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Research paper

The right space at the right time: The relationship between children's physical activity and land use/land cover

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HIGHLIGHTS

- Long-term paired GPS and accelerometry data collected from schoolchildren.
- Physical activity significantly correlated with parks and residential land use.
- Most observations of physical activity exhibit significant geographic clustering.

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ABSTRACT

Research increasingly suggests that moderate to vigorous physical activity (MVPA) is essential to children's health. However, little is known about the extent to which and when different urban environments influence the extent to which children engage in MVPA. To this end, this study explores the relationship between children's MVPA and urban land use and land cover (LULC) for several temporal subdivisions of children's weekly routines (before school, after school and weekends). In particular, the location and corresponding level of physical activity of 4th grade students (n = 134) was recorded using paired global positioning system (GPS) receivers and accelerometers over 33 days for each student. GPS locations were temporally related to accelerometry records and then geographically related to 13 categories of LULC. Mixed linear models were fitted to evaluate the extent to which duration spent in each LULC category can explain individuals' time in MVPA before school, after school, and during the weekends. Geographic cluster analysis was also applied to assess whether any significant spatial relationships between observations of MVPA may exist. Duration of exposure to vegetated parks/open spaces, built residential, and built institutional LULC was found to significantly increase children's time spent in MVPA. Further, most observations of MVPA were found to exhibit significant geographic clustering and were predominately associated with built residential areas (particularly those near schools), indicating the importance of neighborhoods and areas in close proximity to children's households on their level of physical activity.

1. Introduction

It is widely acknowledged that physical activity is central to an individual's health, for both youth and adults (CDC, 2011). However, much less is known about where and when different individuals are active and the influence of geographic and temporal dimensions on physical activity (Jackson, 2003; McCrorie, Fenton, & Ellaway, 2014; Sugiyama & Thompson, 2007). A key problem underlying this issue is that the spatial and temporal dynamics of individu-

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als' can be very complex, making collection and analysis of such behaviors extremely challenging. Efforts to collect such individual level data have often relied upon voluntary self-report and direct observation methods (Davison & Lawson, 2006; Ding, Sallis, Kerr, Lee, & Rosenberg, 2011; Mackett, Lucas, Paskins, & Turbin, 2005), but inconsistencies in the geographic and temporal detail of the data reported can present problems in its analysis. Automated data collection devices such as global positioning systems (GPS), heart rate monitors, and accelerometers now offer a more consistent mechanism for collecting information about individual's physical activity and can record a greater amount of geographic and temporal detail about the locations at which it takes place (Dunton, Almanza, Jerrett, Wolch, & Pentz, 2014; Eyre, Duncan, Birch, Cox, & Blackett, 2015; Evenson, Wen, Hillier, & Cohen, 2013).

While GPS and accelerometry can be jointly collected from individuals and used to learn more about the types of environments within which physical activity occurs, little is known about how schoolchildren use space and how their temporal budgets over different portions of the day or week can affect physical activity levels. In order to analyze patterns of physical activity, one must account for both the geographic location of the activity (i.e. via self-reported activity diaries and global positioning systems) as well as the level of physical activity occurring at that location (i.e. via accelerometers) (Jones, Coombes, Griffin, & van Sluijs, 2009; Mackett et al., 2005). Many protocols for the frequency at which locations are recorded (GPS records location at discrete intervals) and level of physical activity (accelerometers record activity over epochs) have been suggested. For example, some collection efforts have used 1.0 min intervals/1.0 min epochs (Oliver, Badland, Mavoa, Duncan, & Duncan, 2010; Quigg, Gray, Reeder, Holt, & Waters, 2010), 30.0 s intervals/30.0 s epochs (Almanza, Jerrett, Dunton, Seto, & Pentz, 2012; Dunton et al., 2013), 10.0 s intervals/10.0 s epochs (Cooper, Page, & Wheeler, 2010), 5.0 s intervals/1.0 min epochs (Troped, Wilson, Matthews, Cromley, & Melly, 2010), 15.0 s intervals/15.0 s epochs (Klinker et al., 2014). Given the variation in collection efforts, comparison among study results is cumbersome at best. For any reliable relationship between physical activity and location to be evaluated, collection efforts should ideally be structured to minimize temporal deviation among the measurement devices and maximize the frequency at which observations are recorded. That is, a finer temporal resolution in data collection can provide a more detailed record of an individual's behavior. Also, finer resolution data can easily be aggregated to coarser analysis units if desired. Likely the diversity of collection protocols that have been explored are largely due to attempts to tradeoff collection device limitations (i.e., battery power, storage capability, etc.), data processing capabilities, and the ability to adequately capture individuals' behavior. Research on the relationship between physical activity and location has also utilized a broad range of protocols for sampling periods. For instance, studies have considered observations of individuals' physical activity and location over a period of two days (Cooper et al., 2010), four days (Eyre et al., 2015; Jones et al., 2009; Troped et al., 2010), or seven days (Dunton et al., 2013, 2014; Jerrett et al., 2013; Klinker et al., 2014; Oliver et al., 2010; Quigg et al., 2010. Since no studies have involved collection efforts over seven days, there is really no proof that these short-term collection periods are adequate for accounting for individuals' physical activity and locational patterns though. Further, the number of individuals observed over the course of the sampling periods has also varied, from 100 to 367 individuals, with Klinker et al. (2014) being the only study to consider over 300 participants. Likewise, studies have differed in the geographic extent of the study site from which observations of physical activity and location were sampled. For instance, Cooper et al. (2010) and Oliver et al. (2010) focus on physical activity that occurs during transportation between locations such as home and school, Jones et al. (2009), Troped et al. (2010); Almanza et al. (2012), Dunton et al. (2014) consider activity occurring within some distance of home and work/school, Quigg et al. (2010), Evenson et al. (2013), and Wolf and Wohlfart (2014) assess individuals' activity within parks, Klinker et al. (2014) and Andersen, Klinker, Toftager, Pawlowski, and Schipperijn, (2015) confine observations of activity to schoolyards and other specific types of 'domains', while Jones et al. (2009) and Dunton et al. (2013) associate activity with the broader type of land use within which it was observed. This latter approach is important given that more records of physical activity are retained within a study region instead of limiting analysis to those occurring within a specific type of environment. The types of land use that are considered in the analysis of physical activity as well as the way in which portions of the study site are associated with a particular land use category have differed though. For example, Jones et al. (2009) use a variety of sources of land use data to group areas into nine different land use categories (buildings, other built land, gardens, parks, roads and pavements, beaches, woodland, grassland, and farmland). Dunton et al. (2013) rely upon a local land use database classification scheme and associate areas of their study site with one of six land use types (residential, commercial, open space, educational, public facilities, and other uses).

