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implications of unreported travel and locations**

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Traffic exposure near the Los Angeles–Long Beach port complex: using GPS-enhanced tracking to assess the implications of unreported travel and locations

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ABSTRACT

Traffic exposure assessments could misclassify the extent and locations of exposure if traditional recall surveys and self-reported travel diaries do not record all participant activities. The Harbor Communities Time Location Study (HCTLS) examines the nature, extent and implications of underreported locations/trips in a case study which used portable Global Positioning Systems (GPS) devices to track the diurnal patterns and traffic exposure of 47 residents of communities near the Los Angeles–Long Beach port complex. Participants were similar to adults nationwide in time spent indoors, in-vehicle, and outdoors, but spent more time indoors at home (78% vs. 66%). Overall, participants did not report nearly half (49%) of the locations and trips identified in GPS-enhanced data on their activity diaries, resulting in about 3 h/day in unreported locations and 0.6 h/day in unreported trips. The probability of a location/trip being under-reported was systematically correlated with participant and location/trip characteristics. Self-reported data missed about 50 min of heightened air pollution exposures during the 5 h/day on average participants spent in high-traffic areas and about 30 min during the 4 h/day near truck routes. GPS-enhanced methods provide opportunities to more precisely characterize exposure periods and tools to identify facility, roadway, and land use types of the greatest concern for mitigation efforts.

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1. Introduction

Human environmental exposures are directly related to location and travel patterns over the day (Ott, 1985) and not accounting for air pollution concentrations at locations such as workplaces and schools and in transportation microenvironments could result in exposure misclassifications and inadequate policy and planning remedies (Beckx et al., 2009). Traditional exposure assessment methods account for location and travel patterns based on recall activity surveys and self-reported activity and trip diaries (Klepeis et al., 2001; Marshall et al., 2006), but these data are often incomplete since respondents tend to not report all locations and trips (Bricka and Bhat, 2006; California Department of Transportation, 2002). Incomplete activity profiles could result in air pollution exposure misclassification given that gaps in location and travel information can be extensive and systematically correlated with individual and household characteristics and location and trip characteristics (Bricka and Bhat, 2006).

The Harbor Communities Time Location Study (HCTLS) examines the implications of underreported locations and trips

on exposure classification in a case study in which portable Global Positioning Systems (GPS) devices were used to track 47 residents of communities adjacent to the Ports of Los Angeles and Long Beach in everyday activities. We developed a GPS-enhanced time-activity database for participants by using GPS data to validate participant-reported time-activities for 2–3 days, identifying locations and trips participants did not report, and completing activity and microenvironment profiles in follow-up interviews. We begin this article by reviewing the literature and providing an overview of our study design and methodology. Our analysis starts by profiling the time-location patterns of HCTLS participants and comparing these patterns to those of respondents to the National Human Activity Pattern Survey (NHAPS) in order to understand whether our non-random sample spent a disproportionate amount of time at or near their residence in port-adjacent communities which are heavily impacted by nearby port, goods movement, and refinery operations (Hricko, 2008; Kozawa et al., 2009). Next we examine the rate at which participants underreported locations and travel in their activity diaries and identify the individual, household and trip characteristics associated with underreported patterns. We then use proximity-based measures to examine the implications of participant diurnal location patterns on their exposure to heavily-traveled roadways and truck

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routes, and the extent to which underreported locations and travel could result in misclassifications of traffic exposure. We conclude by discussing insights from our HCTLS case study which enhance our understanding of how dynamic exposure assessment methodologies can more precisely identify environmental exposures compared to traditional approaches, can help resolve exposure misclassifications for underreported locations and trips, and can strengthen policy and urban planning strategies to mitigate air pollution exposures.

2. Background

2.1. Traffic exposure in goods movement corridors

Vehicle-related air pollutants are highly localized during the day within approximately 200–300 m downwind of major roadways (Zhu et al., 2002) and residential proximity to major roadways and heavy-duty diesel truck (HDDT) routes has been associated with adverse health impacts including asthma prevalence, reduced lung function, and mortality (Lipfert and Wyzga, 2008; McConnell et al., 2006; Perez et al., 2009). Disadvantaged communities tend to experience heightened levels of traffic exposure and low-income and minority communities in southern California disproportionately reside in high-traffic areas and may experience heightened exposure to vehicle-related pollutants (Houston et al., 2004). Environmental justice concerns are heightened in goods movement corridors in which substantial volumes of HDDTs transport shipping containers on arterials near residences and sensitive uses (Houston et al., 2008; Hricko, 2008; Perez et al., 2009), a pattern which results in elevated near-roadway concentrations of diesel exhaust particulate matter, a toxic air contaminant (California Air Resources Board, 2008; Kozawa et al., 2009).

Location-specific methods have been used to assess the potential magnitude of near-roadway pollution impacts and their environmental justice implications for populations in residential (Gunier et al., 2003; Houston et al., 2004), school (Appatova et al., 2008; Green et al., 2004), and childcare locations (Houston et al., 2006), but fail to evaluate the impact of individual time activity on diurnal traffic exposure. Concentrations of vehicle-related pollution in indoor, in-transit, and outdoor microenvironments can vary substantially (Fruin et al., 2008; Kozawa et al., 2009; Zhu et al., 2002, 2005), and linking time-location information with pollution proximity measures provides a valuable tool for estimating personal exposure and identifying where traffic exposures occur over the course of the day (Klepeis et al., 2001; Ott, 1985).

