Kids' daily activity spaces, physical activity and stress: Linking real-time geospatial data with other real-time data sources in a sample of Southern California children

Malia Jones[1]
Department of Preventive Medicine
University of Southern California

Genevieve Fridlund Dunton[1]
Department of Preventive Medicine
University of Southern California

September 26, 2014

[1] Department of Preventive Medicine, Keck School of Medicine, University of Southern California, 2001 N. Soto St Los Angeles, CA 90033

Short abstract

This study combines several emerging methodologies in spatial demography. In a sample of children ages 9-13 in Southern California (n=120), we used ecological momentary assessment (EMA) to capture in-situ self-reports of stress, affect, and other markers of psychological state. Using timestamps, we linked these reports to the participants' corresponding geographic locations as recorded by global positioning systems (GPS) and to their levels of physical activity as measured by accelerometer. Our study addresses three methodological issues: 1) abstracting characteristics of places from GPS data and comparing them to subjective perceptions of places; 2) linking GPS data to EMA and physical activity accelerometer data; and 3) constructing activity spaces as a tool for summarizing geospatial data across specific time windows of interest. Finally we address the substantive question of associations between characteristics of GPS-identified places and the study participants' physical activity, affective state, and stress level.

Extended Abstract

Introduction

Childhood obesity is arguably the largest threat to public health in the United States today, affecting 1 in 5 children, up about 250% from just 25 years ago (Centers for Disease Control and Prevention 2014). The urban poor seem most at risk for childhood obesity, creating dramatic disparities across socioeconomic and race/ethnic groups. Childhood obesity is associated with devastating lifelong complications (Dietz 1998) including 7 out of the top 10 causes of death in the population as a whole (Centers for Disease Control and Prevention 2012; Mokdad, Marks et al. 2004) and costs the US healthcare system billions of dollars each year (Finkelstein, Trogdon et al. 2009).

Rising rates of overweight and obesity among U.S. children have been partially attributed to characteristics of home and neighborhood environments that favor inactive forms of leisure and transportation (Committee on Environmental Health 2009; Salmon and Timperio 2007). Conversely, obesity is inversely related to the availability of environmental resources for physical activity such as home equipment, parks, open space, trails, and recreational facilities(Davison and Lawson 2006). However, little is known about why and under what conditions children *use* home and neighborhood resources for physical activity. Safety concerns, lack of shade, high traffic volumes, lack of social companionship and other characteristics may impact the intensity, duration, and frequency of children's physical activity across these settings. Recent evidence from animal models suggests that stress may also play a role in obesity (Kuo, Czarnecka et al. 2008), and may mediate the link between place-based exposures and obesity outcomes (Aneshensel 2010).

Several vexing issues related to the timing and mode of data collection have impeded progress in this field of research. In the past, researchers have often relied on residential location as a proxy for exposure to places, but most people frequently travel away from their place of residence and in fact may spend most of their waking hours away from home (Matthews 2011; Palmer 2012; Sastry, Pebley et al. 2004). Furthermore, we have historically relied on survey formats asking respondents to recall information sometimes long into the past as a proxy for what people are actually doing and feeling when they are at home or elsewhere. Such "recall" based surveys may introduce a host of data issues related to recall biases (Stone and Shiffman 1994). New technology has created an opportunity to substantially advance these research methods. It is now possible to obtain real-time data which tracks where a person went throughout the course of a day, objectively measures physical activity level, and captures in-situ self-reports of affect and stress state.

Study Aims

We aim to inform methodological questions about how to use three new data types--global positioning systems (GPS), ecological momentary assessment (EMA)

(Shiffman, Stone et al. 2008), and physical activity accelerometer data—in an activity spaces framework. First, we link three simultaneous sources of realtime data based on time stamps: GPS, EMA, and accelerometer data. We perform sensitivity analysis to elucidate issues of matching different realtime data sources. Second, we construct activity spaces from GPS point data for temporal windows of interest around each EMA prompt, identify appropriate geospatial variables in a geographic information system (GIS), and present associations between characteristics of places as reported by study participants (including traffic volume, vegetation, and crime) and as identified by the GIS. Finally, we identify associations between the characteristics of GPS-identified places and the study participants' simultaneous physical activity, affective state, and stress level.

