



## Note from the editor

Hello everyone

I hope you are all having an enjoyable and productive year.

This issue of the GPS-HRN newsletter features excellent articles from two of our distinguished colleagues. Dr Genevieve Dunton from the University of Southern California describes her intriguing work on how and where parents and children are active together. Her research is a vital step in understanding the best way of promoting physical activity among families.

Prof Ester Cerin also contributes a feature article that focuses on statistical analysis of GPS and physical activity data. Her advice about dealing with multiple sources of dependency will be of assistance to those working with GPS and/or activity data that do not have a background in statistics.

There are also a number of new publications that have been released since the last newsletter, many of which involve GPS-HRN members. While I try and maintain an up-to-date record on the GPS-HRN website ([www.gps-hrn.org](http://www.gps-hrn.org)), please feel free to post any GPS-related articles you or your colleagues have published or located online. I will choose a selection of these articles to include in each newsletter. Every registered member has the authority to post on any part of the website, so please use it as a repository of all GPS-related news, research, and technology updates.

All the best for the rest of the year!

Dr Scott Duncan, Lead Editor  
AUT University  
Auckland, New Zealand  
[scott@gps-hrn.org](mailto:scott@gps-hrn.org)

## Parents and children active together



Dr Genevieve F Dunton  
University of Southern California

While evidence has shown that physically active parents are more likely to have physically active children, until recently there has been little research about how much time parents and children actually spend engaged in physical activity together and where that activity takes place. Evidence is less consistent about whether parents' modeling of physical activity influences the amount of physical activity that their children perform. Research in this area typically does not distinguish between parents' physical activity, performed *separately from* versus *together with* their children.

In two recent papers, we combined GPS and accelerometer data that were collected among parent-child pairs to address these questions. We examined minute-to-minute correspondence in physical activity levels in parents and children who both wore an accelerometer and GPS device over the same 7-day period. The Actigraph, Inc. GT2M model activity monitor provided an objective measure of physical activity. Geographic locations were logged for a 7-day period with the BT-335 Bluetooth GPS data logger device by GlobalSat Technology Corp (Taipei) attached to a belt worn around the waist along with the accelerometer, both recording at a 30-second epoch. Linear distance between the parent and child was calculated using geographic

coordinates from the GPS. Overnight (11pm-5am) and school (8am-3pm on weekdays) hours were removed from the analyses. "Joint" or "together" behaviors were defined as activities of the same intensity level (sedentary or MVPA) that occurred at the same time and in the same location. A maximum separation of less than 50m between the parent and child was selected because this distance is approximately equivalent to the length of a ball court or large residential yard.

GPS data points for joint parent-child behavior were given land use classification in a geographic information system (GIS) using a Southern California Association of Governments (SCAG) database. Data points were assigned the land use classification of the area nearest to the point that had land use data. For analyses, land uses were grouped into six major categories: residential (e.g., houses, apartments, condos), commercial (e.g., retail, restaurants, office use, manufacturing), open space (e.g., vacant lots, parks, golf courses, gardens, beaches), educational (e.g., schools and school grounds), public facilities (e.g., community centers, churches, libraries), and other (e.g., military, mixed uses, airports, freeways, roads, utilities).

We found that parent-child pairs spent an average of 233.6 minutes (SD = 80.0) per day in the same  
**(continued on next page)**

(continued from previous page)

location during non-school waking hours, not accounting for time spent together in the car. Of this time, 2.4 minutes (SD = 4.1) per day were spent performing MVPA together and 92.9 minutes (SD = 40.1) per day were spent engaging in sedentary behavior together. While their child was engaging in MVPA nearby, parents engaged in 7.4 minutes (SD = 7.2) per day of sedentary behavior and 2.6 minutes (SD = 2.4) of light activity. On the other hand, children engaged in 1.9 minutes (SD = 2.3) per day of sedentary behavior and 2.7 minutes (SD = 4.5) per day of light activity while their parent was engaging in MVPA nearby.