Continuous recording of observations of activity over space and time may provide a way to better understand the complex relationship between physical activity and land use across a short period of time. However, measuring the location of physical activity at the frequency and over the duration needed to capture the behavior for children necessitates a tremendous amount of data recording and storage for just a single individual, let alone a set of individuals. Longer-term, higher resolution data collection and evaluations are likely needed to capture the geographic and temporal dynamics of younger individuals. Shorter accelerometer epoch length is likely more suitable for estimating the time spent in sporadic, short bursts of MVPA (Edwardson & Gorley, 2010). Additionally, the analysis of the land uses and land covers that may influence physical activity levels necessitates an in-depth collection effort to better account for changes in LULC and physical activity over a larger period of time. To better understand these issues, a longer-term, multi-period data collection effort was conducted to capture the location and activity levels of schoolchildren to provide further insight on the relationship between their level of physical activity and the urban land uses and land covers (LULC) to which they are exposed. To this end, a cohort of schoolchildren were enrolled in a longitudinal study to capture detailed observations of their physical activity and location using paired GPS and accelerometry. The relationship between MVPA and LULC throughout the study region as well as over different temporal regimes (i.e. times of day, days of week) were then statistically analyzed.

2. Methods

To better understand the relationship between MVPA, LULC, and children's physical activity, 4th grade students ($n = 134$ with those of 12 years ($n = 1$), 11 years ($n = 11$), 10 years ($n = 105$), and 9 years ($n = 17$)) from four elementary schools in Columbia, Missouri (Fig. 1) were recruited. Children of this age were selected because their cognitive maturation is sufficient for them to responsibly participate in the data collection (with support from parents/caregivers) by following basic protocols for wearing and caring for the measurement instrumentations. Both written consent from parent/guardian and assent from the child were obtained as part of the institutional review board approval of this study. Students were provided a GPS receiver (QStarz BT-1300) and an accelerometer (ActiGraph) so that the location and intensity of physical activity could be jointly measured. The students were instructed to

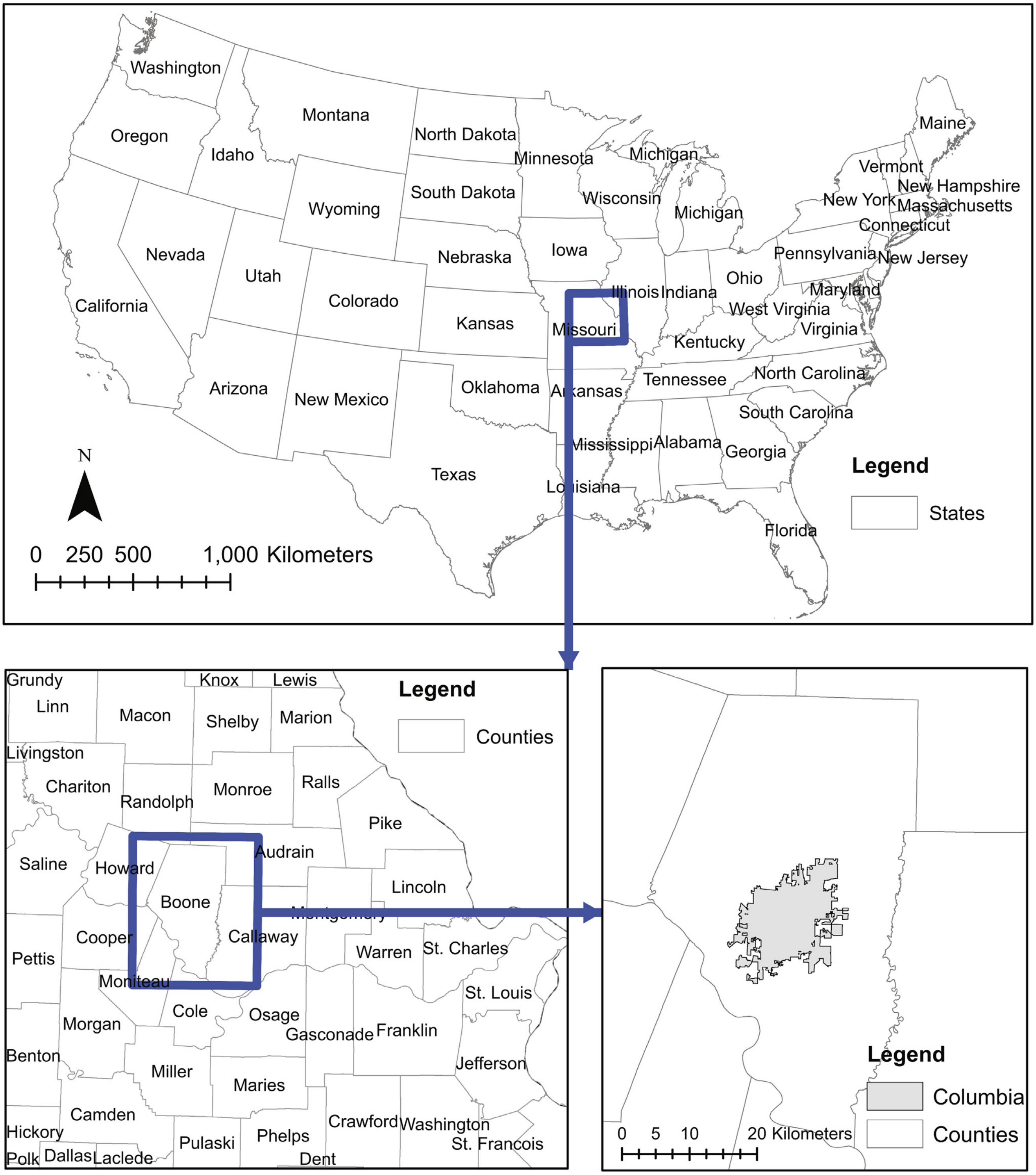

Fig. 1. Location of study site within the United States.

wear these instruments for eleven continuous days in each of three collection periods in shoulder seasons (April 20–May 30, 2011; September 20–October 30, 2011; April 20–May 30, 2012) for a total of 33 days of measurements per participants in an effort to safeguard against data loss and collect as much quality data covering both school days, weekends as well as different seasons. The students were asked to wear the instruments from the time they awoke to the time they went to bed, except for times at which data was being off-loaded from the instruments. Each school day students met with trained research staff to discuss equipment use and were also assisted by teachers, and parents/guardians who were provided written guidance on the operation of the collection instruments. Research staff retrieved GPS and accelerometer data daily and charged the GPS devices to mitigate data loss. Of the 134 students enrolled in the project (62 girls and 72 boys), 95 students participated in all three data collection periods with 19 and 21 students taking part in only two or one of the eleven day sampling periods respectively. These variations in student participation were primary due to children leaving or entering the study schools between collection periods.

As described earlier, a wide variety of collection intervals for GPS and accelerometry data have been utilized in prior research. While other studies have attempted to make use of less frequent measurements and different measuring intervals for the GPS and accelerometers, frequent and consistent measurements are very important when observing the behavior of school children. Therefore, in this study, the GPS and accelerometers were configured to record information at five second intervals in order to preserve as much spatial and temporal detail as possible and to facilitate the temporal linkage among records from both devices. The accelerometers were configured to record the number of movements (termed counts) occurring within each five second epoch (the five seconds *prior* to the time at which the record was reported). The GPS receivers were configured to record an instantaneous measurement of location every five seconds. Given that records are reported for both devices at five second intervals, accelerometry records were related to GPS records based upon their temporal proximity. If the temporal range of an acceleromery record did not span the collection time of any GPS record, it was not retained given the absence of a locational identifier. Only data from those students having GPS records within the city boundary (Fig. 1) that could be related to accelerometry records on at least three different days of each eleven day collection period were retained for analysis. In the end, data from 133 participants met this criteria (some variation in the students between collection periods – 77 students with qualifying data in all three periods; 35 with qualifying data in two periods; and 21 with qualifying data in a single period). In total, approximately 18,887 h (∼13.6 million records) of usable paired GPS-accelerometry observations were retained for subsequent analysis. The paired records for all qualifying students were then rendered as point features in a GIS, with each point representing the approximate location of five seconds of physical activity.