Methods

We use a subsample of data from a longitudinal study known as Mobile Healthy PLACES in Chino, CA (Dunton, Liao et al. 2011). Time-stamped data are available for 120 4^{th} – 8^{th} grade children from three simultaneous sources (see Table 1).

First, EMA survey prompts were delivered to participants via a custom application (app) on a study-provided mobile phone. Each EMA survey asked participants to respond to a series of questions about their current location, mood, and activities up to 7 times per day across four study days (Friday – Monday) during non-school hours. Prompts were given according to a modified random design. In order to ensure even distribution of prompts across the study period and to minimize respondent burden, prompts were randomly given within predetermined time windows. We will focus on the EMA items in which participants reported subjective characteristics of their location (e.g., safety, traffic, vegetation), their mood, their level of stress, and their current activity (e.g., exercise/sports, watching TV, homework).

Second, study participants wore an Actigraph GT2M accelerometer during the same study days. We will use time-matched data to identify the step count and total time spent in moderate or vigorous physical activity in 15 minute "temporal windows of interest" before and after each EMA prompt.

Third, we will use locational data collected from the receivers built into the study-provided mobile phones at 30-second intervals. The GPS data are also time-stamped, making it possible for us to create links between *where* study participants were and what they were doing, observing, and feeling at that time. We will create activity spaces for those same 15-minute temporal windows of interest around each EMA prompt and summarize the characteristics of each of those activity spaces. Characteristics of places will be abstracted from a GIS and can be divided into two domains: walkability (land use type, traffic volume, greenness, intersection density, availability of sidewalks and bike lanes) and social setting (crime, segregation, and poverty).

Once these three data sources are linked, we will investigate correlations between the characteristics of the EMA-centered activity spaces abstracted from the GIS and perceived characteristics of places as reported in the time-matched EMA prompt, including traffic volume, vegetation, and crime. Finally we will present associations between characteristics of EMA-centered activity spaces and physical activity, mood, and stress using multivariate regression modeling approaches.

Preliminary Results

Our study is currently in progress. In preliminary work, matched, based on time stamps, the GPS coordinates that occur within 15 minute windows of interest on either side of each EMA prompt. Previous studies have already matched accelerometer data to GPS data in this sample (Almanza, Jerrett et al. 2012) and accelerometer data to the 15 minute temporal windows of interest on either side of each EMA prompt (Dunton, Liao et al. 2011).

Study participants answered an average of 81% of EMA prompts, 5.02 prompts per participant for a total of 611 prompts, of which about 14% are missing accelerometer data (mostly due to nonwear of the device). In EMA surveys, participants reported moderate levels of stress (2.2 on a scale of 1 to 3) and overall positive affect ("sadness" mean 1.3 on with range 1-3; "happiness" mean 3.4 with range 1-4). On average, a "GPS cloud" of 51 discrete GPS points is captured by the temporal window of interest 15 minutes before or after each EMA prompt.

Implications

Our results will help to validate the use of EMA methodology to measure perceived physical environmental factors in larger-scale studies. It will also significantly advance the field by informing methodological questions in spatial-temporal analysis that integrates GPS, accelerometer, and EMA survey data in an activity spaces/GIS framework. Our substantive questions on the relationships between characteristics of places and physical activity, mood, affect and stress state will fill a gap in the literature by informing exactly how children use particular settings for physical activity, and how they respond psychologically to the characteristics of those settings.

