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Understanding variability in time spent in selected locations for 7–12-year old children

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This paper summarizes a series of analyses of clustered, sequential activity/location data collected by Harvard University for 160 children aged 7–12 years in Southern California (Geyh et al., 2000). The main purpose of the paper is to understand intra- and inter-variability in the time spent by the sample in the outdoor location, the location exhibiting the most variability of the ones evaluated. The data were analyzed using distribution-free hypothesis-testing (K–S tests of the distributions), generalized linear modeling techniques, and random-sampling schemes that produced "cohorts" whose descriptive statistical characteristics were evaluated against the original dataset. Most importantly, our analyses indicate that subdividing the population into appropriate cohorts better replicates parameters of the original data, including the interclass correlation coefficient (ICC), which is a relative measure of the intra- and inter-individual variability inherent in the original data. While the findings of our analyses are consistent with previous assessments of "time budget" and physical activity data, they are constrained by the rather homogeneous sample available to us. Owing to a general lack of longitudinal human activity/location data available for other age/gender cohorts, we are unable to generalize our findings to other population subgroups.
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Introduction: Context of the issue

Undertaking exposure modeling for any consecutive multi-day period longer than 3 days requires that a decision rule be used to combine days of human activity/location data from different individuals to represent a single individual, since longitudinal data on the subject are limited. EPA's Comprehensive Human Activity Database (CHAD: McCurdy et al., 2000), which consolidates publically available activity/location data in the United States, contains only three random-probability studies with more than one day of sequential data for an individual: a 2-day study in Denver, Colorado; a 2-day study across the nation undertaken by the University of Michigan; and a 3-day study in the Cincinnati, Ohio metropolitan areas (Johnson, 1984; Akland et al., 1985; U. Michigan, 1997).

Environmental exposure and risk assessments typically are focused on relatively long time periods of analysis: a month; a year; or even a lifetime. Since health effects can only be properly analyzed in a time-series manner, a sequential-day approach is needed to adequately model a receptor's dose profile (McCurdy, 1997). Undertaking such an exercise for multi-day periods involves, first of all, the use of a simulation approach to human activity/location modeling, since some type of sampling of data — generally with replacement — is required to increase the "data pool" available for modeling any particular individual or cohort in a population. Secondly, it requires that a decision rule be implemented to address the proper amount of intra- and inter-individual variability inherent in human activity/location choices.

When assessing human exposure to environmental contaminants, modelers frequently proceed in this fashion: the population is divided into age/gender and other relevant categories[2] and one of four general decision rules regarding human activity/location data are implemented to obtain daily longitudinal exposure/dose profiles from cross-sectional data:

1. An individual person-day of data is used repeatedly for every day-block in the simulation; this is also known as the diary re-use approach.
2. A random draw from a set of person-days of data is used for each day-block.
3. A mixed approach, where an individual person-day is used for each day-block, but is changed periodically during the modeling period — usually on a seasonal basis.
4. A conditional probability approach where a person-day of data is selected based upon that occurred on the previous day, or a previous series of days.

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[2]Such as weekday/weekend distinctions (often called a day-type) and a daily ambient temperature indicator of season-of-the-year. See, for example, Johnson et al. (1996), Graham and McCurdy (2003), and McCurdy and Graham (2003). Other discriminating factors can be used, such as employment status, housing type, and physical activity level. We call any such discriminating approach a "day-block" method.

The first approach is used in most modeling efforts, particularly those based upon specific-percentile (the 50th or 90th, etc.) estimates found in EPA's *Exposure Factors Handbook* (NCEA, 1997). It will systematically overstate the day-to-day autocorrelation in a person's activities, ignoring intra-individual variability known to exist (see below). The second is used in many of the airborne pollutant exposure assessments undertaken by the Office of Air Quality Planning Standards (OAQPS) in EPA.[3] This approach recently has been criticized by the Agency's Science Advisory Board (SAB) as artificially reducing inter-individual variance in the model population by not maintaining autocorrelation in an individual's activities over time, which inflates intra-individual variance (SAB, 2001). The third approach has been used by OAQPS in its Hazardous Air Pollution Exposure Model (HAPEM) (Palma et al., 1996; Glen and Shadwick, 1998). It also is being discussed for use by EPA's Office of Research and Development in its Stochastic Human Exposure and Dose Simulation (SHEDS) models (Burke et al., 2001; Zartarian et al., 2002). The fourth approach, to our knowledge, has not been implemented to date, but is under consideration for selected EPA modeling efforts (Glen, 2000). It is similar to a first-order Markov chain process, where the probabilities for randomly selecting an activity diary for day *N* depend upon the selection made for day *N*-1, but not on any earlier choice. The Markov process could be extended back in time, however, using data for days *N*-2, *N*-3, etc., but "carrying" conditional joint probabilities in an exposure model becomes computationally complex and burdensome. In addition, as cohort sizes become smaller, all randomization sampling methods potentially will reduce inter-individual variability due to few "choices" being available to draw from. None of the four approaches have been adequately analyzed to determine if they are statistically rigorous with respect to replicating longitudinal patterns in measured activity data. This paper is intended to shed light on the *structure* of intra- and inter-individual variability in human locational patterns.

Other objectives of this paper are to (1) explore the Harvard dataset in order to understand intra- and inter-individual variability inherent in the time spent by 160 children in three major locations over at least 30 days in a year, and (2) provide some guidance on how many days of activity/location data are needed to obtain a "reliability correlation coefficient" (described below) of 0.8, the criterion measure used by exercise physiologists to indicate "valid" longitudinal physical activity information. We approach both of these objectives from a number of angles, including using correlation analyses, generalized linear modeling, and plots of interclass correlation coefficients (ICC's) against the number of days of available data.