In order to evaluate the landscape characteristic of the locations at which MVPA was observed, areas within the study region were first associated with a land use/land cover type based upon a well-accepted biotope mapping approach (Cilliers, Muller, & Drewes, 2004; Freeman & Buck, 2003; Frey, 1999; Werner, 1999). GIS and photogrammetric interpretation of the study site, the City of Columbia, MO, were used to digitize LULC polygons corresponding to one of ten different categories documented on the city's zoning ordinance map. These categories were further subdivided into one of 142 distinct LULC types based on vegetation structure and pattern. While LULC types can be rendered in a variety of ways, it is important to represent them in such a way to best denote the space utilized by the subject of interest (Cilliers et al., 2004; Freeman & Buck, 2003; Frey, 1999). To this end, the 142 LULC types in this study were systematically reclassified into 13 categories thought to be most relevant to children's daily activities (Fig. 2). The LULC categories examined denote the primary use of areas of the city—water, agricultural, commercial, industrial, residential, and institutional (e.g., school). The later five categories were further subdivided into those areas that are primarily comprised of vegetation or built features. For instance, agricultural, residential, commercial, institutional, and industrial areas could be classified as vegetated if they are dominated by features such as woodland, shrubland, grassland/lawns, or riparian areas (i.e. an area zones as residential comprise of mostly woodland). Areas that are dominated by paved areas, buildings, and other structures would be classified as built (i.e. a single family housing unit with some lawn and trees).

Next, the point observations of physical activity were spatially related with the 13 LULC categories in a GIS to attribute each point observation with a LULC category. Point observations were then attributed with a binary variable indicating the presence of MVPA, where MVPA is defined as at least 2296 activity counts per minute (or 191.33 counts per 5.0 s record) which would equate to a metabolic equivalent (MET) of 4.43 and 0.05 EE using the energy expenditure (EE) equation (Freedson, Melanson, & Sirard, 1993; Puyau, Adolph, Vohra, & Butte, 2002). While some studies have considered higher thresholds on the number of activity counts thought to correspond with MVPA (Ekelund et al., 2012), the 2296 count threshold is utilized here given the diverse nature of the students and the activities within which they are engaged (Nilsson et al., 2008). In order to account for the influence of changes in the weekly routines for the students, the point observations were classified into three analysis groups: a) weekends (5am-11pm), b) weekdays before school (5–8am), and c) weekdays after school (3–9pm). Out of the qualifying observations of location and MVPA, ∼221.2 total hours of MVPA was observed during the weekends, with ∼69 total hours of MVPA observed weekdays before school and ∼370 total hours of MVPA observed weekdays after school.

To explore how LULC may influence MVPA over the three subdivisions of the week (weekends, weekdays before school, and weekdays after school), mixed linear models were specified. The mixed linear model approach was selected given the hierarchical structure of the data collection effort—i.e. each student was enrolled at one of four schools and participated in three different measurement periods. Specifically, models were fitted as shown in Eq. (1) where the dependent variable is the amount of time (number of 5.0 s epochs) during measurement period k in which student i attending school v was observed in MVPA (Y_{kiv}) and where the duration (number of 5.0 s epochs) in measurement period k in which individual i was exposed to each LULC type j (X_{kij}) are the fixed effects. Thus, the three data collection periods are modeled as repeated measurements for each student where the student level observations are further grouped by school to account for random effects among schools(λ_v), among students(τ_{iv}), and within a student's set of measurement periods(ε_{kiv}).

$$Y_{kiv} = \beta_0 + \sum_j \beta_j X_{kij} + \lambda_v + \tau_{iv} + \varepsilon_{kiv} \quad (1)$$

Areas of the study site classified as major transportation infrastructure were not included in the statistical analysis given that they support heavy vehicle traffic and as such are not likely utilized by children of this age range for physical activity. Additionally, any measurements of physical activity along these major corridors cannot be reliably separated from vehicle movement given the mode of transportation was not recorded. The results for each of the mixed linear models can be summarized using Akaike's Information Criterion (AIC) and Schwarz's Bayesian Criterion (BIC) computed for the fully specified models as well as a null specification (no fixed effects/intercept only). To better summarize the ability of the models to account for variation, the marginal R^2 and conditional R^2 proposed by Nakagawa & Schielzeth (2013) as well as the proportion change in variance (PCV) of the random effect components between the null and fully specified models can also be assessed. Aside from the statistical relationship between LULC and MVPA, it is also important to consider the geographical relationships among locations in the study site that may influence MVPA (McCrorie et al., 2014). To accomplish this while protecting the privacy of participant information, the study area was partitioned into 8051 areal units approximately 150 m × 150 m in size (note: data was not aggregated in this manner for the mixed level modeling detailed earlier). The paired GPS-accelerometry records corresponding to the three analysis periods (before school, after school, and weekend) were then related to the areal unit within which they are located. Next, the local G_i^* statistic of Getis and Ord (1992) was applied to test for the presence of significant geographic cluster-