Table 1

	n (%)
Age (years)	M = 11.01 (SD = 1.18)
Sex	
Male	61 (50.8)
Annual Household Income	
Less than $45,000	30 (25.0)
$100,000 and above	28 (23.3)
Race/Ethnicity	
Hispanic/Latino	39 (32.5)
Non-HispanicWhite/Caucasian	28 (23.3)
Non-Hispanic Black	12 (10.0)
Asian	15 (12.5)
Biracial/Mixed	19 (15.8)
Other	7 (5.8)
Weight Status	
Underweight (BMI < 15%)	12 (10.0)
Normal weight (BMI = 15- 84%)	62 (51.2)
At risk for overweight (BMI = 85-94%)	21 (17.4)
Overweight (BMI ≥ 95%)	25 (20.7)

Note: N = 120

Bibliography

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

Aneshensel, Carol S. 2010. "Neighborhood as a Social Context of the Stress Process." in *Advances in the Conceptualization of the Stress Process: Essays in Honor of Leonard I. Pearlin*, edited by W. R. Avison, C. S. Aneshensel, S. Schieman, and B. Wheaton: Springer Science+Business Media, LLC.

Centers for Disease Control and Prevention. Adult Obesity Facts. Centers for Disease Control and Prevention; 2012. Available at http://www.cdc.gov/obesity/data/adult.html; accessed June 24.

—. Childhood Obesity Facts. 2014. Available at http://www.cdc.gov/obesity/data/childhood.html; accessed September.

Committee on Environmental Health. 2009. "he Built Environment: Designing Communities to Promote Physical Activity in Children." *Pediatrics* 123:1591-98.

Davison, K. K. and C. T. Lawson. 2006. "Do attributes in the physical environment influence children's physical activity? A review of the literature." *Int J Behav Nutr Phys Act* 3:19.

Dietz, W. H. 1998. "Health consequences of obesity in youth: childhood predictors of adult disease." *Pediatrics* 101:518-25.

Dunton, G. F., Y. Liao, S. S. Intille, D. Spruijt-Metz, and M. Pentz. 2011. "Investigating children's physical activity and sedentary behavior using ecological momentary assessment with mobile phones." *Obesity (Silver Spring)* 19:1205-12.

Finkelstein, E. A., J. G. Trogdon, J. W. Cohen, and W. Dietz. 2009. "Annual medical spending attributable to obesity: payer-and service-specific estimates." *Health Aff (Millwood)* 28:w822-31.

Kuo, L. E., M. Czarnecka, J. B. Kitlinska, J. U. Tilan, R. Kvetnansky, and Z. Zukowska. 2008. "Chronic stress, combined with a high-fat/high-sugar diet, shifts sympathetic signaling toward neuropeptide Y and leads to obesity and the metabolic syndrome." *Ann N Y Acad Sci* 1148:232-7.

Matthews, S.A. 2011. "Spatial polygamy and the heterogeneity of place: studying people and place via egocentric methods." Pp. 35-55 in *Communities, neighborhoods, and health: Expanding the Boundaries of Place*, vol. 1, *Social disparities in health care*, edited by Linda M. M. Burton, Stephen A. P. Matthews, ManChui Leung, Susan P. A. Kemp, and David T. T. Takeuchi. New York, NY: Springer.

Mokdad, A. H., J. S. Marks, D. F. Stroup, and J. L. Gerberding. 2004. "Actual causes of death in the United States, 2000." *JAMA* 291:1238-45.

Palmer, J. R.B., Espenshade, T. J., Bartumeus, F., Chung, C. Y., Ozgencil, N. E., & Li, K. New approaches to human mobility: Using mobile phones for demographic research.; 2012. Available at http://www.princeton.edu/~jrpalmer/NewApproaches.pdf; accessed

Salmon, J. and A. Timperio. 2007. "Prevalence, trends and environmental influences on child and youth physical activity." *Med Sport Sci* 50:183-99.

Sastry, N., A R. Pebley, and M. Zonta. 2004. "Neighborhood Definitions and the Spatial Dimension of Daily Life in Los Angeles." *California Center for Population Research On-Line Working Paper Series*.

Shiffman, S., A. A. Stone, and M. R. Hufford. 2008. "Ecological momentary assessment." *Annu Rev Clin Psychol* 4:1-32.

Stone, A. A. and S. Shiffman. 1994. "Ecological Momentary Assessment (EMA) in Behavioral Medicine." *Annals of Behavioral Medicine* 16:199-202.