Before describing the work undertaken, we turn to a brief review of the extant time budget and physical activity literature on intra- and inter-individual variability in order to put our work into perspective.

Review of the relevant literature

Schwab et al. (1990) reported a 2-day study of personal NO_2 exposures that contained two 24 h activity diaries focused on seven activity/location combinations (called microenvironments: MEs). The data were disaggregated into six different age/gender groups. There was low intra- and inter-individual variability in some highly generalized MEs, such as inside-the-home (excluding time in the kitchen), but relatively high daily variability in others. The authors found that approximately 50% of the sample visited narrowly defined MEs on only one day of the two sampled, and that the daily *difference* in daily time spent between the two days was about equal to the average time spent in these MEs (Schwab et al., 1990).

Many of the same researchers conducted a longer activity/location study in 4th–6th grade children as part of a prospective epidemiological study in Kanawha County West Virginia (Schwab et al., 1992). The analyzed sample focused on children having at least 12 consecutive days of activity diary data in one of two seasons: 62 children in the non-school period (July) and 72 in the school period (September). There was considerable variability in the time spent outdoors and in travel for the sample as a whole. The data for each child was averaged for all days to determine how much inter-child variability existed. Individual children exhibited very different, and statistically significant, patterns for time spent outdoors and in travel. Girls and boys differed significantly only in the time spent outdoors; boys spent more time there on both school and non-school days. Asthmatics did not differ significantly from non-asthmatics in the time spent in any ME, including outdoors (Schwab et al., 1992). Within-child differences were considerable for some ME's, especially on non-school days. For example, there was a *mean daily difference* of 2.6 h ($\pm$1.0 h)[4] in time spent outside during non-school days, 4.2 h ($\pm$1.7 h) in the time spent inside at home, and 3.5 h ($\pm$1.8 h) in time spend in the inside-other location.

The Kanawha children spent most of their indoor time in quiet activities; outdoor and non-home ME's exhibited the most active exertion levels (Schwab et al., 1991). There was significant between-child variability in the time spent in moderate and vigorous exertion, and there were weekend *versus* weekday differences also. The within-child variance in

[3]These include the NEM (NAAQS Exposure Model) and the probabilistic NEM (pNEM) models (Johnson, 1995; McCurdy, 1995), and the Air Pollution Exposure (APEX) model currently under development (Richmond et al., 2002). The approach also is used on a modified basis by non-EPA modelers (see, for example: Lurmann and Korc, 1994; Freijer et al., 1997).

[4]Standard deviation is shown in parentheses.

moderate/vigorous activities was considerable (Schwab et al., 1991).

Schwab et al. (1992) also present an analysis of how many days of locational data are required from a child to reduce the proportion of daily mean-time ME mis-classifications on a quartile basis. The aim of their analysis was to place a child into her or his correct mean-time quartile of the sample distribution using as little daily data as possible. A "gross mis-classification" was defined to be two quartiles away from the actual quartile of an individual's "true" mean time spent in various ME's over 8 school days and 14 non-school days. To reduce gross mis-classifications to a 10% level required that 6 days of school-day data (75% of the total available) and 12 non-school days (85% of the total available) be collected. Although not reported, to reduce the mis-classifications to a one quartile level required that even more days of data be obtained.

These findings are consistent with the general physical activity (PA) literature for both short-term (days) and long-term (years) time periods, although the terminology used in the two disciplines is quite different. For instance, physical activity researchers use the terms "tracking" and "stability." *Tracking* is the continuation of an activity over time, and it generally decreases as the intervening time increases, as does participation in most energetic activities (Butcher, 1985; Raitakari et al., 1994). While there is tracking of specific activities over even long periods of time,[5] there is significant intra- and inter-individual variability in the amount of time spent in both specific and general physical activities (Butcher, 1985; Kemper et al., 1989; Kelder et al., 1994; Van Mechelen and Kemper, 1995; Anderssen et al., 1996; Pate et al., 1996,1999; Stofan et al., 1998; Kimm et al., 2000). *Stability* is the maintenance of a person's *relative activity level* within a group or cohort over time (Lefevre et al., 2000); and evidence exists that both supports and refutes this phenomenon. For instance, Fortier et al. (2001) find that 30–35% of the population remains in the lowest (sedentary) and highest (exercisers) quintile groups over a 7 year period, while 20% would be expected if stability did not occur. Eaton et al. (1993) find that 72% of middle-aged people remained in their same PA categories over a 4 year period; 60% of these were sedentary and 12% were active "maintainers." The remainder changed PA category (16% increased PA and 12% decreased). In general, low-to-moderate correlation coefficients of physical activity levels over time have been found: $r_s \approx 0.35$–0.40 for an 8-year period (Lee et al., 1992) and $r \approx 0.50$–0.60 for a 3-year period (Pate et al., 1996). Sternfeld et al. (1999) report that only 34% of older people have stable PA participation rates.

