	1.5	3.0	0.32*	0.38*	12.8	7.2	90	72	163	113
Assumed path			3.1	3.8	0.52*	0.56*	10.7	6.3	78	65	129	96
Actual path		100	14.5	10.8								
Mean values					0.18	0.20	9.8	6.5	68	61	110	84

* Significance at 0.05 level.

Table 2
Mean values and Pearson's *R* correlation with actual path of exposure to junk food sites by dominant mode.

Container type	Point of origin	Buffer size	Active (bike, walk)		Car		Bus		Mixed – Active Dominant		Mixed – Sedentary Dominant	
Fast food												
Circular buffer	Home	500	2.3	0.08	1.4	−0.08	1.7	0.61*	1.2	−0.02	1.1	0.16
		800	6.1	0.42*	4.8	−0.13	3.6	0.52*	4.9	0.14	5.3	0.18
		1000	10.5	0.23*	7.8	−0.05	6.0	0.48*	9.9	0.08	8.0	0.09
		1600	34.5	−0.02	19.3	−0.03	14.6	0.33*	23.2	0.09	21.3	−0.08
	School	500	2.4	0.01	2.2	0.02	1.5	0.23*	2.0	0.07	2.0	−.29*
		800	5.1	−0.01	6.3	0.19*	3.8	0.40*	4.3	0.17	5.1	−0.21
		1000	7.8	0.08	8.9	0.20*	5.6	0.39*	6.2	0.22	6.8	−0.21
		1600	25.0	−0.03	23.3	0.27*	17.0	0.35*	23.0	0.25*	20.5	−0.22
Network buffer	Home	500	1.0	−0.02	0.4	−0.11	0.8	0.63*	0.6	0.00	0.3	0.20
		800	2.5	0.13	1.4	−0.15	1.5	0.63*	1.2	0.07	1.2	0.11
		1000	3.8	0.22*	2.6	−0.12	2.6	0.56*	2.5	0.17	2.7	−0.13
		1600	15.9	0.08	8.2	−0.08	7.2	0.42*	10.8	0.12	9.3	−0.12
	School	500	1.2	0.01	1.0	0.18*	0.6	0.35*	1.4	0.06	0.9	−0.22
		800	2.9	0.00	4.3	0.13	2.5	0.42*	2.5	0.25*	3.4	−0.13
		1000	4.6	0.00	5.8	0.17*	3.7	0.43*	4.1	0.27*	4.9	−0.18
		1600	10.2	0.08	11.4	0.20*	7.7	0.48*	10.0	0.25*	9.6	−0.18
Census tract		Home	9.3	0.11	6.2	0.08	6.2	0.33*	5.8	0.31*	7.5	−0.12
		School	8.5	−0.10	7.7	0.13	9.0	0.12	4.2	0.42*	8.1	0.35*
Dissemination area		Home	1.5	0.04	1.2	0.10	1.2	0.53*	1.3	−0.11	1.5	−0.10
		School	1.0	−0.17	2.7	0.06	1.7	0.53*	0.4	0.30*	2.4	0.13
Assumed path			1.0	0.45*	6.8	0.40*	5.5	0.59*	1.9	0.08	4.9	0.64*
Actual path		100	3.8		24.5		12.6		9.0		24.7	
Average correlation				0.08		0.07		0.45		0.15		−0.02
Convenience stores												
Circular buffer	Home	500	2.6	0.13	1.8	−0.03	1.7	0.35*	1.8	0.07	1.6	0.07
		800	6.9	0.11	5.1	−0.11	3.9	0.23*	4.8	0.30*	4.2	−0.12
		1000	11.1	0.02	8.0	−0.13	6.1	0.23*	8.1	0.30*	7.0	−0.13
		1600	31.1	−0.09	20.1	−0.04	15.4	0.16*	22.1	0.22	18.5	−0.22
	School	500	3.4	−0.03	3.1	0.06	2.3	0.38*	2.9	0.22	3.0	−0.06
		800	5.9	−0.05	14.2	0.22*	9.1	0.45*	6.3	0.21	10.4	0.14
		1000	9.1	0.03	18.1	0.22*	12.6	0.46*	9.2	0.13	13.5	0.12
		1600	21.8	0.07	37.0	0.26*	30.2	0.64*	25.0	0.26*	31.4	0.12
Network buffer	Home	500	1.3	−0.04	0.7	−0.02	0.7	0.40*	0.9	0.11	0.4	0.25
		800	3.2	0.04	1.7	−0.05	1.6	0.39*	1.7	0.18	1.1	0.20
		1000	5.0	0.04	3.0	−0.08	2.8	0.22*	3.0	0.22	2.1	0.00
		1600	14.8	0.04	9.3	−0.14	7.9	0.24*	10.3	0.26*	8.9	−0.15
	School	500	1.8	0.01	2.0	0.14	1.2	0.50*	1.8	0.28*	1.7	0.09
		800	3.2	0.02	10.3	0.20*	6.2	0.45*	3.4	0.32*	7.2	0.18
		1000	4.6	−0.02	13.6	0.21*	8.7	0.47*	4.7	0.32*	9.8	0.18
		1600	10.5	0.12	23.4	0.23*	16.3	0.48*	12.5	0.16	17.4	0.14
Census tract		Home	6.3	0.07	6.4	0.06	5.6	0.32*	6.4	0.18	7.3	−0.15
		School	5.0	−0.11	12.0	0.26*	9.8	0.42*	5.4	0.35*	10.1	0.41*
Dissemination area		Home	1.0	0.26*	1.1	−0.02	0.9	0.30*	1.2	0.06	1.1	0.11
		School	0.8	−0.16	7.3	0.20*	3.9	0.44*	0.4	0.56*	5.2	0.33*
Assumed path			1.2	0.29*	7.8	0.42*	6.5	0.57*	2.5	0.32*	7.1	0.63*
Actual path		100	2.6		18.3		9.7		6.5		17.5	
Average correlation				0.04		0.09		0.39		0.24		0.10

