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Spatial Classification of Youth Physical Activity Patterns

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Background: Physical activity is an essential element in reducing the prevalence of obesity, but much is unknown about the intensity and location of physical activity among youth—this is important because adolescent health behaviors are predictive of behaviors in adults.

Purpose: This study aims to identify the locations where youth moderate-to-vigorous physical activity (MVPA) occurs, and to examine how MVPA varies according to urbanicity (urban, suburban, rural).

Methods: Participants included adolescent students (N=380, aged 12–16 years) from Halifax, Nova Scotia. Locations of MVPA were measured using accelerometers and GPS data loggers for up to 7 days. Specialized software was developed to integrate and process the data. Frequencies of MVPA by location were determined, and differences in MVPA were assessed for association with urbanicity.

Results: Active commuting accounted for the largest proportion of time in MVPA among urban and suburban students. Rural students achieved most MVPA at school. Other residential locations, shopping centers, and green spaces accounted for a majority of the remaining MVPA. Minutes in MVPA varied significantly overall (196.6±163.8, 84.9±103.2, 81.7±98.2); at school (45.7±45.2, 18.6±28.0, 29.8±39.7); while commuting (110.3±107.1, 31.5±55.2, 19.5±39.7); and at other activity locations (19.7±27.1, 14.8±26.8, 12.0±22.1) and by urbanicity.

Conclusions: Findings reveal that the journeys between locations are as important as home and school settings in contributing to greater MVPA in adolescent youth. The relative importance of context as a contributor to MVPA varies with urbanicity. Combining actimetry and GPS data provides a precise link between physical activity measurements and contexts of the built environment.

Introduction

Promoting physical activity during periods of formative development is critical, as many health-related behaviors cultivated in adolescence track into adult behaviors[1,2] and carry important consequences for future health.[3] Guidelines recommend a daily accumulation of 60 minutes of moderate-to-vigorous physical activity (MVPA) for children and adolescents aged 5–17 years to achieve tangible health benefits.[4,5] Sedentary behaviors such as TV viewing and computer use present a challenge to meeting recommended physical activity guidelines, occupying a large proportion of time— up to 6 hours per day—among children and youth.[6] Increases in screen time, the scheduling of organized activities, as well as the proclivity of youth and their parents to over-report physical activity, provide strong justification to employ objective activity measurement strategies, and a basis from which to develop successful intervention efforts.

It is well established that broader socioeconomic and built environment conditions, in addition to individual factors, are associated with levels of youth MVPA. Neighborhood conditions can be conceptualized as compositional (characteristics of the individuals and families living within them, such as neighborhood-level income) or contextual (features of neighborhoods and not the population living within them, such as amount of green space). Compositional measures of neighborhood and school catchment area SES have been associated with physical

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activity, even after controlling for household SES, individual income, and education.[7,8]

Results from studies measuring the relationship between contextual neighborhood characteristics and physical activity are mixed. Neighborhoods that are walkable,[9] with access to green space and recreation facilities,[10,11] and that have strong supportive social networks are more likely to support active lifestyles,[12,13] although several recent reviews found insufficient evidence of a contextual influence on physical activity.[14,15] Inconsistencies in the association between built environments and physical activity may be due in part to challenges in the measurement of physical activity, the influence of other contextual activity mediators such as weather and seasonality,[16] or the introduction of bias associated with the misclassification of study participants to characteristics of the built environment. Misclassification bias in the context of physical activity research may occur when characteristics of the built environment are associated with an individual without direct knowledge of exposure and is common among studies using buffers to define "exposure."[17]

Wearable sensors such as GPS loggers and accelerometers have been employed to objectively measure levels of physical activity, as well as the time–activity patterns of people in free-living conditions. Accelerometers provide reliable and precise measurement of activity intensity over time,[18] despite known limitations associated with sensor removal.[19,20] Spatial methods and GIS have been used to link physical activity with features of the built environment,[9] but analyses are generally restricted to features within close proximity to residential locations. Researchers have been encouraged to investigate physical activity in specific settings[21] to avoid dilution or misestimation of associations between physical activity and characteristics of the built environment.[22]

A recent review of the geographies of cardiometabolic risk factors found that more than 90% of studies limited the scope of built environment influences to the residential neighborhood.[23] In reality, individuals do not limit activities and travel to their residential neighborhood. Using detailed time–activity data, several studies have demonstrated that the use of fiat boundaries such as census geographies or geographic buffers neither accurately nor adequately measures the spatiotemporal realities of daily life.[24,25] Recently, it was found that more than 60% of MVPA occurs in locations more than 1 km from home or work locations,[22] a finding that has important implications for public health policy.