2.2. Methods for assessing activity patterns

Conventional time-location studies generate activity profiles for large samples using recall interviews or diaries, but these studies are associated with concerns about recall, reliability, and compliance and do not capture detailed temporal-spatial data that can be matched to immediate environmental hazards (Klepeis et al., 2001). Several regional travel surveys have tracked travel activities by equipping passenger vehicles with Global Positioning Systems (GPS) devices (Bricka and Bhat, 2006; Murakami and Wagner, 1999) and recent cohort studies demonstrate that portable GPS loggers and GPS-enabled cell phones are valuable tools for monitoring subject locations in exposure studies and can lessen respondent reporting burden and enable data collection over longer periods (Elgethun et al., 2007; Phillips et al., 2001). GPS location tracking can also enhance traditional methods by providing a nearly continuous location database and highly-resolved enhanced insights into the environmental exposures associated with health outcomes across 'activity spaces' occupied over the course of the

day (Chen and McKnight, 2007; Kwan, 2004; Millward and Spinney, 2011).

GPS data can be used to validate self-reported time-activities, identify activities that participants did not self-report, and provide the basis for follow-up interviews to verify activity patterns and microenvironment characteristics (Bachu et al., 2001; Flamm, 2007). It has been used to supplement over ten state and regional travel surveys to identify the rates and characteristics of underreported trips and respondents who underreport, and to develop "correction factors" for adjustment of trip estimates for travel models (Bricka and Bhat, 2006; Wolf et al., 2003). Results indicate a wide range in the rate of underreported vehicle trips (10–81%) and that this rate was associated with driver, household and trip characteristics (Bricka and Bhat, 2006; California Department of Transportation, 2002). The rate was about 35% for a 2000/2001 travel survey in southern California. Drivers who were in low-income households, in households with more vehicles, were under 25 years of age, had lower educational attainment, or were unemployed tended to have higher rates of underreported trips; shorter trips (under 5 min) and trips for discretionary purposes were more often underreported and the total number of daily trips was associated with higher trip underreporting (Bricka and Bhat, 2006). Non-reported trips and locations in traditional surveys could potentially result in a sizeable underestimation or misclassification of environmental exposures and time spent in microenvironments. For instance, Wolf et al. (2003) estimated that trips identified by GPS tracking that were not reported in travel surveys in four California counties were associated with a 40% underestimation of associated vehicle miles traveled.

3. Methods

3.1. Study design and area

The HCTLS population was a nonrandom sample of adult residents (21–65 years old) in the Wilmington area of the City of Los Angeles, California and the western portion of the City of Long Beach, California (Fig. 1a). These communities are immediately adjacent to the Ports of Los Angeles and Long Beach, are predominantly comprised of low-income and Hispanic residents, and are heavily impacted by nearby port, goods movement, and refinery operations (Houston et al., 2008; Hricko, 2008; Kozawa et al., 2009). The ports of Los Angeles/Long Beach combined are the largest port complex in the United States, carry over 40% of country's imports, and are a major economic "engine" which generates substantial jobs, income and tax revenue (Hricko, 2008; Perez et al., 2009). Despite these benefits, the complex comprises the largest air pollution source in the region and emissions from associated ships, yard equipment, railroads and trucks account for about a quarter of nitrogen oxides, about three quarters of the daily sulfur oxides, and about one tenth of the daily particulate matter in the Los Angeles air basin (South Coast Air Quality Management District, 2007). Air pollution associated with port and goods movement activities in California have been associated with as many as 2400 premature heart-related deaths, over 60,000 cases of asthma symptoms, and more than one million respiratory-related school absences every year (California Air Resources Board, 2006; Lee et al., 2010). HDDTs are of particular concern since they emit high levels of particulate matter (PM) and a complex mixture of gas pollutants with high health risks. Our previous models suggest that local traffic near the port complex contributes almost a fourth of total particulate matter less than 2.5 μm in aerodynamic diameter (PM_{2.5}) in near-port communities and that HDDT traffic contributes significantly to the overall fine particulate concentrations in near-port communities (Wu et al., 2009). Fig. 1b presents our