* Significance at 0.05 level.

meanwhile, for children being driven to school; the assumed path (0.40) and 1600 m circular school buffers (0.27) yielded the highest correlations. For exposure to convenience stores, the highest correlations for mixed commuters/active dominant were school dissemination area (0.56) and school census tract (0.35), while for mixed commuters/sedentary dominant the highest correlations were assumed path (0.63) and school census tract (0.41).

3.3. Estimates by neighborhood classification as urban/suburban

Table 3 likewise breaks down the average estimates of fast food restaurants or convenience stores to which children are exposed, this time by the classification of their neighborhood as urban or suburban (as defined by the City of London). Mean values and Pearson's *R* correlations are given to determine whether any exposure proxies are more useful in urban or suburban locations. As before, the assumed path exhibited the highest associations, but these were higher for estimates in urban locations.

Overall, 13 of 21 proxies for fast food and 9 of 21 proxies for convenience stores were positively statistically significant in urban locations, while 9 of 21 proxies for fast food and 8 of 21 proxies for convenience stores were positively statistically significant in suburban locations. Generally, associations between proxies and GPS tracks were higher in urban locations, but as with the overall estimates

Table 3
Mean values and Pearson's *R* correlation with actual path of exposure to junk food sites by neighborhood classification as urban/suburban.

Container type	Point of origin	Buffer size	Fast food				Convenience stores			
			Urban		Suburban		Urban		Suburban	
Circular buffer	Home	500	2.1	0.20*	1.2	0.14*	2.4	−0.02	1.4	0.11*
		800	6.0	0.04	3.3	0.20*	6.3	−0.18*	3.3	0.08
		1000	10.3	−0.07	5.5	0.28*	10.0	−0.30*	5.4	0.17*
		1600	27.7	−0.25*	14.8	0.22*	26.5	−0.34*	13.2	0.15*
	School	500	2.8	0.01	1.4	−0.06	4.6	0.06	1.7	−0.13*
		800	6.5	0.36*	4.6	0.00	15.2	0.42*	5.0	−0.03
		1000	9.7	0.36*	7.4	0.07	19.8	0.42*	8.2	0.03
		1600	31.2	0.11	16.5	0.04	48.7	0.57*	14.9	0.07
Network buffer	Home	500	1.0	0.26*	0.3	0.03	1.1	0.04	0.5	0.07
		800	2.3	0.19*	1.2	0.09*	2.6	−0.02	1.3	0.09*
		1000	3.9	0.06	1.9	0.15*	4.5	−0.17*	2.1	0.11*
		1600	13.8	−0.15*	5.6	0.22*	13.5	−0.31*	6.3	0.18*
	School	500	1.8	0.02	0.2	−0.09*	3.4	0.11	0.2	−0.12*
		800	4.8	0.30*	1.8	0.03	11.1	0.40*	2.1	0.03
		1000	6.8	0.30*	3.3	0.01	15.0	0.42*	3.3	0.04
		1600	16.0	0.28*	6.3	0.03	27.7	0.41*	8.0	0.05
Census tract	Home		7.0	0.19*	6.7	0.05	7.1	0.04	4.4	0.15*
	School		8.2	0.26*	7.6	0.00	11.8	0.46*	5.2	0.02
Dissemination area	Home		1.6	0.25*	0.8	0.00	1.2	0.07	0.7	0.08
	School		2.3	0.34*	0.9	0.09*	6.7	0.40*	0.8	0.03
Assumed path			4.9	0.57*	1.9	0.41*	6.1	0.62*	2.2	0.37*
Actual path		100	18.2		10.8		13.9		7.9	
Average correlation				0.17		0.09		0.15		0.07