A study of the sources of variability in physical activity participation rates is interesting from the perspective of our findings since the results are quite similar to ours. Matthews et al. (2001) report that using multiple measures of variability associated with PA participation rates obtained from 15 repeated daily surveys over a year, the following factors "explain" total variance measured:

Intra-individual differences	50–60%
Inter-individual differences	20–30%
Day-of-the-week impacts	~15%
Seasonal differences	~6%

For objective PA monitoring data,[6] it takes between 2 and 7 days of information to achieve a *reliability correlation coefficient*[7] (R_{CC}) ≥ 0.80 in children of various ages, but you need only 1–2 days to attain the same R_{CC} for estimating their resting heart rate (which has minimal diurnal variability). For adult male teachers, you need 2 weeks of 7-day diaries to achieve a $R_{CC} \geq 0.80$ (Baranowski et al., 1999). Trost et al. (2000) state that you need 8–9 days of objective monitoring in adolescents to attain a $R_{CC} \geq 0.80$ for PA, but you only need 4–5 days for elementary school children for the same reliability criterion. For an annual *total* PA $R_{CC} \geq 0.80$, 7–10 days of objective data are needed for males and 12–21 for females; for a *leisure-time* PA reliability of the same magnitude, you need 21–28 days of data for either gender (Matthews et al., 2001). More days of data are needed to adequately characterize variability when "subjective" information (questionnaire, self-report) is used to measure physical activity (Matthews et al., 2001).

Methods and analytic approach

In this paper, we analyze human activity/locational information collected by Harvard University as part of its Southern California Chronic Ozone Exposure Study (Geyh et al. , 1999, 2000). That Study monitored personal, indoor, and outdoor exposures to ozone for elementary school children in grades 6–12, with most of the children being in grades 8–11. Activity/location data were obtained for each monitoring day. Children in two San Bernardino County communities

[5]The findings related to tracking are not consistent. Most studies find that it occurs, but others do not (both relative to some criterion measure). It is hard to reconcile the disparate findings since there are (1) multiple physical activity metrics used as the dependent variable, and (2) multiple criteria of a significant association used to determine if the phenomenon exists or not. Tracking usually is measured by an "interperiod correlation coefficient" (IPC). See Van Mechelen and Kemper (1995).

[6]Monitoring using an instrumental measure of PA: oxygen consumption, heart rate, accelerometer/pedometer movement "counts," or carbon dioxide production. All of these monitoring techniques require additional physiological data and/or relationships to calibrate the objective measure to a particular individual.

[7]This is the term used by exercise physiologists for the more generally applicable interclass correlation coefficient (ICC) to assess reliability or consistency in PA over multiple days. See the text below.

east of Los Angeles were included: (1) Upland and (2) several small neighboring mountain towns. The total monitoring period stretched over 48 weeks, June 1995–May 1996, but data were not obtained for 2 weeks within that time period. Each child was supposed to be monitored for a 6-day period, Wednesday through Tuesday, during each month, for a total of 66 days per child for the entire study period, but that goal was not attained for any subject.

The data were highly aggregated with respect to location. Only five locations were coded: indoors-at-home; indoors-at-school; indoors-other; outdoors; and in-travel. The original investigators subsequently combined the two non-home indoor categories so that data were reported for only four locations: indoors-at-home; indoors-other; outdoors; and in-transit (Geyh et al., 2000). Our analyses indicated that there was little daily variability in the sample with respect to time spent in either indoor category, so we sometimes combined them into one indoor location for analysis purposes.

Although 244 children from 156 homes were enrolled in the Harvard study, because of drop-outs and missing data, the sample size used for their original analyses was 169 children: 74 boys (40 in Upland and 34 in the "mountains") and 95 girls (44 and 51, respectively). To obtain reasonable intra-individual variability statistics from the sample, we imposed additional criteria on the data that reduced the sample size to 160 children: 71 boys and 89 girls. The child-specific criteria that we used were to have:

- at least 6 days of data for each 3-month season of the year
- at least 30 days of complete (24 h) activity/location information for the year
- reasonably complete housing and demographic data

Using these criteria, the median number of days analyzed for the children was 50, with a range of between 31 and 62 days for individual children. About 70% of the included children reported between 45 and 57 days of complete data.

The resultant multiple-day activity/location data set is the largest that we know of. Still, it must be recognized that it is not truly longitudinal data. It is *clustered* sequential-day information spread out over a school year. In addition, the data came from a rather homogenous sample of children. For instance, 74.2% of the sample was between 8 and 11 years old; 91% lived in a single-family home built after 1960; used gas as a cooking fuel; and had a forced-air heating system (Geyh et al., 2000). These housing type similarities point toward a narrow socio-economic range of participants in the study, but income and ethnic information were not available to evaluate this issue.

Descriptive results

Selective summary statistics for the dataset are provided in Table 1. Locations of interest are disaggregated by important categorical variables, such as gender, day-type (weekday/weekend), and four school-oriented seasons (Summer, Autumn, Winter, and Spring).[8] Information is provided for aggregated locations of interest: total outdoors, total indoors, and in-transit, as well as for the in-home location with respect to day-type differences. The statistics apply to child-averaged data; thus, the mean statistic refers to the mean of the children's multi-day values. The locational statistics are provided for only those categorical variables that have statistically significant distributions as measured by a two-sample K–S test. See footnote d of Table 1 for an explanation of this test. Geographic location (Upland v. mountain towns) was also used as a categorical variable in our analyses, but it was dropped from the table because it did not affect the results significantly.

Table 1 indicates that child-specific daily mean time (C-S.DMT) spent outdoors is significantly affected by gender, day-type, and season. It is not so affected by age groupings (7–9 *versus* 10–12) or by community (Upland *versus* mountain towns in the same County). C-S.DMT spend indoors is significantly affected by the same three variables, although the seasonal effect is not shown in Table 1. The in-transit C-S.DMT is significantly affected by day-type and by some of the seasonal categories (data not shown; the K–S tests indicates a significantly different distribution for the Autumn–Spring, Autumn–Winter, and Spring–Winter pairs, but not for the others). C-S.DMT spent in the home is significantly affected by day-type and partially by season, although only two of the six possible seasonal-pairs show significant differences: Spring–Winter and Summer–Autumn.