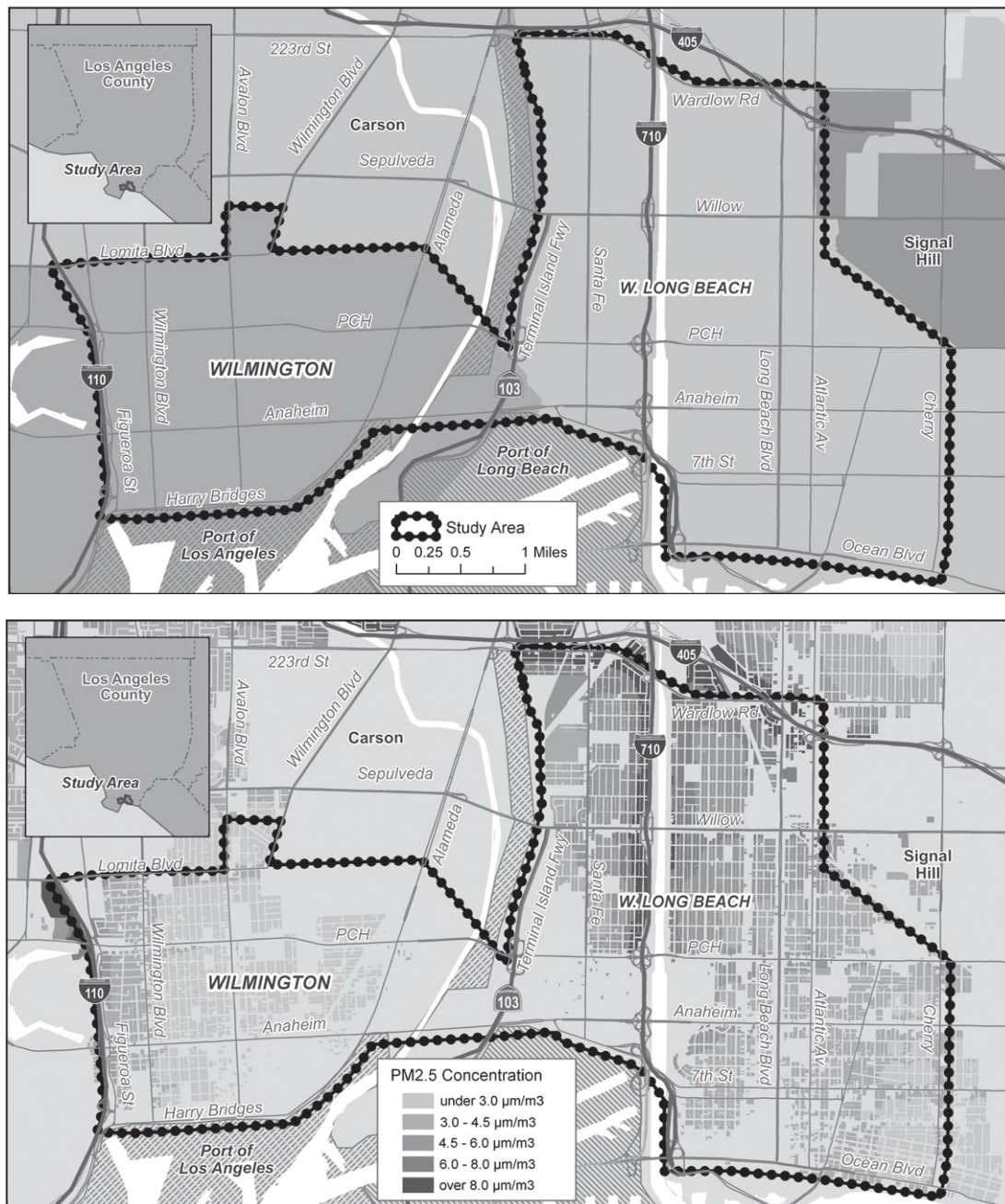


Fig. 1. (a) Study area, Wilmington in Los Angeles and Western Long Beach, (b) modeled concentrations of PM_{2.5} (μm^3) emissions from gasoline and diesel vehicles for residential parcels.

estimates of the concentration of traffic-related fine PM for residential parcels (see Wu et al., 2009 for a description of the methodology).

Over 80% of containers leaving the port complex are transported by HDDTs from the port complex to transloading facilities, off-dock rail transfer yards, or regional and national destinations (Houston et al., 2008). Our participant time-location data tracking occurred between February and June 2008 during a period in which monthly container flows through the port complex were steadily increasing from the drop in container traffic which occurs annually after the holiday delivery period (Port of Long Beach, 2011; Port of Los Angeles, 2011).

The sample size was restricted due to the time and expense of collecting and analyzing highly-resolved individual location data. We recruited participants through contacts with community

health organizations, presentations at adult education classes, informational tables and advertisements in public spaces, and networking through word of mouth. Recruitment, coordination, and interviews were available in both English and Spanish given residents of the study area are predominately Hispanic and Spanish speakers. Participants received grocery gift cards totaling \$50 for their participation which included an in-home baseline survey and training, completion of time-activity logs for 3 weekdays, 10–14 days of GPS location tracking, and an in-home follow-up interview regarding discrepancies between self-reported activities and GPS tracking.

This paper examines the time-location patterns for the 131 days on which 47 of the HCTLs participants adequately recorded their 24-h location patterns using both self-reported activity logs and passive GPS location tracking. Four of the original 51 participants

were eliminated from the analysis because their data for “simultaneous” log-GPS tracking days were incomplete due to GPS device malfunctions or participant failure to carry the GPS or adequately complete activity logs. During the “simultaneous” log-GPS activity tracking days included in the analysis, participants completed a line on the activity log each time they changed location by recording the time and checking whether they were indoors (home, work, school, other), outdoors (walking, biking, other), or in-vehicle (auto, van, or truck, transit, or other) and kept a portable GlobalSat DG-100 GPS device with them during waking hours. These devices were light-weight and were typically carried in a pocket or bag or clipped onto a belt, required nightly charging, and recorded the coordinates of participant locations about every 15 s.

3.2. GPS-enhanced time-location database

We examined GPS patterns using Geographic Information Systems (GIS) to overlay participant GPS coordinate locations over highly resolved and geographically rectified Digital Ortho Quarter Quads (DOQQ) aerial photography for July 2006 from the United States Geological Survey (USGS) in order to compare GPS-derived locations and periods of travel with participant-reported location types and travel modes. Some patterns such as time spent at large facilities and in high-speed travel on major arterials or freeways were readily apparent using DOQQ imagery, but when location types or travel modes were not clear we supplemented our classification of GPS data using online mapping tools such as the “Street View” function of Google Maps (<http://maps.google.com/>). We asked participants in follow-up interviews to identify unreported locations and trips and to clarify travel mode and location types. This process resulted in a highly-resolved 15-s interval spatial database which identified the time participants spent in major microenvironments (indoors, outdoors, and in-vehicle), traveling by mode (walking, biking, on transit, and in-vehicle), and major location types (home/residential, public building, service or retail locations, workplace, restaurant/bar, outdoors, and traveling/waiting outdoors or in an enclosed vehicle). Because of the time required for post-processing GPS data and logistics, follow-up interviews were conducted 2–5 weeks after the monitored days. The resulting GPS-enhanced database integrated time-location data from logs, GPS, and follow-up interviews for 131 “simultaneous” log-GPS tracking days.