Linking GPS to accelerometer data provides an opportunity to investigate the characteristics of "free-living" physical activity and contextualizes physical activity behaviors in a spatiotemporal manner.[26] Several large, well-designed studies have employed GPS/actimetry approaches to identify physical activity levels of children and adults in a variety of environments and at specific moments in time. Contexts that are more walkable and have access to parkland are characteristic of the residential locations of physically active adults.[22,26] Playgrounds and green space are less relevant to children's physical activity[27,28] than safe environments supportive of active transportation and play.[29–31]

Knowledge remains limited about the amount of daily physical activity obtained at different times and locations.[32] For example, studies using activity-linked GPS methods are not reporting fully the spatial characteristics of physical activity, and in some instances continue to rely on arbitrary buffers grouping physical activity locations for statistical comparisons. Studies of free-living physical activity have focused mainly on specific activities or time periods and either on adult or young populations (aged >18 years or <11 years). To date, only two studies have focused on the location of youth activities (locations over time),[33] and only one has linked location information to accelerometry to describe the location and intensity of physical activity.[34]

Insight into the physical activity patterns of youth is crucial for two reasons: (1) health behaviors are predictive of the same behavior in adulthood, and (2) physical activity levels decline during the transition from adolescence to adulthood.[3] The present study builds on previous research using a larger sample of youth (aged 12–16 years) over a longer monitoring period (8 days). The goals of the study are to (1) develop a GIS-based algorithm to spatially identify the percentage of time spent at all locations where MVPA occurs and (2) investigate how MVPA varies according to school SES and urbanicity (urban, suburban, rural).

Methods

Participant Recruitment Process

The study was approved by Dalhousie University IRB and the review panel in the school board from which schools were recruited. Six schools were randomly selected from a larger list of schools stratified by school-level SES and urbanicity (urban/suburban/rural). Schools were eligible for inclusion if they (1) enrolled students in Grades 7 through 9 (typically aged 12–14 years) and (2) did not offer a French immersion program, because schools with these programs tend to draw students from a much broader catchment area. School-level SES was determined by the median household income of the school's catchment area. Classification of school urbanicity was derived from boundaries identified by the municipal planning strategy and consideration of neighborhood age, street patterns, as well as other characteristics of urban form.

Among the more than 1400 students from six schools eligible to take part in the study, 380 individuals (27%) agreed to participate, a rate not uncommon to studies of children and youth using activity-monitoring equipment.[31,35] Questionnaires were distributed to collect demographic, dietary intake and health behavior information, and physical measurements (height/weight) were taken to determine individual BMI. Additional details of the study design, sample characteristics, and measurement instruments are reported elsewhere (CLS, CMB, SFK, unpublished observation 2011).

Equipment

Activity counts were measured using the Actigraph™ GT1M accelerometer, which has been validated for measuring the intensity, volume, and temporal dynamics of several activities and has demonstrated excellent reliability for measuring both steps and counts in children and youth.[36–38] Accelerometers were initialized to 30-second epochs of step data and acceleration counts. Detailed location and velocity data were captured every second using a 20-channel EM-408 SiRF III 12-channel GPS receiver.

Data Collection

Participants were asked to wear the accelerometer and GPS on their hip at all times, except when engaging in contact sports, swimming (or bathing), and sleeping, and were asked to take note of the frequency and duration of time in which the equipment was removed. Eight days of data were requested to capture activity locations on weekdays and weekends. Instructions were provided on how to turn off GPS logging, thus adhering to the ethics principles of voluntary participation.

The GeoActivity Processor

There are currently no broadly accepted methods for the integration and manipulation of GPS and activity counts data. Many studies match data according to the sensor with the least-frequent period of measurement and remove unmatched data from further analysis. A variety of techniques and imputation methods have been applied to deal with issues such as missing data, GPS drift and reception issues, unmatched data, and changing levels of accuracy in position information. GPS data from unexpected locations may arise from periods of poor satellite signal reception related to urban form (canyon effects), vegetative cover, or movement indoors within structures impermeable to GPS signals.

Some studies have treated these data as outliers or discontinuities and eliminate the measurements from further analysis, even though they may be linked to valid activity counts. Lack of knowledge about the assumptions used in data-processing decisions may lead to challenges of replicability. Results should ideally be unrelated to the approach taken to process integrated GPS and activity count data.