Figure 1 shows that the largest proportion of joint parent-child MVPA occurred in residential locations, followed by commercial land uses, open space, educational institutions, public facilities, and mixed/other land uses. Figure 2 shows an example of a parent and child performing MVPA together at a location classified as open space. When joint parent-child MVPA occurred in an open space, 35% of these instances took place within the pair's neighborhood (< 500m of their residence). During non-school waking hours, the majority of child MVPA accompanied by parent sedentary behavior, parent MVPA accompanied by child sedentary behavior, and joint sedentary behavior occurred in residential locations (~75%). Open spaces served as the location for 13% of child MVPA accompanied by parent sedentary behavior, 10% of parent MVPA accompanied by child sedentary behavior, and 8% of joint sedentary behavior during non-school waking hours.

These results not only indicate how much time and where children and parents spend performing physical activity together, but also demonstrate how GPS and accelerometer data can be combined in novel ways to measure "joint" behaviors. When members of a pair or group of people simultaneously wear GPS devices, these location data can be used to estimate their proximity or "togetherness." Of course, there are still methodological challenges to overcome with this strategy such as over- or underestimation of joint activity due to GPS measurement error, GPS data loss indoors, lack of understanding how to best adjust for spatial autocorrelation with these types of data, and difficulty in classifying the land use of active transportation or recreational trips. Nonetheless, as GPS and other location-finding capabilities become more accessible via smartphones, these methods offer much promise for better understanding social and environmental influences on physical activity.

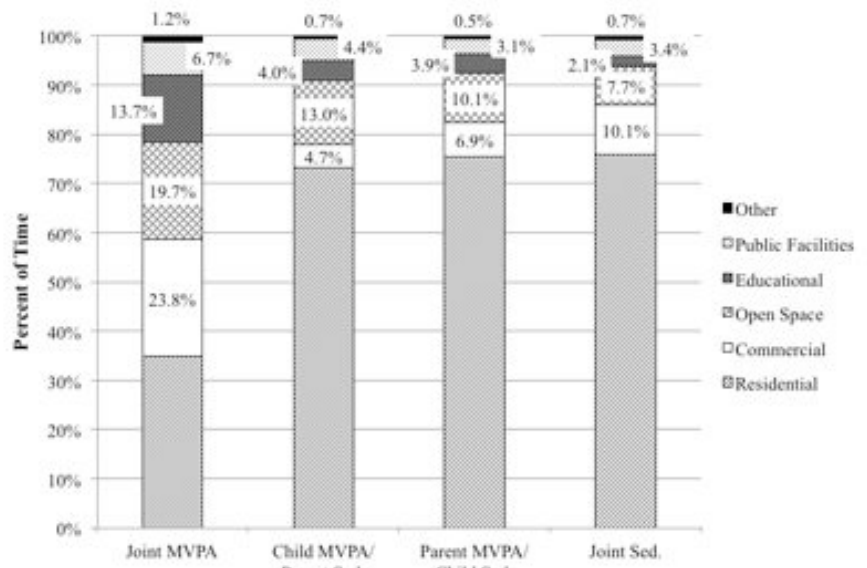


Figure 1. Location of parent and child MVPA and sedentary behavior.

Figure 2. Example of parent and child performing MVPA together at a location classified as open space.



## References

- Dunton, G. F., Almanzo, E., Liao, Y., Jerrett, M., Spruijt-Metz, D., Chou, C., & Pentz, M. Joint physical activity and sedentary behavior in parent-child pairs. *Med Sci Sports Exerc*, 44, 1473-1480, 2012.
- Dunton, G. F., Liao, Y., Almanzo, E., Jerrett, M., Spruijt-Metz, D., Pentz, M. Locations of joint physical activity in parent-child pairs based on accelerometer and GPS monitoring. *Ann Behav Med*, 45, 162-172, 2013.

## Recent Research

GF Dunton, Y Liao, E Almanza, M Jerrett, D Spruijt-Metz & MA Pentz

Locations of joint physical activity in parent-child pairs based on accelerometer and GPS monitoring

*Annals of Behavioral Medicine*, 2013, 45(Suppl 1): S162-172.

S Duncan, TI Stewart, M Oliver, S Mavoia, D MacRae, HM Badland & MJ Duncan

Portable Global Positioning System receivers: Static validity and environmental conditions

*American Journal of Preventive Medicine*, 2013, 44(2): e19-e29.

B Thierry, B Chaix & Y Kestens

Detecting activity locations from raw GPS data: a novel kernel-based algorithm

*International Journal of Health Geographics*, 2013, 12: 14.