3.3. Analysis of unreported locations and trips

We assessed differences between GPS-enhanced data and participant logs for 103 days since logs for these days were sufficient for a meaningful 24-h comparison. Log data were unavailable or unusable for 8 days of the GPS-enhanced data and were unclear or incomplete for 17 days. Participants made errors such as listing multiple times and locations or travel modes per row instead of listing only one time and location or travel mode per row such that patterns were largely indiscernible based solely on log data. We included these 25 days in the final GPS-enhanced database by using information from baseline interviews, available logs, and follow-up interviews. We also excluded data for three additional days in our analysis of unreported locations/travel because participants remained at home on these days.

To compare GPS-enhanced and log data we classified a location as a unique destination regardless of whether the participant was indoors, outdoors or in-vehicle at the location and a trip as the period between locations regardless of travel modes and/or waiting periods between locations. A mother’s walk from-to home to drop her children at school would include one location at home, one trip to school, one location at school, one trip back home, and a second home location. Her route to school counted as one trip even if she

walked to access transit, waited at a bus stop, and rode multiple buses. Her visit to school counted as one location even if she only stopped for a few seconds given it was a purposeful destination.

When comparing logs and GPS-enhanced data, we used as much log information as possible even when participants did not follow instructions to report distinct locations/travel on separate rows. For instance, when a participant listed one time and checked both a location (i.e., “home”) and a travel mode (i.e., “walking”) per row or wrote “drove home” under notes, we assumed she had reported both the location and trip on her log. When a participant listed one row for a trip (i.e., noting the time and checking “transit”) that GPS data reveal and follow-up data confirm was a trip with multiple walking and in-transit segments, we assumed she had reported the entire trip on her log.

We examine the rate of underreporting by location type, location and trip duration, trip travel mode, and travel destination location type, first by examining descriptive statistics and bivariate patterns, and then with a multivariate model.

3.4. Comparison time activity data

We compared the time-location patterns of HCTLS participants with subgroups of the NHAPS survey which is a random sample telephone recall survey conducted by the United States’ Environmental Protection Agency in the continental USA in 1992–1994. NHAPS subjects were contacted by phone and a randomly-selected household member was asked to recount their activities over the 24-h of the previous day. For comparison with HCTLS, we analyzed the time-location patterns of NHAPS respondents between the age of 21 and 65 (5807). Comparisons of time-location patterns between the HCTLS and NHAPS samples were made using an unpaired *t*-test with unequal variance. For comparison, we classified locations in HCTLS and NHAPS data into common location type categories.

3.5. Traffic proximity measures

We identify proximity to heavily-traveled roadways based on traffic volume data from the 2005 Highway Performance and Monitoring System maintained by the California Department of Transportation (California Department of Transportation, 2005). Consistent with previous environmental justice studies on the distribution and impacts of traffic (Houston et al., 2006), participants who were within 200 m of a roadway segment with an annual average daily traffic (AADT) of 50,000 or more, 25,000–49,900, and less than 25,000 vehicles per day, were classified as being in high-, medium- and low-traffic areas, respectively.

Since the study communities are heavily-impacted by port-related HDDT traffic, we measured proximity to truck routes using a novel traffic dataset for the study area previously documented (Wu et al., 2009) which consolidates data from numerous agencies and our original truck counts in the harbor communities (Houston et al., 2008) to identify truck volumes on major arterials and freeways. We classified HCTLS participants who were within 200 m of a roadway with 5% or more HDDT traffic as being near a truck route. Finally, we examine the extent to which underreported locations and travel could result in misclassifications of traffic exposure.

4. Results

4.1. HCTLS and NHAPS time-location patterns

Comparisons of HCTLS and NHAPS activity patterns help assess whether our study’s largely female, low-income, Hispanic, and

immigrant sample spent a disproportionate amount of time in home- or community-based activities in the port-adjacent study area. The national NHAPS sample includes 5807 respondents and the HCTLS sample includes 47 participants. Although the harbor communities of Wilmington and western Long Beach were comprised of 65% Hispanic residents based on 2000 census data (Houston et al., 2008), the HCTLS sample was largely Hispanic (89%), female (85%), and foreign-born (81%) because we were most successful recruiting participants through community and health organizations and daytime education classes which targeted Spanish-speaking residents. In contrast, the NHAPS sample was 7% Hispanic and 54% female. Only about 32% of HCTLS participants were employed compared to about 77% of NHAPS respondents. Roughly three quarters of the HCTLS participants indicated they were homemakers and/or worked at home compared to about a quarter of NHAPS respondents who indicated they were unemployed.

The time-location patterns of HCTLS participants were fairly consistent with those of the NHAPS sample when considered across broad categories (Table 1); they spent about 89% of their time indoors, about 5% of their time in enclosed vehicles, and about 6% of their time outdoors. Of indoor microenvironments, HCTLS participants, however, spent about 12% (~3 h/day) more of their day inside residential locations, about 6% (~1.5 h/day) less of their day inside Public, Service, School, or Workplace locations, and about 3% (<1 h/day) less of their day inside Retail or Restaurant/Bar locations compared to the NHAPS sample. HCTLS participants spent slightly less time outdoors than NHAPS respondents (6% vs. 7%), mainly because they spent less time outdoors of residential locations. This difference could be due in part to differences in

location classification methods given that we were unable to distinguish time on patios or outdoor spaces near buildings from indoor time due to GPS positional error; we generally classified HCTLS participant time after arrival and before departure at residential locations as indoors.

The time-location patterns were most similar between HCTLS participants who were homemakers or worked at home and unemployed respondents in the NHAPS sample. Although there was no statistical difference across samples for time spent inside residential locations, homemaker HCTLS participants did spend slightly more time on average (~1 h) inside Public, Service, School, or Workplace locations than did the unemployed NHAPS respondents. This may reflect that many HCTLS participants were volunteers and/or attended community education classes. Perhaps because we were unable to distinguish time on patios or outdoor spaces near buildings from indoor time due to GPS positional error, homemaker HCTLS participants were found to spend less time outside residential locations. Homemaker HCTLS participants were similar to the unemployed NHAPS sample in terms of the percentage of the day spent traveling (7%).