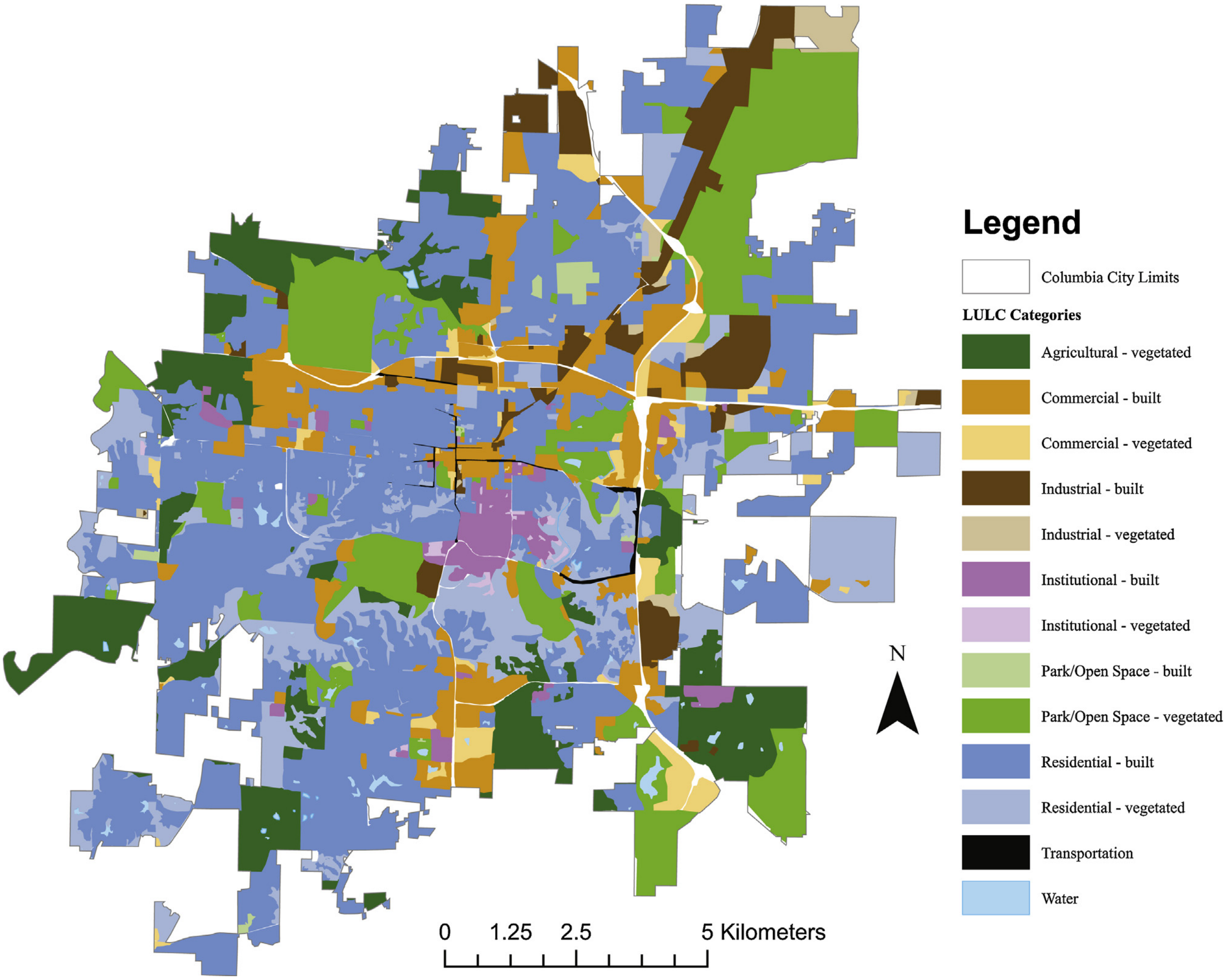

Fig. 2. LULC categories for study area.

ing of areal units having higher number of observations of MVPA or lower number of observations of MVPA. The $G_i^*$was selected given that it evaluates the relationship between the value of an areal unit of analysis with respect to the values of other areal units within a defined neighborhood. Given that the entire study area was partitioned into a systematic grid of areal units of the same size and shape to which the individual level data was aggregated, the Queen's criterion, in which areal units are considered neighbors whenever they share an edge or vertex of their boundary with another areal unit, was used to define the spatial weights in this application.

3. Results

3.1. Weekdays before school

Table 1 summarizes the average exposure to each LULC category (and average proportion of student's time in each LULC) for the cohort of qualifying students for each analysis period: a) over all observations of location, b) over observations of location that are accompanied by some level of physical activity, and c) over observations of location that correspond with MVPA. Weekdays *before school*, individuals were observed spending on average well over 90% of their time, regardless of their level of physical activity, in build residential and institutional areas. While there was on average 834 min spent in these two LULC before school, physical activity was only recorded for an average of 156 min with an average of 30.7 of that being classified as MVPA. On average, a little over seven minutes of any level of physical activity was observed in all other LULC.

A summary of the results of the mixed linear model for weekdays before school is presented in Table 2. The estimated model indicate that, during this period of the week, time spent in each of the LULC categories was only able to explain 33.2% of the variation of time spent in MVPA with the fixed and random factors collectively explaining about 53.6% of the variance (Table 2). The weekday before school hours were the only analysis period in which some variation among schools was present (albeit non-significant). Variation in the random effects among students and within their measurement periods was found to be statistically significant though this variation decreased from that present in the null model as indicated by the PCV values. In before school hours, vegetated parks/open spaces as well as built institutional and built residential LULC were found to be significantly associated with time in MVPA. The coefficients on these independent variables and/or the coefficients bounding the 95% confidence interval can be used to approximate how a unit change in each fixed variable can influence change in MVPA assuming that all other fixed variables do not change. Since, the fixed variables indicated the *number* of 5.0 s blocks of exposure to each LULC, the coefficients can be multiplied by 5.0 to obtain the additional seconds of MVPA that could result from each 5.0 s block of time spent in a particular LULC. For

Table 1
Average time (minutes) in which qualifying participants were observed in LULC categories for all recorded locations, locations associated with some level of physical activity, and locations associated with MVPA.

	All Recorded Locations						Locations of Physical Activity						Locations of MVPA					
	before school		after school		weekend		before school		after school		weekend		before school		after school		weekend	
LULC Category	avg. min	% time	avg. min	% time	avg. min	% time	avg. min	% time	avg. min	% time	avg. min	% time	avg. min	% time	avg. min	% time	avg. min	% time
Park /open space vegetated	34.7	2.62%	163.6	5.57%	237.4	8.76%	1.7	0.71%	59.3	5.94%	67.9	8.50%	0.4	0.74%	17.6	5.99%	17.5	8.94%
Residential vegetated	7.8	0.66%	33.2	1.27%	29.9	1.29%	0.3	0.20%	12.4	1.72%	8.3	1.33%	0.1	0.24%	2.9	1.83%	1.8	1.52%
Commercial vegetated	1.0	0.17%	3.3	0.25%	5.5	0.73%	0.1	0.07%	1.4	0.31%	2.2	0.77%	0.0	0.08%	0.3	0.32%	0.6	0.85%
Industrial vegetated	0.1	0.02%	0.1	0.00%	0.3	0.01%	0.0	0.01%	0.0	0.01%	0.1	0.01%	0.0	0.01%	0.0	0.01%	0.0	0.01%
Agriculture vegetated	2.1	0.27%	10.5	0.93%	6.2	0.81%	0.2	0.08%	3.1	1.07%	2.4	1.24%	0.0	0.10%	0.7	1.20%	0.5	1.10%
Institutional vegetated	0.0	0.01%	0.3	0.01%	1.1	0.04%	0.0	0.02%	0.1	0.01%	0.0	0.01%	0.0	0.01%	0.0	0.00%	0.0	0.00%
Institutional built	234.7	29.28%	94.3	5.35%	33.3	1.84%	67.0	45.96%	32.3	5.38%	12.0	2.08%	13.1	46.00%	7.3	5.54%	2.8	2.26%
Residential built	599.6	63.85%	1902.4	76.64%	1838.1	76.09%	89.1	50.47%	572.3	74.96%	380.8	70.93%	17.6	50.65%	130.6	74.62%	84.3	70.14%
Commercial built	28.4	2.71%	146.2	8.49%	137.2	9.21%	4.1	2.01%	50.8	8.75%	42.5	13.19%	0.6	1.88%	11.1	8.69%	9.6	13.25%
Industrial built	1.7	0.17%	9.4	0.44%	8.4	0.57%	0.2	0.10%	3.7	0.64%	3.0	1.03%	0.0	0.12%	0.8	0.53%	0.7	1.22%
Park/ open space built	0.4	0.05%	16.1	0.65%	5.1	0.19%	0.1	0.03%	6.9	0.76%	2.0	0.21%	0.0	0.01%	1.8	0.86%	0.4	0.20%
Transportation built	1.4	0.19%	5.4	0.29%	5.3	0.40%	0.5	0.33%	1.9	0.34%	1.7	0.57%	0.1	0.16%	0.4	0.28%	0.3	0.40%
Water	0.0	0.00%	1.2	0.09%	1.0	0.06%	0.0	0.00%	0.6	0.11%	0.5	0.13%	0.0	0.00%	0.1	0.12%	0.1	0.11%

Table 2
Before school time in MVPA explained by duration of exposure to LULC categories.