In the current study, integration and processing of GPS and accelerometer data occurred via a seven-step process and several decision rules. It was implemented through the development of a GIS-based toolbar called the GeoActivity Processor (GAP) developed in VBA.net and VBA programming environments and implemented in ArcGIS. A general overview of the process is described below and represented graphically in Figure 1.

Data Analysis

Matched GPS/activity count participant data were imported into a GIS and locations of MVPA were identified using a combination of street network, municipal cadastral data, satellite imagery, and an enhanced points-of-interest file developed by TeleAtlas. For each participant, the total amount of MVPA was attributed to a specific location category (e.g., home, school, commuting, and so on). To find out where youth were expending the most minutes of MVPA, the percentage of time in MVPA was calculated for each location category by gender and urbanicity (Table 1).

In addition, the average minutes of MVPA were calculated according to urbanicity, school SES, at home, school, while commuting, and at all other locations combined. Differences in MVPA locations by urbanicity and school SES were described statistically and comparisons were evaluated using the Kruskall–Wallis H test for independent group comparisons. Data were analyzed using SPSS (version 17.0.3), and significance was determined at $p<0.05$.

Results

Of the 380 participants enrolled in the study, 345 had at least 1 valid day (i.e., ≥8 hours) of activity data, and 316 (83%) had at least 3 days of corresponding GPS and accelerometer data (3 days at >10 hours/day) required for further analysis. The first day of data was removed from analysis to control for the time of day when the equipment was distributed, and to eliminate potential bias associated with behavior changes that can occur when individuals know their activities are being tracked. A total of 78,188,487 GPS locations were available for analysis after running the GeoActivity Processor, resulting in an average of 68.7 hours of location-classified data per student. GPS drift, anomalous and missing location data, common to GPS tracking data, were identified and geographically recategorized to known locations (Figure 2).

Mean student age was 13.3±0.92 years (47% female, 84% Caucasian). On average, girls accrued more minutes of MVPA (129.4±153.8 vs 101.6±103.3), and minutes of MVPA decreased with age (12 years=167.9±148.6 vs 16 years=30.3±39.3). Urban students performed an average of 196.6±163.8 minutes of MVPA, almost three times more than students from suburban and rural environments. School catchment area household incomes ranged from $50,325 to $62,634 for high-SES schools and from $26,614 to $47,821 for lower-SES schools.

Activity and location measurement were affected by equipment removal, GPS power down, or technical issues. Forty-seven percent of students reported removing their equipment for an average of 6 hours; just more than half (55%) were boys. Removals were primarily due to participation in sports- and exercise-related activities and, much less frequently, technical issues and illness (Table 2).

Locations of Moderate-to-Vigorous Physical Activity

The percentage of time in locations where MVPA occurred is shown in Table 3. For urban students, the majority of MVPA occurred while commuting (55.5% for girls, 57.6% for boys), usually to and from school or to