4.2. Location type by time of day

Fig. 2 compares the location by time of day of all HCTLS participants (Fig. 2a) and unemployed NHAPS adult respondents (Fig. 2b). Over 90% of both groups were indoors before 6:00 and after about 23:00, roughly 75–80% were in an indoor location between about 8:00 and 18:00, and roughly 50% or more of their midday time was spent indoors at residential locations. HCTLS participants appear to have spent less time outdoors at a residence and more time outdoors at other locations in the midday period than the unemployed NHAPS sample, but these differences may be partially due to differences in methods.

Although the HCTLS graph appears somewhat jagged due to the small sample size, it shows there was a spike among HCTLS participants for those leaving home in-vehicle or walking between 7:00 and 8:00 when participants were typically taking household children to school. They spent a much larger portion of their time indoors at Public, Service, School, or Workplace locations between 8:00 and 15:00 than unemployed NHAPS respondents largely because they were involved in community classes and volunteer work at local schools and health education organizations. As may be expected, their time in these locations dropped at about 15:00 when they typically picked up their children from daycare and school. The slight increase in this location type between 18:00 and 20:00 is consistent with the fact that HCTLS participants often left home in the early evening for grocery or retail shopping.

4.3. Unreported locations and trips on participant logs

The enhanced time-location database generated from logs, GPS and follow-up interview data significantly improved the amount and quality of time-location data collected through activity logs alone and provides insights into factors associated with underreported locations and travel. Table 2 compares the locations/travel participants reported on logs to the locations/travel included in the GPS-enhanced data. The 39 participants analyzed occupied 1105 locations and made 980 trips during the 103 days analyzed, or an average of about 11 locations and about 10 trips per day. Overall, about half (49%) of these locations and trips in the GPS-enhanced data were not recorded on participant logs.

Over half (52%) of locations were not reported on logs; participants spent an average of over 3 h in these unreported locations each day. Female participants, participants with under \$25,000 annual household income, participants who reported they worked at home, and participants in households with children under 5 years

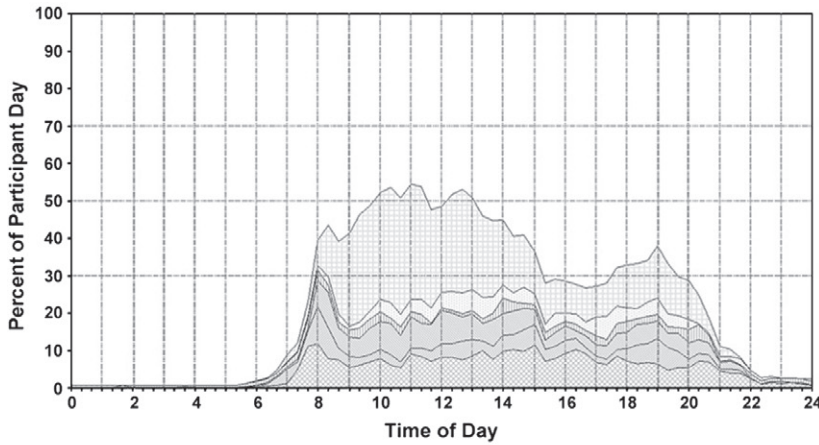
Table 1 Mean percent of day (95% CI) in locations/activities, HCTLS and NHAPS, Age 21–65.

Location type	HCTLS	NHAPS-nation
A. Time by location, all adults age 21–65		
	<i>n</i> = 131	<i>n</i> = 5807
Indoors	89.4 (88.1–90.6)*	86.6 (86.2–87.0)*
Residential	77.5 (75.2–79.8)*	65.6 (65.0–66.1)*
Public, services, school, workplace	9.9 (8.1–11.8)*	16.0 (15.5–16.5)*
Retail, restaurant/bar	1.9 (1.5–2.4)*	5.0 (4.8–5.3)*
Outdoors	5.9 (5.0–6.7)*	7.1 (6.8–7.4)*
Residential	1.0 (0.8–1.3)*	3.0 (2.9–3.2)*
Other	2.7 (2.0–3.4)	2.1 (1.9–2.3)
outdoors traveling or waiting ^a	2.2 (1.7–2.6)	2.0 (1.8–2.2)
Traveling or waiting during travel	6.9 (6.1–7.8)*	8.3 (8.0–8.6)*
Outdoors traveling or waiting ^a	2.2 (1.7–2.6)	2.0 (1.8–2.2)
Enclosed vehicle, traveling or waiting	4.8 (3.9–5.7)*	6.3 (6.1–6.5)*
B. Time by location, unemployed/homemaker^b		
	<i>n</i> = 100	<i>n</i> = 1316
Indoors	89.4 (88.1–90.8)*	87.2 (86.4–87.9)*
Residential	78.7 (76.3–81.2)	78.3 (77.4–79.2)
Public, services, school, workplace	8.7 (6.9–10.5)*	5.0 (4.5–5.6)*
Retail, restaurant/bar	2.0 (1.5–2.6)*	3.8 (3.5–4.2)*
Outdoors	5.9 (5.0–6.8)*	7.6 (6.9–8.2)*
Residential	1.1 (0.8–1.4)*	4.4 (3.9–4.8)*
Other	2.4 (1.7–3.0)	2.0 (1.6–2.3)
Outdoors traveling or waiting ^a	2.4 (1.9–2.9)*	1.3 (1.0–1.5)*
Traveling or waiting during travel	7.1 (6.1–8.1)	6.6 (6.1–7.0)
Outdoors traveling or waiting ^a	2.4 (1.9–2.9)*	1.3 (1.0–1.5)*
Enclosed vehicle, traveling or waiting	4.7 (3.6–5.8)	5.3 (4.9–5.7)