	Parameter	Estimate	Std. Error	t[b]	Sig.	Lower bound[a]	Upper bound[a]
Fixed Effects	Intercept	−41.816	36.323	−1.151	0.294	−130.737	47.106
	Parks−veg.	0.152	0.018	8.287	0.000	0.116	0.189
	Residential−veg.	−0.010	0.036	−0.269	0.788	−0.080	0.061
	Commercial−veg.	−0.349	0.761	−0.459	0.647	−1.847	1.149
	Industrial−veg.	1.622	2.672	0.607	0.544	−3.636	6.881
	Agricultural−veg.	−0.212	0.589	−0.360	0.719	−1.370	0.947
	Institutional−veg.	3.783	4.006	0.944	0.346	−4.103	11.668
	Institutional−built	0.048	0.012	3.864	0.000	0.023	0.073
	Residential−built	0.036	0.004	8.648	0.000	0.028	0.044
	Commercial−built	0.015	0.023	0.665	0.507	−0.030	0.060
	Industrial−built	0.313	0.372	0.842	0.400	−0.418	1.044
	Parks−built	−0.333	1.976	−0.169	0.866	−4.223	3.556
	Water	83.415	50.267	1.659	0.098	−15.537	182.366
Random Effects	Residual	37582.5	3915.1	9.599	.000	30641.8	46095.4
	School	3048.7	3031.7	1.006	0.315	434.2	21408.0
	Student	9380.4	3510.3	2.672	0.008	4504.9	19532.3

AIC (null model) = 4325.87, AIC (full model) = 4204.75, BIC (null model) = 4340.77.
BIC (full model) = 4268.11, Marginal R^2 = 0.3822, Conditional R^2 = 0.536.
PCVresidual = 40.1%, PCVstudent = 30.3%, PCVschool = −165%.

[a] 95% confidence interval.

[b] For random effects the Wald Z is reported.

example, the results indicate that for each additional 5.0 s spent in vegetated parks/open spaces, time spent in MVPA increases ~0.58 (i.e. 5.0 × 0.116) to 0.94 (i.e. 5.0 × 0.189) seconds while for each 5.0 s spent in built institutional and built residential land uses, MVPA increases ~0.12 to 0.36 s and ~0.14 to 0.22 s respectively.

3.2. Weekdays after school

As summarized in Table 1, during weekdays *after school*, individuals spent on average of 75% of their time in built residential areas. An average of 572 min of physical activity was observed in this LULC with an average 131 of those minutes classified as MVPA. While average time in physical activity and MVPA decreased considerably in built institutional areas during after school hours, a greater amount of time in MVPA was observed in built commercial (avg. 11.1 min) and vegetated park/open space (avg. 17.6 min) increased considerably as compared to weekdays *before school.*

The results of the mixed level model for weekdays after school detailed in Table 3 indicate that, approximately 43.5% of the variation in time spent in MVPA is explained by time spent in the LULC categories while 56.0% of the variation can be explained by both the fixed and random effects. Unlike before school hours, no variation among schools was present during this portion of the week and only variation among students and within their measurement periods was found to be present and significant. Significant predictors of MVPA in this analysis period again include time spent in vegetated park/open space as well as built industrial and residential LULC. Out of these predictors, every 5.0 s of exposure to vegetated parks/open spaces results in ~0.48–0.79 additional seconds in MVPA, 5.0 s of exposure to built institutional areas results in ~0.37–1.18 additional seconds in MVPA, while every 5.0 s of exposure to built residential areas results in ~0.25–0.35 additional seconds in MVPA. Although not as strongly significant, each additional 5.0 s of exposure to vegetated residential areas was found to increase time spent in MVPA by ~0.01–0.90 s.

3.3. Weekends

On *weekends,* individuals spent on average more than 70% of their time (physically active or not) in built residential areas with an average of 381 min of physical activity containing an average of 84 min of MVPA. During weekends, individuals were also observed utilizing vegetated parks and build commercial LULC to a greater extent, where they spent on average 20% of their time in MVPA (Table 1).

The results of the mixed level model for weekends indicate that about 30.6% of the variation in time spent in MVPA could be explained by time exposed to the various LULC while 35.0% explainable when accounting for the random affects as well (Table 4). As in weekday hours after school, there was no variation among schools and variation within students' measurement periods was significant, however, while present, variation among students was not found to be significant in the random effects. Again, the PCV values indicate a decrease in both variation within the measurement periods and among students when moving from the null/intercept model to the fully specified model accounting for fixed affects. Likewise, in this analysis period, vegetated parks/open space and built residential, and built institutional were found to be significantly associated with MVPA with additional 5.0 s of exposure leading to increases 0.24–0.50, 0.31–2.93, and 0.11–0.20 s respectively in MVPA.

Although vegetated parks/open spaces and built residential areas appear to account for the bulk of MVPA observed during this study, the geographical distribution of MVPA was assessed more broadly. Fig. 3 shows the location and level of MVPA over the 33 days on which GPS and accelerometry data were recorded for all LULC examined. While all of these locations are classified as hosting MVPA, the number of observations of MVPA (each observation represents 5.0 s of MVPA) in the areal units of analysis vary dramatically. Before school (Fig. 3a), MVPA was observed in approximately 7.3% of the city's area and the number of observations of MVPA per analysis zone was generally rather low, with a mean of 7.6 min (91 observations) of MVPA observed per zone. During this time of day, only about 0.2% of the city's area hosted more than 30 min (360 observations) of MVPA and these areas were primarily located at or near the four school sites. After school (Fig. 3b), MVPA becomes much more geographically distributed, with about 24% of the study region hosting some level of MVPA, with a mean of about 12.25 min (147 observations) per zone. During after school hours, almost 2% of the city's area hosted more than 30 min of MVPA. While some of these areas of higher MVPA were proximate to the schools, they were much more decentralized than before school hours. On weekends (Fig. 3c), some level of MVPA was observed in almost 21% of the city's area, with a mean of 8.5 min (102 observations) of MVPA occurring in each analysis zone. During weekends, about 1.3% of the city's area hosted more than 30 min (360 observations)

Table 3
After school time in MVPA explained by duration of exposure to LULC categories.