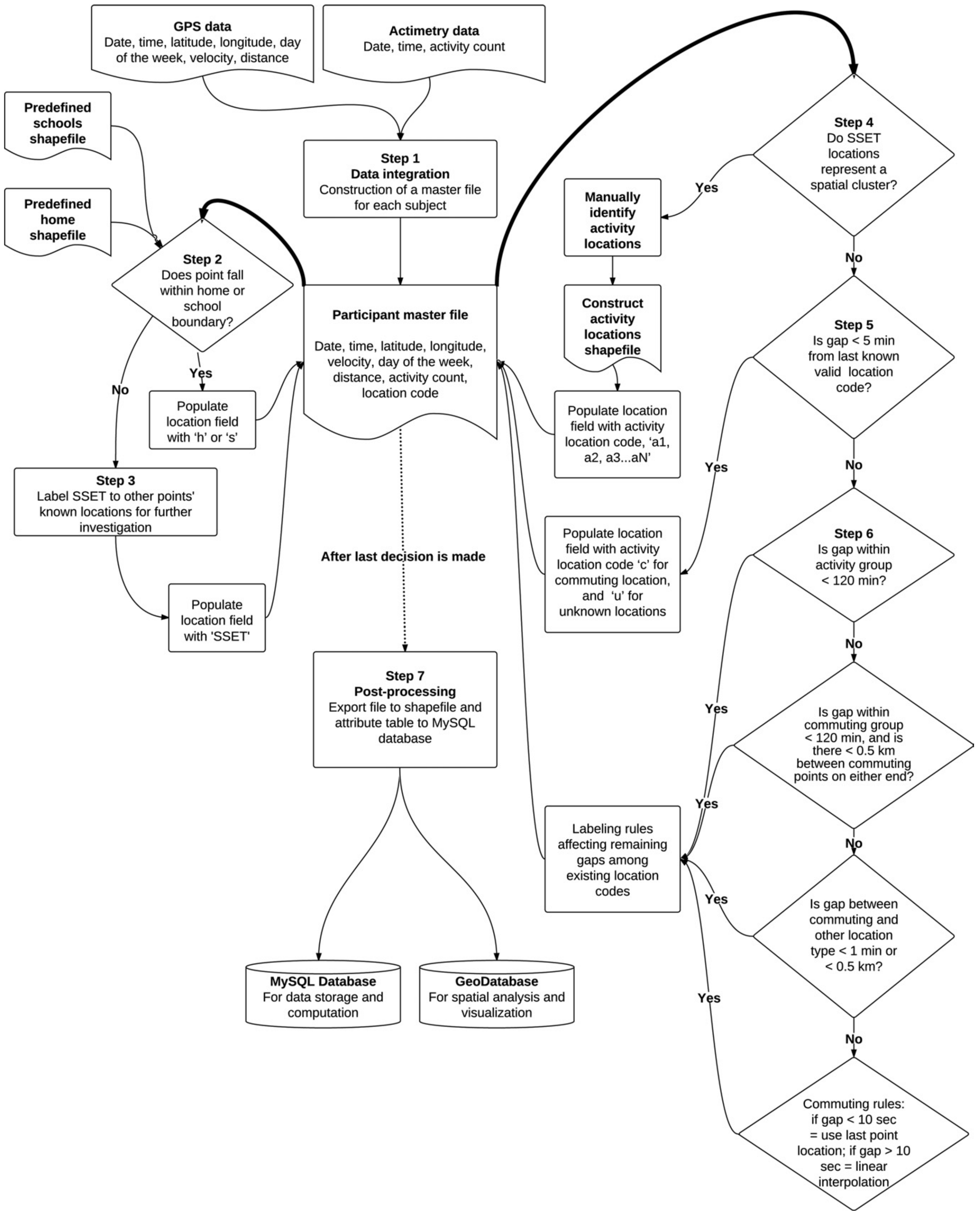

Figure 1. Overview of the GAP

Note: The process is implemented as a toolbar in the ArcGIS environment. Each step is associated with one or more decision rules and requires specification of anchor locations (e.g., home, school, work).

GAP, GeoActivity Processor

Table 1. Process for determining urbanicity

Step 1. Calculate population density Study area divided into dissemination areas (census blocks of 400–700 people) Calculation of population density
Step 2. Identify urban and rural Urban areas have a population density of >1000 people/km^2 [a]
Step 3. Identify suburban from urban Review local municipal planning guidelines Urban: mix of high-density residential, commercial, institutional, and recreation uses Suburban: mix of low- and medium-density commercial, institutional, and recreational uses, as well as pattern of established neighborhoods with low- to medium-density residential development
Step 4. Validate urbanicity categories with local academic or city planner Review urbanicity categories with planner or planning expert and modify as required

[a]www.statcan.gc.ca/pub/92f0138m/92f0138m2008001-eng.pdf

Table 2. Primary reasons[a] for equipment removal

Girls Swimming, gym class, basketball, dance, cheerleading, hockey and skating, soccer, gymnastics, martial arts, lacrosse, sledding, rock climbing, ballet, horseback riding, volleyball, ringette, curling, jogging, trampoline, football, illness
Boys Basketball, hockey, swimming, gym class, soccer, playing with friends, volleyball, baseball, trampoline, martial arts, badminton, fencing, ATV driving, cadets, lacrosse, equipment problems, tennis, running, canoeing, car-washing, sledding, track and field, illness

[a]In order from most to least frequent
ATV, all-terrain vehicle

other activity locations such as malls and restaurants. Home and school locations accounted for an additional and significant proportion of MVPA (~30%). The remaining 10% of MVPA occurred at other residential locations (3%–4%); retail locations such as shopping malls (2%–3%); on green spaces (1%–2%); or at churches, other schools and athletic facilities. Suburban boys recorded more MVPA time at home (30%) than girls did (20%); differences during time at school were much less pronounced. Girls spent more time doing MVPA while commuting (42.5%) than did boys (27.4%).