B Kang, AV Moudon, PM Hurvitz, L Reichley & BE Saelens

Walking objectively measured: Classifying accelerometer data with GPS and travel diaries

*Medicine and Science in Sports and Exercise*, 2013, 45(7): 1419-1428.

D Dueker, M Taher, J Wilson & R McConnell

Evaluating children's location using a personal GPS logging instrument: limitations and lessons learned

*Journal of Exposure Science and Environmental Epidemiology*, 2013, doi: 10.1038/jes.2013.11.

N Hongu, BJ Orr, RG Reed, D Roe & SB Going

Global Positioning System (GPS) watches for estimating energy expenditure

*Journal of Strength and Conditioning Research*, 2013, epub ahead of print.

KR Evenson, F Wen, A Hillier & DA Cohen

Assessing the contribution of parks to physical activity using GPS and accelerometry

*Medicine and Science in Sports and Exercise*, 2013, epub ahead of print.

# Analysing environment and physical activity 'momentary' relations



Assoc Prof Ester Cerin  
University of Hong Kong

Recent developments in GPS technology and the ability to simultaneously process and integrate GPS, accelerometry (motion sensor) and Geographic Information Systems (GIS) data are making it possible to collect large amounts of objective information on 'momentary' (e.g., minute-by-minute) physical activity levels and environmental exposures in the participants' habitual environment and over their daily activities for multiple days (Duncan et al., 2009). Analysing data from such studies can be challenging due to the fact that observations are correlated.

### The problem of correlated data

The validity of "standard" statistical models relies on the assumption of independency of observations, or, more precisely, the assumption of independently and identically distributed residuals (Cerin, 2011). Data collected on the same participants across multiple days clearly violate these assumptions since we can expect observations collected from the same participant to be more similar than those collected from different participants, and observations collected on a specific day (e.g., weekend) to be more similar than those collected on different days (e.g., Sunday vs. Monday). Another source of dependency that is often present in studies using GPS monitors and accelerometry stems from recruiting participants using multi-stage rather than random sampling strategies (Cerin, 2011; Quigg et al., 2010). In other words, participants are often recruited from pre-selected groups or places (e.g., neighbourhoods, schools, or workplaces) rather than randomly (Quigg et al., 2010). In such cases, we would expect participants from the same groups or places to

be more alike in exposure and/or outcome measures than those from different groups or places.

Two additional important aspects of dependency that are particularly relevant to consecutively-collected location (GPS) and activity data are residual temporal and spatial correlation remaining even after recruitment-site, person- and day-level sources of dependencies are accounted for (Almanza et al., 2012; Bailey and Gatrell, 1995). Residual spatial dependency arises from participants being more active in particular locations, of which activity-facilitating characteristics are not captured by a specific statistical model. Suppose we try to examine whether being in a park is associated with being more physically active. To do this we may regress accelerometry counts/min onto a dichotomous variable denoting whether participants were at a specific point in time in a park or not. Suppose also that participants during the study visit multiple parks but are usually active in only one of them (which is often the case). In this instance, the residuals of the regression model will be spatially correlated because activity occurs in specific parks rather than in all visited parks. In other words, having 'park' as a predictor of activity in the regression model does not fully explain the spatial context of one's activity. This leads to spatially correlated residuals. If activity levels were similar across all visited locations of the same type (i.e., parks and non-parks) accounted by the model, errors would not be spatially correlated. Now, let us also assume that participants are not only more active in specific parks but also spend only a proportion of time being active in those specific parks. For example,

(continued on next page)

**(continued from previous page)**

during their 40 minute visit to a park, they may work out for 20 consecutive minutes and then relax and sit down on a bench for the remaining 20 minutes. This pattern of activity will yield temporally correlated errors. Simply put, activity levels at adjacent points in time are more similar than those more distant in time.

**What are the consequences of ignoring the presence of all these sources of dependencies?**

They are serious. Ignoring various sources of dependencies can result in biased standard errors of the regression coefficients and, thus, invalid findings (Bivand et al., 2008; Cerin, 2011). Often we may conclude that an environmental characteristic is a potential determinant of physical activity when, in reality, it is not. However, the opposite can also occur. Standard errors of regression coefficients may be overestimated if activity levels at adjacent point in time are negatively related or if the associations between environmental characteristics and physical activity reflect intra- rather than inter-individual level processes.