While the locational distributions for the categorical variables shown in Table 1 are statistically significant, the absolute differences in the mean time spent in a location, or any of the other metrics used (coefficient of variation [COV] and the 90th percentile range) are small. In general, the COVs for the outdoor and in-transit locations are similar, and about an order-of-magnitude higher than the indoors-total location. Children spend most of their C-S.DMT in the indoors location; about 20 h/day regardless of gender or day-type (or season, not shown in Table 1). It should be noted that while the COV for the in-transit location is relatively large, very little time is spent there. It averages about 1 h/day regardless of gender or season (not shown), and also by day-type, even though that variable has significantly different distributions according to the K–S test. Finally, comparing the in-home and total-indoors locations indicates that about 75% of the time spent indoors is spent in the home. The

[8]Summer = June–August; Autumn = September–November; Winter = December–February; Spring = March–May. Because the South Coast of California has a climatology associated with cold ocean/land interface phenomena that greatly affects monthly temperature/precipitation characteristics which do not fit a school-calendar based seasonal typology, a 3-season breakdown was also used for some analyses (December–March; April–July; August–November).

Table 1. Selected individually averaged descriptive statistics for the time spent per day (h/day) in various locations in the Southern California dataset.

Location	Variable	Sample size (n)	Mean [SD][a] (h/day)	COV[b] (%)	90th %-tile range[c] (h/day)	K–S test stat.[d]	
						D_n	p
Outdoors (total)	Gender						
	Female	89	2.74 [0.85]	31.0	1.4–4.0	0.29	<0.001
	Male	71	3.26 [0.88]	27.0	1.6–4.7		
	Day-type						
	Weekday	160	2.83 [0.81]	28.6	1.4–4.1	0.24	<0.001
	Weekend	160	3.19 [1.28]	40.1	1.2–5.4		
	School day:						
	Yes	160	2.80 [0.82]	29.3	1.4–4.0	0.21	0.001
	No	160	3.14 [1.15]	36.6	1.2–5.1		
	Season						
	Autumn	160	3.37 [1.29]	38.3	1.2–5.7	See footnote[e]	
	Winter	160	2.20 [0.98]	44.5	0.8–3.9		
	Spring	160	2.54 [1.05]	41.3	0.9–4.5		
	Summer	160	3.75 [1.31]	34.9	1.6–6.1		
Indoors (total)	Gender						
	Female	89	20.23 [0.95]	4.7	18.7–21.8	0.27	<0.001
	Male	71	19.69 [0.96]	4.9	18.1–21.5		
	Day-type						
	Weekday	160	20.18 [0.89]	4.4	18.8–21.6	0.23	<0.001
	Weekend	160	19.70 [1.40]	7.1	17.3–21.7		
In-Transit	Day-type						
	Weekday	160	0.99 [0.37]	37.4	0.4–1.6	0.18	0.010
	Weekend	160	1.11 [0.46]	41.4	0.4–2.0		
In-Home	Day-type						
	Weekday	160	15.47 [1.56]	10.1	12.9–17.6	0.34	<0.001
	Weekend	160	16.37 [3.03]	18.5	12.3–20.4		

[a]Standard deviation.
[b]Coefficient of variation: SD/mean.
[c]Range of the 5th–95th percentile value in the distribution.
[d]Kolmogorov-Smirnov test: a two-sample non-parametric, distribution-free, test of H_o: $\text{distribution}_1 = \text{distribution}_2$. The test statistic is D_n, the maximum relative distance between any two points on the distributions. It is tested by a χ^2 approximation at $\alpha = 0.05$; p is the probability of rejecting H_o when it is true.
[e]For the seasonal categories, all possible seasonal-pairs were found to have statistically significant distributions of the time spent in outdoor locations using the 2-sample K–S test ($p < 0.001$).

mean time spent in the various locations shown in Table 1 is similar to that reported by Wiley et al. (1991) and Jenkins et al. (1992) for California children <12 years of age,[9] and by Klepeis et al. (1996, 2001) for a national sample of children/adolescents 5–17.[10] A box plot of the time spent per day in the various location categories for the Southern California sample is depicted in Figure 1.

[9]Mean h/day estimates: indoors — 20.5; outdoors — 2.4; and in-transit — 1.1 ($n = 1{,}200$).
[10]Mean h/day estimates: indoors — 20.7; outdoors — 2.2; and in-transit — 1.0 ($n = 1292$).

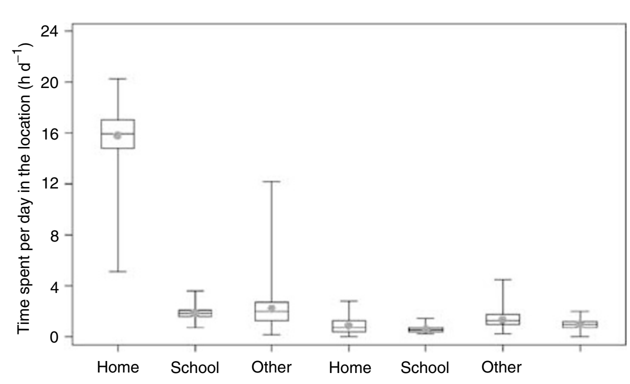

Figure 1. Box plots of the time spent per day in various locations.

Table 2. Person correlation coefficients[a] for the time spent in two locations for different temporal lags.