The remaining counts of MVPA occurred in several locations, including other residential locations (4%–8%) and on green spaces (3%–6%). For boys, more MVPA occurred at retail locations and shopping malls (~3%) than at recreation facilities (1%). Students from rural areas achieved the majority of MVPA at school (33%–40%); at home (~25%); and while commuting (20%–27%). Boys achieved more time in MVPA while commuting than girls. Between 6% and 11% of all

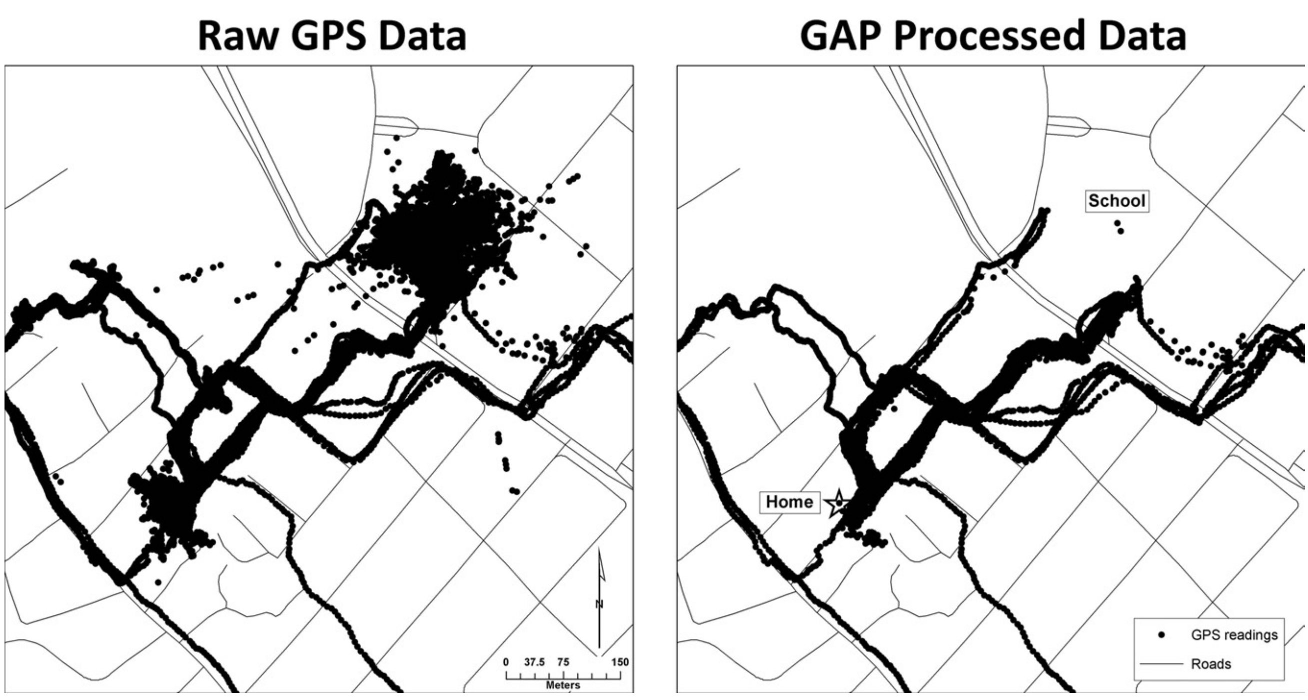

Figure 2. Postprocessing of the GPS data using the GAP
Note: GPS data prone to drift and reception issues, unmatched data, and changing levels of accuracy in position information were accounted for and attributed to specific locations or commuting activities.
GAP, GeoActivity Processor

Table 3. Location and time in MVPA among students aged 12-16 years in Halifax, Nova Scotia, hours (%)

	Urban		Suburban		Rural	
Location of MVPA	Boys	Girls	Boys	Girls	Boys	Girls
Home	13.2 (10.8)	18.4 (10.6)	15.1 (30.1)	18.8 (20.1)	21.9 (25.2)	19.9 (24.8)
School	27.9 (22.8)	41.4 (23.8)	11.4 (22.6)	20.3 (21.7)	28.8 (33.1)	32.3 (40.2)
Commuting	70.5 (57.6)	96.7 (55.5)	13.8 (27.4)	39.8 (42.5)	23.5 (27.0)	16.6 (20.7)
Athletic facility	0.3 (0.3)	3.9 (2.3)	0.9 (1.8)	0.6 (0.6)	3.5 (4.0)	2.0 (2.4)
Entertainment	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.1 (0.1)
Green space	0.8 (0.6)	2.2 (1.3)	2.0 (3.9)	2.3 (2.5)	4.9 (5.6)	3.8 (4.8)
Military	0.0 (0.0)	0.4 (0.2)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
Parking lot	0.6 (0.5)	0.3 (0.2)	0.0 (0.0)	0.0 (0.0)	0.1 (0.1)	0.0 (0.0)
Religious	1.6 (1.3)	0.8 (0.4)	0.2 (0.3)	0.3 (0.3)	0.0 (0.0)	0.1 (0.2)
Residential	4.0 (3.2)	6.6 (3.8)	5.0 (9.9)	7.0 (7.5)	3.8 (4.4)	1.8 (2.3)
Restaurant	0.6 (0.5)	0.3 (0.2)	0.3 (0.6)	0.2 (0.2)	0.2 (0.2)	0.1 (0.1)
Retail	2.4 (1.9)	1.8 (1.0)	1.5 (3.0)	3.4 (3.6)	0.3 (0.4)	3.2 (4.0)
Services	0.2 (0.2)	0.1 (0.0)	0.1 (0.2)	0.0 (0.0)	0.1 (0.1)	0.1 (0.1)
Transportation	0.4 (0.3)	1.3 (0.7)	0.1 (0.1)	0.8 (0.9)	0.0 (0.0)	0.1 (0.2)
Total, hours	**122.5**	**174.2**	**50.3**	**93.6**	**86.9**	**80.2**