	Parameter	Estimate	Std. Error	t[b]	Sig.	Lower bound[a]	Upper bound[a]
Fixed Effects	Intercept	30.723	77.267	0.398	0.691	−121.504	182.951
	Parks−veg.	0.127	0.015	8.321	0.000	0.097	0.157
	Residential−veg.	0.090	0.045	1.991	0.047	0.001	0.179
	Commercial−veg.	0.053	0.493	0.108	0.914	−0.917	1.023
	Industrial−veg.	0.149	19.460	0.008	0.994	−38.142	38.440
	Agricultural−veg.	0.025	0.141	0.176	0.861	−0.252	0.302
	Institutional−veg.	1.229	1.812	0.678	0.498	−2.338	4.795
	Institutional−built	0.155	0.041	3.804	0.000	0.075	0.235
	Residential−built	0.060	0.005	11.184	0.000	0.049	0.070
	Commercial−built	0.026	0.034	0.765	0.445	−0.040	0.092
	Industrial−built	0.007	0.211	0.031	0.975	−0.408	0.421
	Parks−built	0.109	0.109	0.993	0.321	−0.107	0.324
	Water	−0.015	0.463	−0.032	0.974	−0.926	0.897
Random Effects	Residual	374563.92	38907.59	9.627	0.000	305568.03	459138.78
	Student	106058.92	36199.86	2.930	0.003	54327.10	207051.28

AIC (null model) = 5057.34, AIC (full model) = 4924.42, BIC (null model) = 5072.26.
BIC (full model) = 4984.1, Marginal R^2 = 0.435, Conditional R^2 = 0.560.
PCVresidual = 32.6%, PCVstudent = 62.7%.
[a] 95% confidence interval.
[b] For random effects the Wald Z is reported.

Table 4
Weekend time in MVPA explained by duration of exposure to LULC categories.

	Parameter	Estimate	Std. Error	t[b]	Sig.	Lower bound[a]	Upper bound[a]
Fixed Effects	Intercept	69.821	43.516	1.604	0.110	−16.058	155.700
	Parks−veg.	0.075	0.013	5.897	0.000	0.050	0.100
	Residential−veg.	0.035	0.049	0.713	0.477	−0.062	0.132
	Commercial−veg.	−0.696	1.503	−0.463	0.644	−3.658	2.267
	Industrial−veg.	−4.998	6.871	−0.727	0.468	−18.538	8.543
	Agricultural−veg.	0.184	1.249	0.148	0.883	−2.277	2.646
	Institutional−veg.	−2.624	34.396	−0.076	0.939	−70.408	65.159
	Institutional−built	0.324	0.133	2.436	0.016	0.062	0.587
	Residential−built	0.031	0.005	6.775	0.000	0.022	0.040
	Commercial−built	0.033	0.025	1.300	0.195	−0.017	0.082
	Industrial−built	0.058	0.102	0.567	0.571	−0.143	0.259
	Parks−built	5.524	3.105	1.779	0.077	−0.596	11.643
	Water	−4.254	6.636	−0.641	0.522	−17.332	8.824
Random Effects	Residual	144634.85	18184.36	7.954	0.000	113045.89	185050.86
	Student	9612.84	12973.09	0.741	0.459	682.50	135393.75

AIC (null model) = 3372.947, AIC (full model) = 3328.34, BIC (null model) = 3394.575.
BIC (full model) = 3382.855, Marginal R^2 = 0.306, Conditional R^2 = 0.350.
PCVresidual = 23.2%, PCVstudent = 66.5%.
[a] 95% confidence interval.
[b] For random effects the Wald Z is reported.

of MVPA and unlike before and after school hours, this activity was generally not located on school grounds.

The results of the $G_i{}^*$ statistic are shown in Fig. 4 to better assess the extent to which locations may exhibit significant geographic clustering of high or low observations of MVPA. Therefore, clusters can be interpreted as zones of concentrated MVPA indicating an environment amenable to MVPA in order to better discriminate against more isolated observations of MVPA. In this study, only clustering among areas having a higher number of observations of MVPA (e.g. areas having a high number of observations of MVPA neighboring other areas having high number of observations of MVPA) was found to be significant at the 90% confidence level or greater. In fact, the majority of the areas exhibiting clustering of higher observations of MVPA were significant at the 99% confidence level (98% of areas before school – Fig. 3a, 84% of the areas after school – Fig. 3b, and 78% of the areas on the weekend – Fig. 3c). Before school observations of MVPA were generally found to be significantly clustered within 600 m of each school location. Also, before school 86% of all observed MVPA in the study area occurred within the areas of significant clustering. Land use in these small clusters was dominated by residential (76% built and 4% vegetated) with 17% vegetated parks and open spaces and 6% built institutional areas. However, nearly all observations of MVPA in these clusters occurred in built residential LULC (53%) or built institutional (46%) LULC. After school, the geographic extent of significant clusters of high occurrence of MVPA greatly increases (Fig. 3b). During this time period, significant clustering around each school expands, involving more distant locations (within 1600 m) of the schools. Aside from school locations, notable clusters can also be found at five other locations in the study region. After school, 73% of all MVPA recorded in the study region was found to occur within the areas of significant clustering. The land use associated with significantly clusters of MVPA after school is predominately residential (63% built and 5% vegetated) with notable amounts of park and open spaces (13% vegetated and 1% built), commercial (11%—mostly built) and vegetated agricultural (6%) areas. However, 81% of the MVPA within the clusters occurred in built residential LULC, 11% in vegetated parks and open spaces, and 5% in built institutional LULC. On weekends, 67% of MVPA in the study region was part of a significant cluster and the extent of clustering resembles that observed after school (Fig. 3c), but with a notable decrease in the size of the clusters associated with the school locations. During