Location	Basis of the correlation	Correlation stats.[b]	
		r	n
Indoors-at-home	1 day lag[c]	0.45	5952
	2 days lag[d]	0.21	4577
	3 days lag[e]	0.13	2936
	4 days lag[f]	0.18	1399
Outdoors-total	1 day lag[c]	0.36	5952
	2 days lag[d]	0.23	4577
	3 days lag[e]	0.21	2936
	4 days lag[f]	0.26	1399
Indoors-at-home	Sunday–Monday[g]	0.35	1444
	Monday–Tuesday	0.51	58
	Wednesday–Thursday	0.46	61
	Thursday–Friday	0.37	1425
	Friday–Saturday	0.49	1472
	Saturday–Sunday	0.60	1491
Outdoors-total	Sunday–Monday	0.37	1444
	Monday–Tuesday	0.63	58
	Wednesday–Thursday	0.54	61
	Thursday–Friday	0.39	1425
	Friday–Saturday	0.35	1472
	Saturday–Sunday	0.40	1491

[a]Note every correlation coefficient reported in this table is significantly different (than 0) at $p<0.001$.
[b]Abbreviations used: n is the number of the same-individual pairs available for each correlation, r the Pearson product-moment correlation coefficient and Stats. the Statistics.
[c]Day of week is not considered; it is day 1 *versus* day 2, 2 *versus* 3, etc.
[d]Day of week is not considered; it is day 1 *versus* day 3, 2 *versus* 4, etc.
[e]Day of week is not considered; it is day 1 *versus* day 4, 2 *versus* 5, etc.
[f]Day of week is not considered; it is day 1 *versus* day 5, 2 *versus* 6, etc.
[g]For the named paired days, only adjacent individual-specific day-pairs are used (starting on the first day of available data)

Analyses were undertaken to understand the correlation structure of two of the locational categories, indoors-at-home and total outdoors. The correlations are season-specific: they do not include days from different seasons. The calculated Pearson product-moment correlations (r) are depicted in Table 2. The correlations were done for various lag lengths between days — up to 4 — and for specific days of the week. Longer lag-lengths could not be universally calculated because of diminishing sample availability for long lags. All correlations shown in Table 2 are significant at $p<0.001$. The r's for a one-day lag are modest for the two locations, and generally drop off after that. The indoors-at-home 1-day lag r of 0.45 is very similar to the 0.48 value reported by MacIntosh (2001), but we could not find comparable data to evaluate our multi-day lag correlations.[11]

[11]MacIntosh (2001) provides correlation coefficients for lags up to 6 days, but they are not calculated in the same manner as ours so they cannot be compared.

Modeling results

A series of analyses were undertaken using the General Linear Modeling (GLM)[12] method of testing alternative models to estimate the time spent outdoors and in the home. Other locations were not investigated, but the "zero-sum" nature of the diary data means that analogous results are expected for non-tested locations. Three model-types were tested for the two locations. The first included age and gender as independent variables and did not allow repeated measurements. The second included four seasons, two day-types, and individuals as independent variables; this model-type controlled for repeated measurements (by individual ID). The third model used a 3-season year but the remaining variables were the same. Results of the GLM analyses for the first two models appear in Table 3; there were no significant

[12]The PROC GLM procedure of SAS® was used for this modeling (Version 6: Cary, NC: SAS Institute, 2002). Basically, the procedure used was analysis of variance, with and without repeated measures.

Table 3. Results of the general linear modeling analyses[a].

Dependent variable	Ind. variables	Model statistics and tests				Percentage of variance explained		
		DF	ΣΣ	F	p	Total	Model	$\bar{x}$ RMS
Outdoors-total	Age (7–9, 10–12)	1	1.2	1.63	0.204	1.0	10.7	
	Gender (♀, ♂)	1	10.8	14.53	<0.001	8.3	89.3	
	Model	2	12.0	8.08	<0.001	9.3[c]	100.0	2.98 0.86
	Error	157	116.9	—	—	90.7	—	
Outdoors-total	Individuals[b]	159	5837.9	7.42	<0.001	12.3	65.8	
	Season (A, W, Sp, Su)	3	3059.9	180.20	<0.001	5.9	31.6	
	Day-type (Weekday, Weekend)	1	246.1	45.65	<0.001	0.5	2.6	
	Model	163	9651.0	10.98	<0.001	18.7[c]	100.0	2.98 2.32
	Error	7771	41887.8	—	—	81.3	—	
Indoors-at-home	Age (7–9, 10–12)	1	8.0	1.99	0.160	1.3	92.9	
	Gender (♀, ♂)	1	0.8	0.21	0.651	0.1	7.1	
	Model	2	8.8	1.10	0.335	1.4[c]	100.0	15.83 2.00
	Error	157	630.8	—	—	98.6	—	
Indoors-at-home	Individuals[b]	159	31471.8	9.22	<0.001	15.4	88.5	15.81 4.66
	Season	3	2283.1	35.60	<0.001	1.1	6.3	
	Day-type	1	1440.3	66.30	<0.001	0.9	5.2	
	Model	163	35592.1	10.05	<0.001	17.4[c]	100.0	
	Error	7771	16818.9	—	—	82.6	—	

[a]Abbreviations and symbols used: DF the degrees of freedom, F the F-test statistic ($\alpha = 0.05$), Ind. the independent, p the p-value (probability of making a Type I error), RMS the root mean square (SD of the dependent variable (equal to the standard error), Seasons: A = Autumn, Sp = Spring, Su = Summer, W = Winter, SD the standard deviation, ΣΣ the sum of squares; ΣΣ, DF = variance, $\bar{x}$ the mean of the dependent variable.
[b]Intra-individual effect.
[c]Percentage form of R^2 (proportion of total variance "explained" by the model).

differences between results for the different seasonal definitions modeling efforts, so only the 4-season model output is shown.