MVPA, moderate-to-vigorous physical activity

MVPA for all students occurred at locations other than home or school, or while commuting, predominately at other residential locations, in green space, and at retail locations such as shopping malls. Students from suburban areas were more likely to attain MVPA in "other" locations.

Variation in Moderate-to-Vigorous Physical Activity by Urbanicity and SES

Minutes in MVPA were calculated according to urbanicity and SES, accounting for location (Table 4). No differences in youth MVPA were found for home locations by urbanicity or SES. Minutes in MVPA varied for school

Table 4. Urbanicity, SES, and time in MVPA among students aged 12-16 years in Halifax, Nova Scotia

	Minutes of MVPA (M±SD) by location				
	Home	School	Commuting	Activity locations	Total
Urban (n=91)	20.8±25.1	**45.7±45.2**	**110.3±107.1**	**19.7±27.1**	**196.6±163.8**
Low SES (*n*=54)	17.7±19.9	39.2±42.9	93.7±107.7	20.0±26.3	170.4±165.1
High SES (*n*=37)	25.8±30.8	55.3±47.4	134.4±102.8	19.4±28.5	234.8±156.3
Suburban (n=102)	20.0±29.5	**18.6±28.0**	**31.5±55.2**	**14.8±26.8**	**84.9±103.2**
Low SES (*n*=79)	16.7±25.2	16.0±19.9	37.5±60.3	13.9±24.4	84.2±101.5
High SES (*n*=23)	31.0±39.5	27.6±45.8	10.9±20.0	17.7±34.3	87.2±110.9
Rural (n=123)	20.4±29.2	**29.8±39.7**	**19.5±39.7**	**12.0±22.1**	**81.7±98.2**
Low SES (*n*=73)	22.0±30.2	38.9±46.8	26.2±52.6	14.4±25.6	101.6±116.3
High SES (*n*=50)	18.0±27.9	16.5±20.1	9.8±18.2	8.4±15.2	52.7±51.9

Note: Boldface indicates significant difference in MVPA by urbanicity. Activity locations category includes >5 minutes spent at other locations than home or school and not commuting. Commuting=active transportation; low SES is defined as <$50,000 in household income.
MVPA, moderate-to-vigorous physical activity

(H=25.6, p<0.001); commuting (H=49.5, p<0.001); and at other locations (H=7.0, p=0.03) described in Table 3, according to urbanicity. However, these variations did not vary according to SES across urbanicity. Overall, urban students achieved more time in MVPA at home, school, or while commuting, and overall regardless of location when compared to suburban and rural students.

Discussion

The current study adds to an increasingly active field of research in GPS–activity measurement[22,30,34] and employed a GIS-based data integration tool to combine and process accelerometer and GPS data using explicit rule-based decision methods. Up to 60% of MVPA was successfully assigned to a specific location or to periods of time between locations.

Although several recent studies have examined levels of MVPA at specific locations or times throughout the day,[30,33,39] we are unaware of previous efforts to characterize in detail the built environment locations where MVPA occurs according to urbanicity and gender. The addition of a suburban category represents a further novel aspect of the present study, because the majority of studies limit analyses to simple urban–rural differences.[15] The current study avoided the use of buffers or artificial boundaries to geographically classify MVPA data; instead, MVPA counts were assigned to one of four locations (home, school, commuting, and other). Actual locations of MVPA from the “other” location group were noted and categorized to allow for comparison across groups.