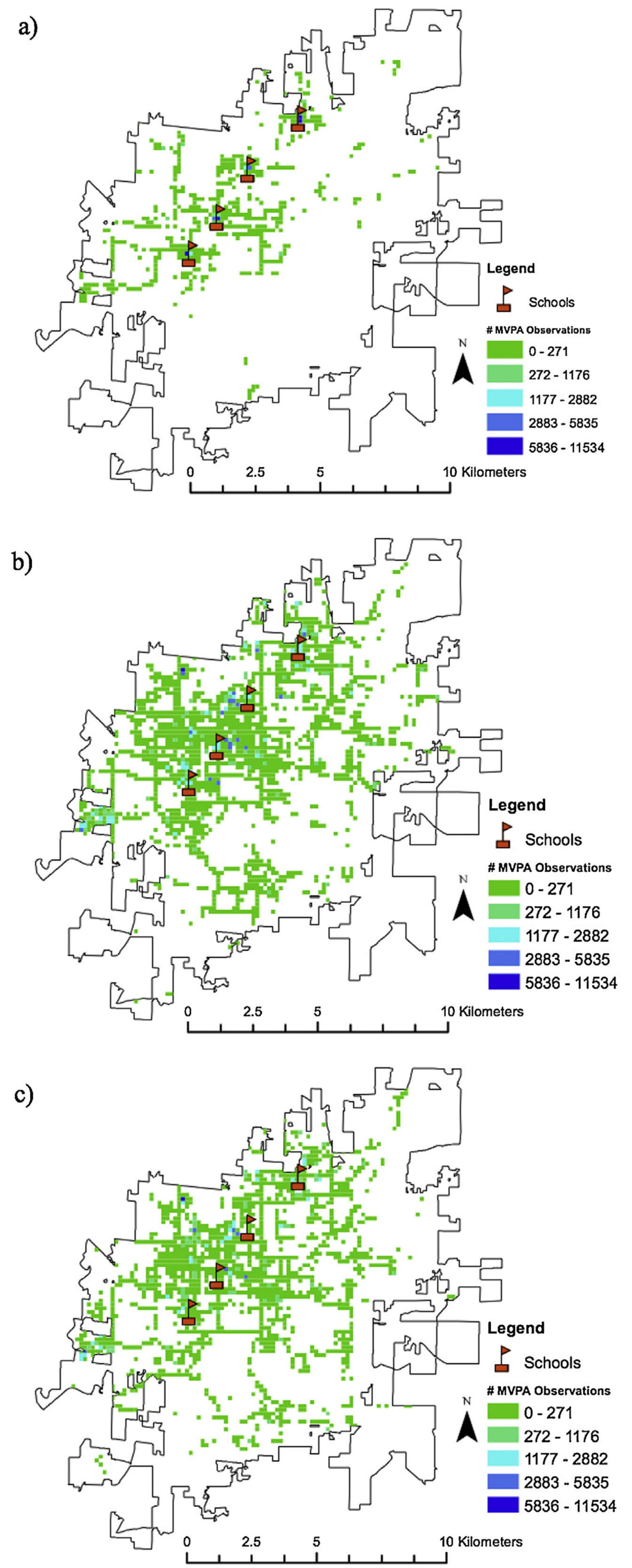

Fig. 3. Location and number of observations of MVPA: (a) before school, (b) after school, and (c) weekends.

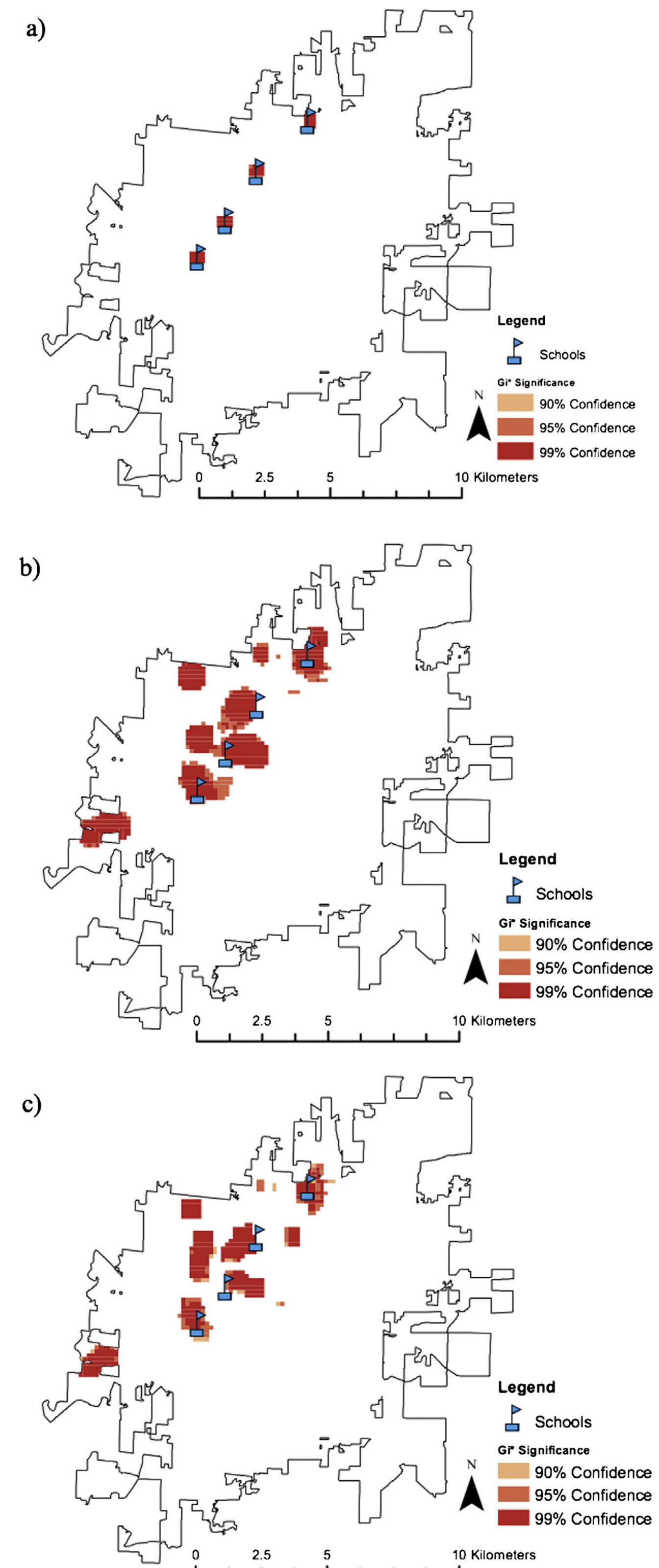

Fig. 4. Significant clustering of MVPA: (a) before school, (b) after school, and (c) weekends.

this period, there is also a discernable growth in a few of the other non-school clusters. In general, the LULC associated with significant clusters is still predominately residential (56% built and 4% vegetated), with an increase in parks and open spaces (26% vegetated and 1% built), commercial (8%—mostly built), and vegetated agricultural (3%). As in the other time periods, observed MVPA occurred mainly in built residential (~79%) with much of the remainder occurring in vegetated parks and open spaces (~19%) and built commercial (~2%) LULC. These clustering results indicate that not only does built residential LULC underlie a vast majority of the observed MVPA, but the land use surrounding built residential areas is also an important factor contributing to higher MVPA. Moreover, the parks and open spaces within the clusters in which MVPA was observed were either very proximate to one of the four schools and/or adjacent to a built residential area in the cluster. Therefore, these results provide further evidence that neighborhoods and their proximity to schools and parks provide an important environment for MVPA.

4. Discussion

Given the variability in protocols used to analyze physical activity with respect to the urban environment, a variety of results have been reported by studies that have coupled GPS and accelerometry measurements. For instance, research has indicated that most MVPA occurs in close proximity to a child's home (Jones et al., 2009; McCrorie et al., 2014), Quigg et al. (2010) report that parks account for very little of children's daily MVPA, while Jerrett et al. (2013) report that children in smart growth neighborhoods are more likely to spend more time in MVPA (Jerrett et al., 2013). Further, Dunton et al. (2014) find that 'greenness' can increase park use while the research of Klinker et al. (2014) suggests that children spend larger proportions of their in MVPA on school property, sports facilities, and urban green spaces and a relative small proportion of their MVPA at home. The research reported in this article provides evidence that indeed supports many of these relationships. However, this research also highlights that variations in geographic context and the temporal constraints affecting schoolchildren can also affect the extent to which these relationships present themselves.

This study examines the relationship between LULC and the level children's MVPA in an urban setting. Observations of location and physical activity were recorded using GPS and accelerometers and were then related to underlying LULC. While other studies have limited data collection to at most seven days of observation for each individual, here the level of activity and location for each participant was collected over 33 days. This robust data collection effort was essential for capturing weekday as well as weekend activity data and accounting for variations in children's behavioral patterns. Moreover, each individuals' activity was analyzed for three different time periods (before school, after school, and on weekends) to better understand the extent to which these temporal regimes may affect the relationships between MVPA and LULC. Results indicate that time spent in vegetated parks/open space and built residential areas have a significant positive relationship to time spent in MVPA across all three time periods considered. Although much less overall time was spent in parks in each time period than that spent in residential areas, this seems to substantiate other studies that indicate the positive impact that parks can have on MVPA even though children use these less relative to other LULC (Dunton et al., 2014; Evenson et al., 2013; Quigg et al., 2010). Perhaps more importantly, the finding that the majority of MVPA was clustered in residential areas (and near schools), supporting the high importance of areas close to home and school and neighborhood environments to children's physical activity (Jones et al., 2009; McCrorie et al., 2014). Duration of time spent in LULC classified as built institutional and built residential was also shown to be significantly related to time spent in MVPA before and after school and on weekends. Given the age of the participants, a possible explanation for the greater relationship between MVPA and build institutional, residential and vegetated parks is that these LULC may be more conducive to joint parent/guardian and child activities (Dunton et al., 2014).