* Significance at 0.05 level.

the proxies tended to underestimate exposure even when they were correlated. Importantly, some proxy measures became negatively correlated to the GPS tracks for urban children, suggesting that such proxies may have some value for estimating exposure in suburban but not urban locales.

4. Discussion and conclusions

The correlation between proxy estimates of exposure to junk food and the real exposure to junk food as measured by GPS tracking is generally not strong enough to support the uncritical use of exposure proxies. The basic assumption is that when initial exposure estimates are inaccurate, the potential for error propagation increases and subsequent summary estimates decrease in value. When broken down by mode of travel to school, few consistent strong associations were found between proxies and GPS tracks. For most modes but especially for active commuters (those with the most autonomy and thus those for whom these estimates would be most useful), few measures were statistically significant, and those that were significant had high error estimates, suggesting parallel but highly separated regression lines. Such underestimated by correlated proxies may be useful if an appropriate metric can be devised to adjust the values up to the likely values. Still, research cannot only consider mode of travel as a determinant of exposure in the absence of personally-derived measures, because proxy measures for active commuters exhibited the highest error and least correlation to GPS tracks.

Estimates also varied widely when split by level of urbanicity (urban/suburban). This variation could be due to a number of factors. As traditional urban grid networks provide more direct routes, the buffer approaches used may be more likely to provide direct estimations in urban areas. Using varied distance buffers based on level of urbanicity may also provide a better estimate than using a single buffer distance for all children. As well, shorter or more varied paths to school in urban areas could mean that certain container proxies perform better at predicting exposure. In suburban areas, avoidance of major commercial strips by walkers or long, car-oriented trips could introduce bias into exposure estimates and contribute to proxies having less value. The uniformity of suburban land use (e.g. lack of land use mixing) could mean that proxies are not able to capture the full range of environments to which children are exposed in suburban areas. Conversely, the inverse correlations for some estimates (negative in urban areas, positive in suburban areas) suggest that proxies also cannot be used uncritically in urban areas. The geographically diffuse exposure pattern among suburban children may have yielded better estimates for these proxies, since proxies in urban areas could enclose vastly different environments than what is actually experienced.

Responding to concerns that insufficient, unidimensional methods continue to be employed in spatial epidemiologic research (Leal and Chaix, 2011; Kestens et al., 2012), the central objective of this paper was to quantify the bias created by using proxies of exposure to junk food. We compared a range of methods (including circular and network buffers at a range of distances, container approaches for census tracts and dissemination areas, measurements from home and school locations, and assumed shortest network paths) with validated GPS tracks of children. Unequivocally, exposure proxies generate substantial errors. Assumed network paths most closely approximate real exposure, but even they only correlate moderately with GPS tracks. Proxies in urban areas tend to perform better, but also generate negative correlations to GPS tracks in some cases. This research supports the literature suggesting that exact measures for estimating exposure to junk food *must* be used where possible because exposure proxies are consistently inaccurate either by underestimating exposure or generating negative correlations to GPS tracks.

By employing GPS tracks to measure exposure to junk food, ours is one of the first studies to quantify the errors in using proxy-derived measures, building on recent work by Shearer et al. (2014). This study has important implications for researchers examining children's health and the built environment, since it shows the necessity of using measures based on GPS tracking. Since most of the exposure proxies also underestimated exposure to junk food, these results are also important for policymakers to consider when assessing junk food siting policies near schools and in residential neighborhoods. Broadly, it lends support that healthier food environments must be pursued at all levels of policymaking, as the concentration of exposure to junk foods is even higher than most estimates would suggest. Given the ongoing childhood obesity epidemic, future research must link more exact measures of exposure with dietary behaviors to determine the net impact of junk food environments on food consumption. It is only through combining the best methods for environmental exposure and food consumption that we can develop the knowledge base toward meaningful interventions that promote healthy behaviors for children to continue throughout their lives.

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