Time spent commuting contributed the largest proportion of time spent in MVPA, followed by school and home environments. These findings echo the results of a smaller pilot study measuring the travel patterns of adolescent females using GPS-enabled smartphones.[33] By contrast, a study using buffer-based approaches concluded that the school location, followed by home and neighborhood locations contributed the largest proportion of time spent in MVPA.[34] The differences in the locations where MVPA occurred are likely due to GPS processing methods. Many studies of free-living physical activity use buffers or network-based geographic boundaries to categorize MVPA. Such approaches work very well if the main interest is to compare statistically significant differences in MVPA by location; however, the selection of buffer size is usually arbitrary, and studies may not capture well the contribution of commuting and active transportation alone to time doing MVPA.

Findings suggest that the importance of capturing MVPA through active commuting, at least for children and youth, cannot be understated. Several other studies have shown physical activity to be higher among youth who walk or cycle to school than among youth who travel by automobile.[40,41] Among studies that have utilized objective measures of location and MVPA, children who walk or cycle to school experience 50% more MVPA during commute times than children transported by car.[30,42] Therefore, similar studies of free-living individuals should reconsider the use of buffers to categorize MVPA, at least as an approach to guard against the misclassification of context to individual activity levels.

These results also support the notion that MVPA among youth occurs at locations other than home, school, or through active transportation. Locations such as malls and retail land uses, green spaces, and residential land uses also support physical activity in youth.[43] Past research has identified shopping malls as a prominent location for light physical activity,[44,45] usually walking.[45] However, it is not clear what activities occurred at retail locations and malls that would result in MVPA.

Green spaces, including parks, wooded areas, and vacant land are also locations where youth attained MVPA. Evidence about the relationship between access to green space and physical activity, derived from studies using objective physical activity measures, appears to be mixed.[32,46] Regardless of how physical activity is measured, studies are consistent in that the linkage of green space to the individual is derived from measures of proximity.[47] Green space exposure is measured as distance from residential origin, or as a contextual feature of an individual’s neighborhood within a predetermined buffer size. However, the relative proximity of green space to residential location will vary considerably within any one sample, and the cost of distance will vary with stage in the life course. The current study did not explicitly examine proximity to locations of MVPA; however, it is clear that MVPA will occur at locations at distances well beyond those typically used to derive buffers or other measures of proximity (Figure 3).

Minutes of MVPA were analyzed at home, school, while commuting, and other locations, by urbanicity and SES. Findings are consistent with studies reporting higher levels of adult physical activity in urban rather than rural environments.[48] However, the results in the present study are inconsistent with similar research on physical activity in children and youth that reported no differences among urban, suburban, and rural environments.[15] Differences in findings may be attributed to objective versus self- or parent-reports of youth activity, or to the approach employed in analysis of physical activity locations. For example, self-reports are vulnerable to over-reporting and recall bias.[49]

Further, multiple approaches have been developed to explore and analyze space–time activity data,[17] including