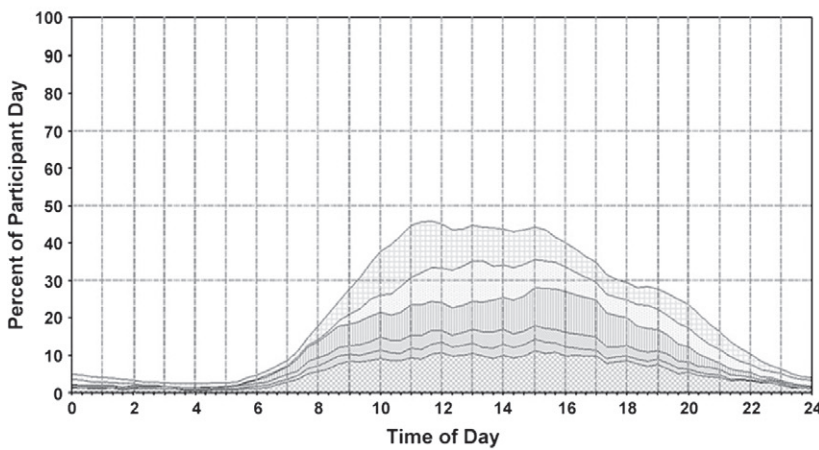
^a Time Outdoors traveling or waiting is included in both outdoors and traveling categories and tabulations.

^b The unemployed/homemaker category includes NHAPS respondents who were unemployed and HCTLS participants who were homemakers and/or worked at home.

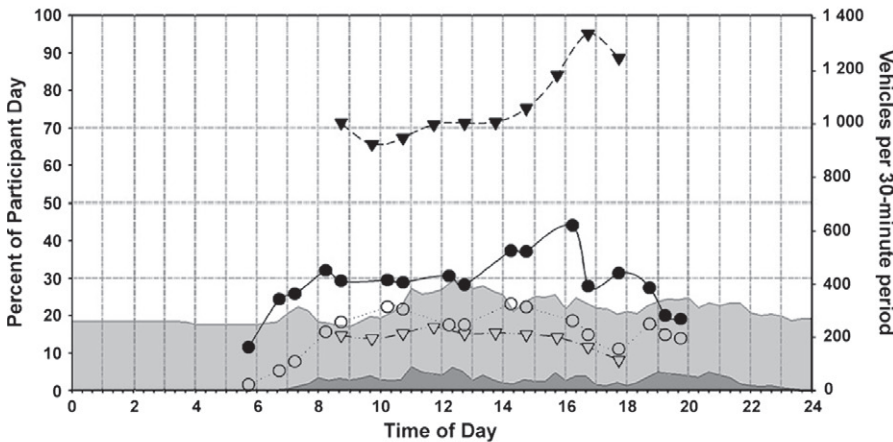
* Denotes the difference between HCTLS and NHAPS is significant (unpaired *t*-test, *P* < 0.05).



(a) Location type by time of day, HCTLS, Adults Age 21-65 (N=131 Days)



(b) Location type by time of day, NHAPS, Unemployed Adults Age 21-65 (N=1,316 Days)



(c) Proximity to major roadways by traffic volume, HCTLS Adults Age 21-65 (N=131 Days), and sample arterial traffic volumes on truck routes in study area by time of day

Location type

- Indoors - Residential
- ▤ Indoors - Public, Service, School, Work
- ▥ Indoors - Retail, Restaurant
- ▦ Outdoors - Residential
- ▧ Outdoors - Other
- ▨ Outdoors - Traveling/Waiting
- ▩ Enclosed Vehicle - Traveling/Waiting

Traffic volume within 200m

- Low Traffic (<24 999 AADT)
- ▤ Medium Traffic (25 000-49 999 AADT)
- ▥ HighTraffic (>=50 000 AADT)

Traffic on major arterial truck routes

- Total Traffic, Truck Route A
- Diesel Traffic, Truck Route A
- ▲ Total Traffic, Truck Route B
- ▽ Diesel Traffic, Truck Route B

Note: Location pattern graphs represent 20-minute average for illustration purposes. HCTLS patterns are based on the GPS-enhanced activity database. AADT=Annual Average Daily Traffic

Fig. 2. (a) Location type by time of day, HCTLS adults. (b) Location type by time of day, NHAPS unemployed adults. (c) HCTLS participant proximity to major roadways by traffic volume, and diurnal traffic patterns on two major arterial truck routes.

old had a slightly higher rate of unreported locations and participants who attended school or worked away from home had a slightly lower rate of unreported locations. Households with no car had significantly lower rates of unreported locations than households with a car. Participants who had over 15 location

arrivals per day had a higher rate of unreported locations than those who had under 10 location arrivals per day. Even though only about 21% of home arrivals were not listed on logs, this time at home (usually during the day) accounted for a large portion of time in unreported locations (about 1.5 h/day). Participants did

not report 70% or more of arrivals at other residential, school (including trips to drop-off and pick-up children), and retail and community locations; combined these locations accounted for about 1 h/day of time spent in unreported locations. Over three-quarters of locations occupied for less than 15 min were unreported and totaled just under 20 min/day. Although about a third of locations occupied for 15 min or more were unreported, participant time in these locations lasted much longer, about 3 h/day.

Just under half (47%) of participant trips in the GPS-enhanced data were not recorded on participant logs; these unreported trips lasted on average for about half an hour (0.6 h/day). Participants in households with less than \$25,000 annual income, with more adults, or with more than three household vehicles were more likely to have unreported trips. About 54% of walking or biking trips were unreported, about 44% of non-transit vehicle trips were

unreported, and about 19% of transit trips were unreported. This lower rate of underreporting of transit trips could be in part due to the inclusive method we used to classify transit trips. That is, a participant's transit trip was a "match" with GPS data even if she only reported one segment of a longer trip with multiple connections. About 60% of trips destined for home or other residential locations were unreported and totaled about 20 min/day. About 50% of trips less than 15 min were unreported and also totaled about 20 min/day.