None of the models tested performed well with respect to the unadjusted R^2 statistic; only 1% and 9% of total variance was "explained" by the no-repeated measurements models for total outdoor time and indoors-at-home time, respectively. However, both models were statistically significant. The only statistically significant variable for explaining model (and total) variability of outdoors-total time is gender. Boys spend significantly more time outside. On the other hand, neither age or gender explain a significant amount of model or total variability in the time spent-at-home. That time is related to the almost-universal needs of sleeping, eating, and other personal care.

Since age and gender are included in the inter-personal variability metric, they cannot be included in a repeated measure model. The repeated measures models are statistically significant ($p < 0.001$) and "explain" 19% and 17% of variance in total outdoor and indoors-at-home time, respectively, regardless of the number of seasons included. Intra-individual variability is by far the most important independent variable, explaining at least 81% of model variance for outdoors-total time and $\geq 82\%$ of indoors-at-home time. Season explains between 29% and 32% (depending upon the definition of season used) of outdoors-total time and only 6% of indoors-at-home time in the models, which is a logical finding. It is expected that the seasonal variable — a surrogate for climatic conditions — affects time spent outdoors and is not an important factor in affecting time spent at home. We could not explicitly test for climatic effects *per se* since data were not gathered in the study on daily temperature and precipitation. Day-type, while being a statistically significant independent variable in the repeated measures models, explains $< 1\%$ of model and total variance. Intra-individual variability swamps out the other independent variable effects.

The GLM modeling results are disappointing in general in that they do not have much explanatory power. Human activity and locational decisions are affected by many other factors than we have been able to account for in our models. This of course is a function of what type of data were available for analyses, itself a function of what information was collected in the field.

Estimating the number of days of data needed to adequately capture time spent outdoors

We utilize the interclass correlation statistic (ICC) to assess how many days of data are needed to adequately capture the time spent outdoors by children in the Harvard dataset. An ICC basically is the ratio of inter-individual (between-subject) variability to the sum of inter- and intra-individual (within-subject) variability in a sample. It is obtained via repeated measures of analysis of variance techniques, and *one* definition of the statistic is

$$\mathrm{ICC} = \sigma_{\mathrm{B}}^2/(\sigma_{\mathrm{B}}^2 + \sigma_{\mathrm{I}}^2) \quad (1)$$

where σ_{B}^2 is between-subject variance and σ_{I}^2 is within-subject variance over which the measure is obtained (Baranowski and de Moor, 2000). Assumptions have to be made regarding the between- and within-subject variance/covariance structure to calculate an ICC. These are known as compound symmetry, heterogeneous compound symmetry, and "unstructured" symmetry (Baranowski et al., 1999).

The Spearman–Brown "prophecy formula" uses the ICC to predict the required number of monitoring days (N) to achieve a "target reliability," variously represented as R_{CC} or $\mathrm{ICC}_{\mathrm{Target}}$ (DuRant et al., 1992; Baranowski and de Moor, 2000; Trost et al., 2000). A target reliability of 0.8 or 0.9 is considered to be acceptable. The simplified formula is

$$N = [R_{\mathrm{CC}}(1 - \mathrm{ICC})]/[\mathrm{ICC}(1 - R_{\mathrm{CC}})] \quad (2)$$

For a R_{CC} of 0.8, the formula collapses to $N = 4*[(1-\mathrm{ICC})/\mathrm{ICC}]$. Using the within- and between-variances calculated from the Harvard sample, $N = 28$ days are needed to achieve a reliability correlation coefficient of 0.8.

We wanted to ascertain the stability of the ICC metric when the number of days of data sampled per person varied from 2 to 50 days. Since the number of days available was between 31 and 62 days for any child, the sample size available for the stability assessment decreases as the number of days increase. For each child and day-set combination (2 days, 3 days, etc.), we calculated an ICC for outdoors time. A plot of outdoor-total ICC *versus* the number of sampled days appears as Figure 2. The outdoor-total ICC decreases rapidly as the number of days per person increases until approximately 10 days are attained; the change in ICC slope per day is -0.05 between 2 and 10 days. It then levels out gradually to about -0.002 per day until a rough asymptote is reached around 25 days. This approximates the N of 28 calculated above for a R_{CC} of 0.8, providing confirmatory evidence for both approaches. These are important findings, indicating that to adequately characterize time spent in the outdoor-total location in the children studied, you need about 4 weeks of activity/location data per child spread over the year. Having even 10 days of data per child, however, significantly improves the situation compared to the 2–3 days of data that exists in CHAD.

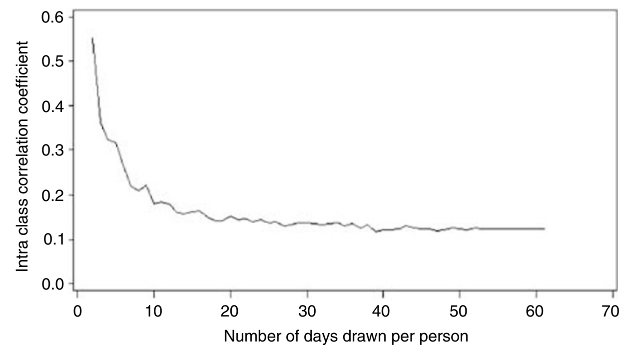

Figure 2. Plot of the intraclass correlation coefficient (ICC) for the daily total time spent outdoors *versus* the number of days of data drawn from each person.