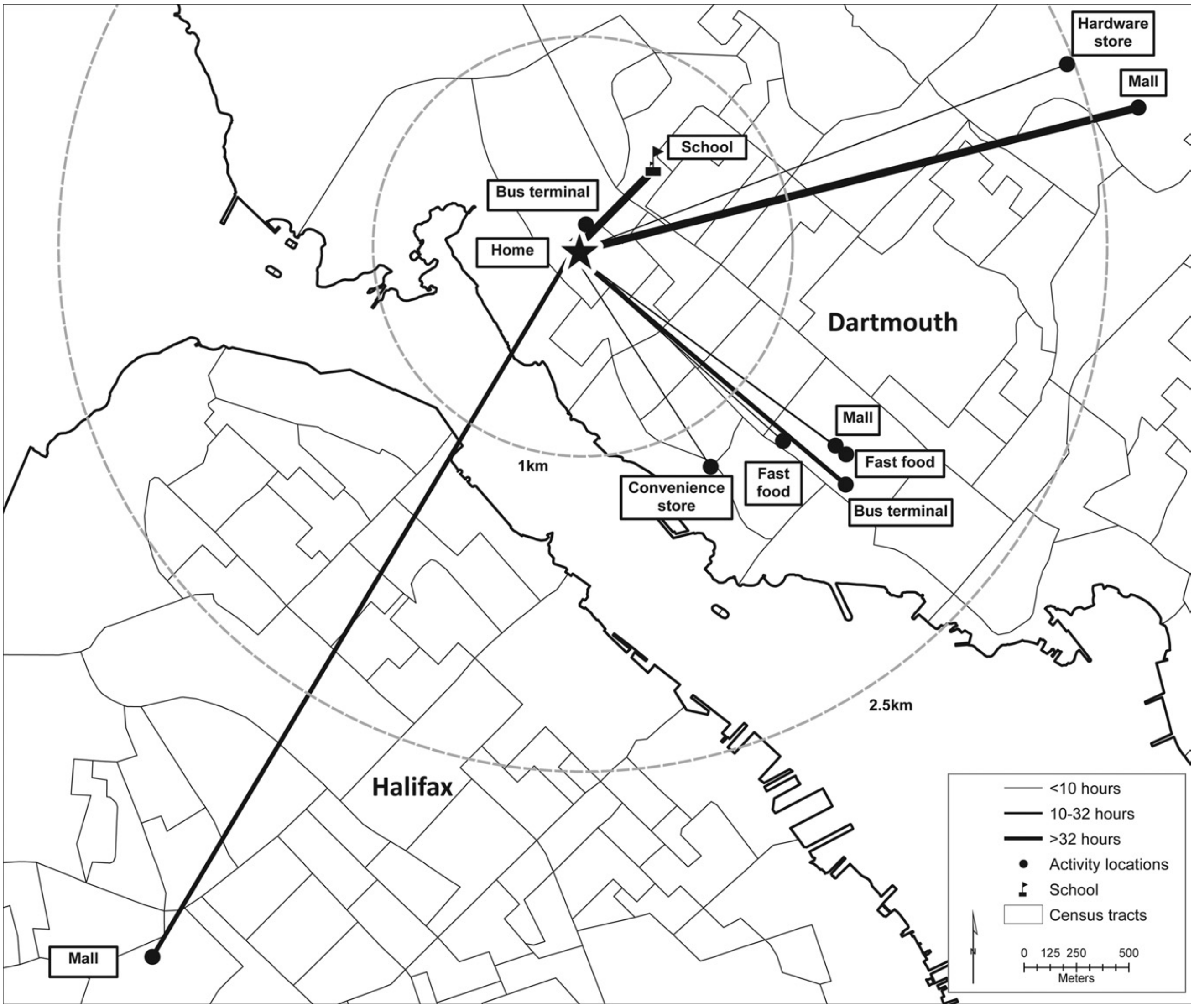

Figure 3. Distance and duration of MVPA locations for one urban participant
Note: Duration is represented by relative line thickness.
MVPA, moderate-to-vigorous physical activity

visualization and related analytics,[50,51] multidimensional time–activity sequencing methods,[52] and pattern morphology metrics.[53] The application of pattern analyses and complementary visualization techniques may provide valuable insights into the role of urbanicity in explaining variations in physical activity. Knowing how MVPA varies according to SES and urbanicity supports targeted built environment interventions to improve youth health.

Empirical analysis suggests overall differences in the locations where MVPA occurs by urbanicity. The finding that urban youth attained more time in MVPA is consistent with the results of studies also using objectively measured physical activity and GIS-derived features of the built environment, such as walkability, residential density, and intersection density.[9] These kinds of built environment features are more prevalent in urban than suburban and rural environments and track closely to the study finding that the majority of MVPA was accumulated while commuting.

The current study has a number of strengths, including the use of objective measures to assess location and physical activity levels, a relatively large sample of adolescent youth who represent an important target population for intervention, and sophisticated data-integration procedures supplemented with details about the treatment of location data. Notable limitations are the absence of data collected during the summer months and more complete measurement of MVPA when equipment was removed. Youth engaged in sports were often asked to remove the GPS logger and accelerometer so that total MVPA was underestimated. Sampling only during the school year precluded the measurement of the locations supportive of MVPA during summer months.

Future research of youth that is inclusive of younger children, and conducted in all seasons, will provide important insight as to whether the results observed in the present study are illustrative of MVPA patterns and their associated locations. It is recommended that researchers employ more detailed time–activity questionnaires and shorter periods of participant recall to capture activities and locations not captured by GPS and accelerometers.

Conclusion

This study used objective measurement of location and physical activity to advance knowledge about how MVPA varies among youth according to gender and urbanicity. The results show that during the school year, MVPA occurs in a variety of settings and that the importance of different settings varies with urbanicity. Policymakers should be aware that active transportation is an important source of MVPA for urban youth and much less so for youth living in suburban and rural areas. Policies developed to promote physical activity should sustain the walkability and active transport options in urban areas and, concurrently, improve and enhance options for youth outside of the urban core to engage in active commuting. Because of the novelty of this study, replication is warranted before new policies and interventions are implemented.

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Supplementary data

A pubcast created by the authors of this paper can be viewed at www.ajpmonline.org/content/video_pubcasts_collection.