We use logistic regression models to identify the independent contribution of various factors to underreporting. The model assumes that the probability (P_{UR}) that a location or trip was unreported is a nonlinear function of the independent variables and takes the following form:

$$P_{UR} = e^{a+bx} / (1 + e^{a+bx}),$$

where a is a constant, b is a vector of parameters, and x is a linear combination of $f(P_i, H_i, L_i, T_i)$.

P_i is a vector of participant characteristics including sex, educational attainment, work status and school status; H_i is a vector of household characteristics including household income and the number of persons and vehicles in the household; L_i is a vector of location characteristics including arrival time at a location, amount of time spent at a location, and location type; T_i is a vector of trip characteristics including trip start time, length, destination type, and travel mode.

Table 3 presents the results of our logistic regression models. Personal, household, and location characteristics were related to the probability of underreporting a location. Female participants and participants in households with more vehicles or under \$25,000 annual income were more likely to underreport locations they visited, and participants with lower educational attainment or who worked away from home or attended school were less likely to underreport locations. Locations where participants spent less time were more likely to be underreported. Home locations were less likely to be underreported while locations at other residential locations and retail and community-oriented locations were more likely to be underreported. A higher number of daily trips was positively associated with higher rates of trip underreporting. Participants with more adults were more likely to underreport trips and participants who worked away from home were less likely to underreport trips. Walking trips were more likely to be underreported than the omitted category, vehicle trips. Trips to school, service, and recreational locations were less likely to be underreported.

4.4. Traffic exposure and unreported locations/trips

We examined the implications of participant diurnal location and travel patterns on their traffic exposure given the study area is heavily impacted by as many as 16,000 HDDTs which serve the Ports of Los Angeles and Long Beach (Port of Long Beach and Port of Los Angeles, 2006), resulting in 500–600 HDDTs per hour on major arterials in the study area (Houston et al., 2008). Fig. 2c displays HDDT volumes on two major arterial truck routes based on our original truck counts to exemplify diurnal traffic patterns within our port-adjacent study area (Houston et al., 2008). Truck route A is a grade-separated roadway immediately adjacent to schools, a daycare center, and a veteran housing complex on which HDDTs transport containers to-from the port complex and an intermodal rail facility. Truck route B is a major surface street immediately adjacent to restaurants, commercial strips, and residences on which container HDDTs transport containers to-from the port complex and a major goods movement freeway. Trucks often park, queue, or stop for amenities on or near truck route B.

Table 2
Unreported locations and trips in GPS-enhanced data compared to participant self-reported diaries.

	Locations		Trips	
	Av. daily locations	Percent unreported locations	Av. daily trips	Percent unreported trips
Total	10.7	52%	9.5	47%
<i>Locations/trips per day</i>				
Under 10 locations	3.2	46%	3.3	43%
10–14 locations	4.4	50%	4.3	49%
Over 15 locations	3.1	60%	1.9	48%
<i>Personal/household Characteristics</i>				
Female	8.7	53%	7.7	47%
Less than high school educational attainment	4.2	51%	3.7	50%
Household income under \$25,000	5.2	56%	4.7	49%
Works away from home	3.4	44%	3.0	43%
Works at home	9.0	54%	8.0	48%
Attends school	3.6	46%	3.1	44%
Total household persons 0–5 years old	5.0	54%	4.5	48%
Total household persons 6–17 years old	2.9	48%	2.5	44%
Total household persons, 18 or more years old	0.8	49%	0.8	55%
No household auto	0.9	38%	0.8	46%
1 household auto	3.9	55%	3.5	50%
2 household autos	4.3	50%	3.8	42%
3 or more household autos	1.7	57%	1.5	54%
<i>Location/trip start time</i>				
Before 12:00	4.6	49%	3.7	44%
12:00–17:00	3.6	54%	3.4	47%
17:00–23:99	2.6	53%	2.4	52%
<i>Location/trip duration</i>				
Under 5 min	2.3	87%	3.6	52%
5–14 min	2.0	76%	4.4	47%
Over 15 min 6.5	32%	1.4	35%	
<i>Location/destination type</i>				
Home	3.9	21%	2.8	59%
Other residence	1.2	81%	1.0	58%
School (incl. drop-off/pick-up)	1.4	70%	2.1	27%
Work	0.5	32%	0.5	50%
Restaurant/bar	0.5	58%	0.5	52%
Retail and community	2.0	74%	1.6	53%
Service (medical, bank, etc.)	0.9	67%	0.7	36%
Park/recreation/other	0.4	66%	0.3	21%
<i>Travel mode</i>				
Walking, biking			3.2	54%
Vehicle travel			6.0	44%
Transit travel (incl. access/waiting)			0.3	19%

Table 3
Logistic regression results on the probability that a location or trip was unreported.