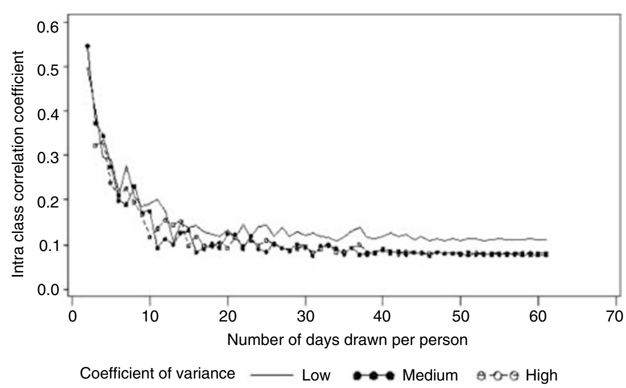

Figure 3. Plot of the intraclass correlation coefficient (ICC) for the daily total time spent outdoors *versus* the number of days of data drawn from each person by stability class.

We then disaggregated the sample into three groups based on their inherent variability in order to determine if there was an effect between variability and the number of days needed to be sampled. There is, but it is minor as the plot in Figure 3 represents. COVs for all of the children were ranked and classified into low (COV $<69\%$), medium (COV 69–89%), and high (COV$>89\%$) variability groups. The patterns for the three groups are similar and stability is again attained around 25 days. We believe that the fluctuating variability after 25 days is primarily due to smaller sample sizes of data being available as the number of days increase. It follows from the definition of ICC that it would be higher for the low-variability group for any number of days drawn per person because ICC increases as σ_{I}^2 decreases in the denominator (see Eq. (1)).

We could not do more sophisticated analyses of whether or not the number of days needed to adequately represent intra-individual variability can be reduced further if days are chosen strictly on a random probability basis for an entire year, since the sampling frame used in the Harvard Study was a stratified, fixed-block design using school-period

Table 4. Descriptive statistics for the time spent outdoors per day associated with different random probability sampling schemes applied to the Geyh et al. (2000) data.[a]

Cohorts used for binning the data for each sampling scheme	# Person-days sampled /persons[b] in the defined cohort	n	Descriptive statistics				K–S test results[c]		
			Med.(h/day)	Mean (h/day)	SD (h/day)	COV (%)	D_N	p	ICC
Age and gender (no other bins used): four cohorts	1	160	2.25	2.81	2.36	83.9	0.33	<0.01	1.00
Age, gender, and day-type (weekday/weekend): eight cohorts	1	320	2.46	2.81	1.86	66.1	0.24	<0.01	0.59
Age, gender, and season (Autumn, Spring, Summer, Winter): 16 cohorts	1	640	2.66	2.87	1.58	55.1	0.21	<0.01	0.38
Age, gender, day-type, and season (defined as above): 32 cohorts	1	1280	2.88	3.03	1.22	40.4	0.14	0.10	0.21
Same cohorts as above: 32 cohorts	2	2560	2.99	3.01	1.03	34.1	0.06	0.96	0.16
Original data set: all person-days of data used	All	7935	2.94	2.97	0.90	30.3	—	—	0.12

[a]Abbreviations and symbols used: COV the Coefficient of variation: SD/Mean, D_N the K–S test statistic; see footnote c below, K–S the Kolmogorov–Smirnov test; see Table 1 for more information, ICC the interclass correlation coefficient, Med. the median, n the total number of person-days of data drawn from the original dataset for the sampling scheme, p the probability of rejecting H_O when it is true, SD the standard deviation.
[b]Two age groups were used for both genders; the number of persons in each cohort are: 7–9 ♀–45; 7–9 ♂–44; 10–12 ♀–36; 10–12 ♂–35. Thus, for the age/gender cohort–the first sampling scheme depicted, 45 person-days were randomly selected (with replacement) from the 7–9 ♀ cohort, etc. The same holds for the other schemes; the number of days sampled varies with the number of children in each cohort. As the cohorts are defined more narrowly, the number of person-days of data available decreases, but still exceeds (on average) 200 person-days of data for each of the 32 most-disaggregated bins (age/gender/day-type/season).
[c]The H_O of this test is: frequency distribution of the sampling scheme is the same as the original's distribution.

months as the unit of analysis. Theory would say yes, but we cannot analyze it. We could, but chose not to do so in this paper, analyze the other locations to determine if the number of days needed to adequately capture intra-individual variability in those locations follow the same pattern as outdoors-total time. Undoubtedly, the number of days needed for indoors-at home and indoors-total locations are less than for the outdoor location, since their total variance — as measured by a coefficient of variation — is less than the total time spent outdoors. See Table 1. Less total variance decreases the denominator of the ICC statistic, making it larger for the sample. A larger ICC decreases N in the Spearman–Brown prophecy formula (Eq. (2)). Of the locations available for analyses, the outdoor location is the "limiting" one for properly capturing intra-individual variability.

It should be noted that the 28 day figure is similar to that determined by exercise epidemiologists and physiologists to adequately address intra-individual variability in time spent by children in moderate and vigorous levels of physical activity (Matthews et al., 2001). There seems to be some convergence here, probably because most children's moderate/vigorous activity occurs outdoors (Kohl and Hobbs, 1998 ["percentage of time spent outdoors is strongly related to physical activity" p. 551]). Schwab et al. (1991) make the same conclusion.