**What type of statistical models can we use to address all these multiple sources of dependency?**

Two very flexible classes of statistical models that can address multiple sources of dependency are generalized linear mixed models (GLMMs; Fitzmaurice et al., 2004) and generalized additive mixed models (GAMMs; Woods, 2006). Both types of models can easily address recruitment-site, person-, and day-level sources of dependency in the data, and can be used with

normally and non-normally distributed outcomes. However, GAMMs have the advantage of being able to more flexibly estimate non-linear relationships between continuous predictors and the outcomes of interest. Residual spatial autocorrelation can be modelled with GLMMs as well as GAMMs by including a smooth spatial function or specifying a spatial correlation structure describing the patterns of associations among residuals. However, it is perhaps easier to incorporate a smooth spatial function accounting for residual spatial correlation within a GAMMs framework. Correlation structures describing residual temporal dependency can be included in GLMMs as well as GAMMs. These types of statistical models are available in R, which is a free software programming language and a software environment for statistical computing and graphics (R Development Core Team, 2013). R packages such as *gamm4* and *mgcv* (Wood, 2006) fit GAMMs, while *glmmPQL* in R package MASS fits GLMMs (Venables and Ripley, 2002).

Try them out with your GPS/accelerometry data and have fun!

**References**

Almanza E, Jerrett M, Dunton G, Seto E, Pentz MA. (2012). A study of community design, greenness, and physical activity in children using satellite, GPS and accelerometer data. *Health & Place, 18*, 46-54.

Bailey T, Gatrell T. (1995). *Interactive spatial data analysis*. New York: John Wiley.

Bivand RS, Pebesma EJ, Gomez-Rubio V. (2008).

*Applied spatial data analysis with R*. New York: Springer.

Cerin E. (2011). Statistical approaches to testing the relationships of the built environment with resident-level physical activity behavior and health outcome in cross-sectional studies with cluster sampling. *Journal of Planning Literature, 26*, 151-167.

Duncan MJ, Badland HM, Mummery WK. (2009). Applying GPS to enhance understanding of transport-related physical activity. *Journal of Science and Medicine in Sport, 12*, 549-556.

Fitzmaurice GM, Laird NM, Ware JH. (2004). *Applied longitudinal analysis*. Hoboken, NJ: Wiley-Interscience.

Quigg R, Gray A, Reeder AI, Holt A, Waters DL. (2010). Using accelerometers and GPS units to identify the proportion of daily physical activity located in parks with playgrounds in New Zealand children. *Preventive Medicine, 50*, 235-240.

R Core Team. (2013). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing.

Venables WN, Ripley BD. (2002). *Modern applied statistics with S*. 4th Ed. New York: Springer.

Wood SN. (2006). *Generalized additive mixed models: an introduction with R*. Boca Raton, FL: Chapman & Hall.



IPEN was launched by Professor Jim Sallis (USA), Dr Ilse DeBourdeaudhuij (Belgium) and Professor Neville Owen (Australia) at the International Congress of Behavioral Medicine in Mainz Germany in August 2004.

Physical activity habits are determined by multiple levels of influence – personal, family, social, environmental, economic and other

factors. Ecological models of health behaviour have been used to synthesize research at these different levels, and to focus attention on relationships of particular physical activities with specific attributes of physical environments, including the built environment.

While physical activity environments will vary within countries, the greatest and most informative sources of variation in the relationships of environmental attributes with physical activity are likely to be between countries. The IPEN initiative seeks to stimulate, inform, and support systematic and rigorous studies of physical activity and the environment, in as many countries as possible.

Please contact Jacqueline Kerr ([jkerr@ucsd.edu](mailto:jkerr@ucsd.edu)) or Nicole Bracy ([nbracy@projects.sdsu.edu](mailto:nbracy@projects.sdsu.edu)) if you would like more information.

[www.ipenproject.org](http://www.ipenproject.org)



Production of the GPS-HRN newsletter is supported by AUT University, Auckland, New Zealand.

Chair: Prof Yves Schutz  
Vice Chair: Dr Scott Duncan  
Secretary: Dr Melody Oliver  
Treasurer: Dr Jacqueline Kerr  
Comms Officer: Dr Jasper Schipperijn  
Publisher: AUT University  
Ph: +64 9 921 9999 ext 7678  
Fax: +64 9 921 9746  
Private Bag 92006, Auckland, New Zealand

[www.gps-hrn.org](http://www.gps-hrn.org)