Although MVPA was observed in all LULC, it is clear that the geographic distribution of MVPA is affected by the temporal regime. Thus, given the limitations on time before school, the activity space for MVPA is relatively consolidated around home and school as confirmed by the spatial distribution of MVPA illustrated in Fig. 2a. After school and weekends certainly would offer a greater amount of temporal flexibility for the children, allowing them to engage in physical activity over a broader range of LULC, again as depicted in Fig. 2b–c.

Though a statistical cluster analysis, areas of significant geographic clustering of areal units of analysis were identified. Coupled with the mixed linear model results, the clusters provide some further insight on factors that may influence the geographic distribution and magnitude of MVPA before and after school as well as on the weekends. Before school, MVPA is geographically dispersed (Fig. 2a), likely very near to the students' residence with the majority (86%) significantly clustered in very close proximity to school (Fig. 3a). After school, when there is presumably more time available to engage in a broader range of activities, the location of MVPA becomes more geographically dispersed (Fig. 2b) with the majority of MVPA significantly clustered in built residential or in adjacent vegetated parks and open spaces LULC (Fig. 3b). During this period, nearly 73% of all MVPA within the region was observed within the significant clusters identified. On weekends, a geographic distribution of MVPA (Fig. 2c) similar to that occurring after school was found. However, on weekends, the size of the clusters did decrease in some instances and only 67% of the total MVPA in the study region was within one of the clusters. This change indicates that on weekends, children's locational constraints may be more relaxed, resulting in less clustering of physical activity.

4.1. Limitations

With the growing amount of research exploring the relationships between physical activity and the environment, it is important to detail those factors that are likely to vary study-to-study. In studies such as this one where physical activity is observed over extended periods of time for populations that are relatively mobile, it can be expected that there will be less consistency in participation. For example, over the duration of this study, some participants were not involved in all collection periods for reasons such as transferring schools, illness, etc. Given this type of attrition/addition is a reality of longer term data collection efforts, shoulder season collection periods were selected in this study in an attempt to reduce the impact of variations in participation over the collection periods. Additionally, variations in the data collected from individuals can manifest from a range of factors such as problems with the measurement devices (i.e. pairing, functionality, storage, data retrieval, etc.) and differences in user's/care giver's adherence to usage protocols. As an example, one might anticipate that participation in organized sports on weekends might in part explain MVPA, there were instances when students had to remove the devices at the request of their instructors for safety reasons. Another limitation that can arise in studies such as this are those due to the spatial scale of analysis. For instance, the cluster analysis presented in this article was based upon individual point observations aggregated to 150 m × 150 m polygons. While this type of spatial aggregation helps to keep individual information anonymous, one must then take into account how the choice of areal unit may affect the outcome of the analysis (Matisziw & Hipple 2001; Matisziw, Grubesic, & Wei, 2008; Openshaw, 1984). The factors that may underscore physical activity levels in children are likely to be very individualistic and not easy to generalize. As such, the decision was made in this analysis to not mix the automatically collected location and physical activity with self-reported characteristics given that the former are dynamic while the later are more static. Also, a number of confounding factors could be present in self-reported information for this age group. For instance, reported household location and characteristics may have little to do with the student's actual living conditions given that a child's residence could have changed during the study period or they may have spent time at the homes of others under that care of a different adult. While other studies have found that many health and socioeconomic characteristics, such as BMI, age, elements of community design, income, and race in children of age 9–12 (Almanza et al., 2012) were not significantly related to MVPA, those types of characteristics should still not be ruled out in future work. While data was collected during the school day, it was not included for a variety of reasons. First, recess time is limited to 15 or 20 min a day. There is some movement to lunch room but little moderate or vigorous physical activity during the school day by nature of the how schools are run in the United States. Second, there were times during the day when the GPS devices were serviced by research staff, so consistent collection of data would be very difficult.

While attempts to classify GPS records by mode of travel (i.e. walking, vehicular, etc.) or as belonging to a geographic feature with a very small footprint (i.e. a building) are relatively common, such classifications were not applied in this study given their potential for introducing misclassification error. In order to reliably classify GPS records by mode of travel or as inside/outside a building, the GPS records must be supplanted by some other observation of location such as self-reported or directly observed information. Given that direct observation of many participants in long term studies is generally not feasible, it is preferable to apply simpler classifications schemes to the locational data to capture the basic geographic context recognizing the positional uncertainty of the GPS data and the other geographic information with which it is being compared. Thus, while dozens more LULC could have been evaluated in this study, this was a major reason for limiting analysis to 13 broader LULC.

5. Conclusion

Given the dynamic nature of children it is necessary to examine their activity in different temporal regimes (i.e. weekdays and weekends) as well as in different seasons. Therefore, this study required obtaining a larger set of individual observations than that typically acquired. In this study, data were collected from each individual for three, eleven day periods and the relationship between these data and LULC in the study region were observed over the course of the entire 33 days of observation. While the resulting data were voluminous and labor intensive to collect and process, this type of spatial-temporal detail was beneficial and likely necessary for a variety of reasons. First, when working with school children, consistent data collection over is not a reality. For instance, collecting data over large periods of time (as done here) risks loss (and/or gain) of participants as they may transfer schools, variation in recorded observations due to device failure or non-compliance, as well as uncertainty in measures of location and physical activity given technological limitations of the measurement devices. Given the records of location/activity qualifying for analysis after accounting for these issues, it is likely that a 3–7 day observation period for younger populations is insufficient. Rather, future studies should consider analysis periods spanning at least two weekend periods, i.e. at least 10–15 days to ensure that adequate data remains pending any disruptions in the collection process. With rigorous adherence to protocol for the lengthy data collection period, this study was able to characterize the variability in location of MVPA and demonstrate the importance of MVPA close to home but also show the importance of vegetated parks/open space as a vital environment for children's MVPA.

The relationship between vegetated parks/open space and built residential with time in MVPA across all time periods speaks to the importance of these areas in land use planning. The less time spent in parks despite this relationship indicates that these may be an important setting for increasing youth physical activity. Therefore, providing better access to vegetated parks/open space from built residential and institutional areas could be an important strategy for increasing children's physical activity. Moreover, given the time children spend in built residential and institutional LULC, these areas should be of general interest to those seeking ways of enhancing children's MVPA levels since it is likely that children of this age group are more constrained to these LULC given their dependence on caregiver routines and availability. Although the locational distribution of children within a community is something that is always changing, the results of this study suggest that those charged with urban planning and design could improve children's potential for MVPA by creating the right spaces at the right places.

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