Finally, we evaluated the extent to which the ICC statistic varies under different cohort definitions, such as those based solely on age/gender classes versus those based on more detailed categorizations. As the number of cohort "bins" increase, differences among each child in a cohort should be less, thus reducing inter-individual variability in a cohort. On the other hand, the number of children in each cohort also is reduced, so the "pool" of days available to model each cohort bin becomes smaller. We investigated the relationship between the number of cohorts used and total time spent outdoors using a K–S test. The H_O of the test was that the distribution of time spent outdoors is the same for the defined cohorts as for the original sample (using a χ^2 approximation of the D_N statistic at an $\propto = 0.05$). The results of this testing are shown in Table 4.

The original dataset was partitioned into the cohorts depicted in the left-most column. Age and gender was used in every case to define the cohorts, and other variables were added to further subdivide, or stratify, the sample into smaller cohorts. The number of cohorts tested varied between

4 and 32. A random probability sampling of person-days contained in each cohort was used to obtain one person-day ''realization'' (draw) for each person in a cohort. The sample size (n) for each analysis was obtained by multiplying the 160 children — uniquely defined by an age/gender combination — by the number of choices for the other variables used to further subdivide the cohort. Hence, $n=320$ for the day-type-only analysis (160*2) and $n=640$ for the season-only analysis (160*4).

The distribution of the time spent outdoors is statistically different than the original distribution until the cohorts are defined using age, gender, season, and day-type distinctions — the fourth sampling scheme. In other words, H_O can be rejected at $p<0.001$ for the first three schemes, but cannot for the fourth or fifth cohort schemes. The mean and median values for the last two schemes approach those of the original dataset: less than a 2% difference. The SD and COV values for those schemes also approach the original data. The ICC metrics for the fourth and fifth sampling schemes also approach the original ICC of 0.12. It should be noted than the fourth scheme contains only 16% of the total person-days of available data. The fifth sample is like the fourth, but two person-days per person in the cohort are included (with replacement). These are comforting results from a modeling perspective in that they indicate that inter-individual variability — in at least the time spent outdoors — can be adequately addressed in an exposure model by subdividing activity/location data into logical cohorts that maintain whatever intra-individual structure exists in the data. Basically our analyses provide statistical support for the cohort or population binning approaches used in some exposure models, including OAQPS's NEM, pNEM, and APEX models, and NERL's SHEDS-P model.

Summary and conclusions

Clustered sequential activity/location data were obtained for 160 children in two communities in Southern California (Geyh et al., 2000) and analyzed using a variety of statistical techniques. These data are the most comprehensive ''longitudinal'' activity/location information that we know of, in terms of both the sample size obtained and the number of days obtained per subject. Time spent in various aggregated locations by the children in the sample was shown to be representative of time/activity data collected by others in both California and the United States as a whole, so the sample seems representative of children in the 7–12 age range. The time spent outdoors by these children varied significantly with respect to gender, day-type (weekday/weekend), and season (three or four categories). The total time spent indoors varied significantly by gender and day-type categories but not by season. In-transit and in-home time varied significantly only by day-type. Age was not an important discriminating variable for any of these locations, but probably that is due to the rather narrow age range of the sample which reduces its variance relative to the other variables investigated. This is an important shortcoming of the dataset which affects our findings. Other important caveats are: (1) the time use survey focused only on time periods when the children were available locally (i.e., were not on vacation); (2) the locations used for temporal assessment were highly aggregated; (3) the sample was relatively homogeneous with respect to housing characteristics — and probably socio-demographic attributes also; and, (4) the data were not completely longitudinal in the sense of being continuous data for the time period of assessment. We expect that these shortcomings of the dataset systematically reduce both the absolute and relative variance in the alternative dependent and independent variables what were analyzed here. Thus, at present our findings have to be treated as conditional to the data used until additional information can be gathered on longitudinal human activities. Even so, the Harvard Southern California study provided a wealth of information for understanding intra- and inter-individual variability in human activity/location data.

Data shortcomings are particularly noticeable for the GLM modeling work, which resulted in a set of models with low predictability. However, when used in a relative sense — where alternative independent variables are evaluated within a consistent statistical framework — the GLM models indicate that intra-individual variability is much more important in explaining time spent in the outdoors and in the home than any other variable available to us. Day-type and season show statistically significant effects also, but the amount of model variance explained after the intra-individual effect is accounted for is quite low. These findings are very similar to those regarding physical activity participation rates in children (Matthews et al., 2001).

The correlation analyses undertaken on the dataset indicate that modest day-to-day associations exist with respect to the time spent in the indoors-at-home and outdoors-total locations. These analyses do not show much difference in various day-pair combinations, but do show a large drop-off after a one-day lag in the r statistic as the lag between days increase.

Finally, the random sampling analyses of alternative ''binning'' decision rules used to set up sub-group population cohorts indicates that this approach can replicate the overall sample statistics (median, mean, SD, and COV) while still maintaining the intra- and inter-individual relationships found in the original data (as measured by the ICC statistic). Using the ICC estimate and the Spearman–Brown prophecy formula favored by exercise epidemiologists (Baranowski and de Moor, 2000), indicates that a sample of 28 days of diary data spread over four seasons of the year is needed to adequately address intra- and inter-individual variability in the sample of children available to us. Whether or not that figure can be generalized to other population groups cannot be analyzed at present. It probably can be reduced if a strict random probability sampling scheme is used to collect the activity/location data. It was noted that the biggest improvement in ICC occurred when the number of days per child included in the analyses increased between 2 and 10 days, with a more gradual improvement per day after that.

Disclaimer

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