Independent variables	Probability a location was unreported		Probability a trip was unreported	
	Model 1 Coefficient sig.	Model 2 Coefficient sig.	Model 3 Coefficient sig.	Model 4 Coefficient sig.
Intercept	−2.97***	−1.65***	−1.70***	−1.07***
<i>Locations/trips per day</i>				
Total locations	0.05 ⁺			
Total trips			0.05 ⁺	0.05**
<i>Personal/household characteristics</i>				
Female (1/0)	0.78**	0.66**	−0.25	
Less than high school educational attainment (1/0)	−0.74**	−0.64**	0.29	
Household income under \$25,000 (1/0)	1.33***	1.05***	0.06	
Works away from home (1/0)	−0.85***	−0.75***	−0.41 ⁺	−0.48**
Works at home (1/0)	−0.44		0.07	
Attends school (1/0)	−0.47*	−0.50**	0.14	
Total household persons 0–5 years old	−0.06		0.06	
Total household persons 6–17 years old	0.03		0.11	
Total household persons, 18 or more years old	0.32 ⁺		0.25 ⁺	0.31**
Total household autos	0.20 ⁺	0.28***	0.16	
<i>Location/trip start time</i>				
12:00–17:00 (1/0)	−0.02		0.05	
17:00–23:99 (1/0)	−0.05		0.22	
<i>Location/trip duration</i>				
Under 5 min (1/0)	2.70***	2.70***	0.36	
5–14 min (1/0)	1.82***	1.86***	0.30	
15–59 min (1/0)	0.78***	0.73***		
<i>Location/destination type</i>				
Home (1/0)	−0.68 ⁺	−0.98***	0.01	
Other residence (1/0)	1.17**	0.84**	−0.09	
School (incl. drop-off/pick-up) (1/0)	0.42		−1.40***	−1.29***
Retail and Community (1/0)	0.88**	0.59**	−0.25	
Service (medical, bank, etc.) (1/0)	0.25		−0.98**	−0.85**
Park/recreation/other (1/0)	1.00 ⁺		−1.76***	−1.61***
<i>Travel mode</i>				
Walking, biking (1/0)			0.51**	0.53***
Transit travel (1/0)			−0.67	
Max-rescaled R-square	0.48	0.47	0.17	0.14
N	1105	1105	980	980

* Significance: $p < .05$.

** Significance: $p < .01$.

*** Significance: $p < .001$.

Table 4
Mean percent of day in proximity to major traffic and heavy-duty diesel truck routes, HCTLs.

Location type	Traffic volume within 200 m					Truck route within 200 m		
	Low Traffic	Medium Traffic		High traffic		No nearby truck route	Nearby truck route	
		% of day	% of day	Hours (unreported hours)	% of day		Hours (unreported hours)	% of day
Total	79.7	18.2	4.4 (0.7)	2.1	0.5 (0.1)	82.9	17.2	4.1 (0.5)
<i>Indoors</i>	81.9	17.3	3.6 (0.5)	0.8	0.2 (0.0)	83.0	17.0	3.6 (0.3)
Residential	84.6	15.1	2.7 (0.1)	0.3	0.1 (0.0)	81.9	18.2	3.3 (0.2)
Public, services, school, workplace	66.4	30.4	0.7 (0.2)	3.1	0.1 (0.0)	94.5	5.5	0.1 (0.1)
Retail, restaurant/bar	56.4	35.8	0.2 (0.1)	7.8	0.0 (0.0)	71.6	28.4	0.1 (0.1)
<i>Outdoors</i>	72.0	21.2	0.3 (0.1)	6.8	0.1 (0.0)	84.2	15.8	0.2 (0.1)
Residential	75.5	23.6	0.1 (0.0)	0.9	0.0 (0.0)	94.6	5.4	0.0 (0.0)
Other	59.6	27.3	0.2 (0.1)	13.1	0.1 (0.0)	79.9	20.1	0.1 (0.1)
Outdoors traveling or waiting	86.2	12.2	0.1 (0.0)	1.6	0.0 (0.0)	84.6	15.4	0.1 (0.0)
Traveling or waiting during travel	64.2	23.6	0.5 (0.2)	12.2	0.2 (0.1)	80.3	19.7	0.4 (0.2)
Outdoors, traveling or waiting	86.2	12.2	0.1 (0.0)	1.6	0.0 (0.0)	84.6	15.4	0.1 (0.0)
Enclosed vehicle, traveling or waiting	55.9	27.9	0.4 (0.2)	16.1	0.2 (0.1)	78.7	21.3	0.3 (0.1)

AADT = annual average daily traffic.

Low traffic is <24,999 AADT; Medium traffic is 25,999–49,999 AADT; High traffic is $\geq 50,000$ AADT.

These patterns raise public health concerns given that diesel-related pollutant concentrations of black carbon, nitric oxide, ultrafine particles, and particle-bound polycyclic aromatic hydrocarbons are frequently elevated within 200 m of these truck routes (Kozawa et al., 2009).

Fig. 2c illustrates that the time HCTLs participants spent near medium- or high-traffic roadways changed very little over the course of the day and fluctuated between 20% and 25% between 8:00 and 22:00 except for when it approached 30% between 11:00 and 14:00. Our traffic counts on two major arterial truck

routes (Fig. 2c) confirm that volumes were highest in these day-time periods, particularly in the evening commute period from about 15:00–18:00.

Although no HCTLS participants lived within 200 m of high-traffic freeways, nine participants lived near a major arterial with medium-traffic. These nine participants spent about 81% of their time (>19 h/day) in a medium- or high-traffic area, whereas HCTLS participants as a whole spent 20% of their time (~5 h/day) in a medium- or high-traffic area (Table 4). About 50 min of the 5 h/day participants spent near a medium- or high-traffic area were during locations/trips which were not reported by participants in their activity diaries. About 30 min of this time was at indoor locations, and about 10 min occurred during unreported periods spent traveling or waiting in vehicle. The eight HCTLS participants who lived within 200 m of a truck route spent about 79% of their time (~19 h/day) near a truck route compared to about 17% of their time (~4 h/day) for HCTLS participants as a whole. About 30 min of these 4 h/day near a truck route were in unreported locations/trips and largely occurred during indoor and in-vehicle periods.

5. Discussion and conclusion

The HCTLS is the first study to integrate participant-reported activity log and passive GPS tracking with follow-up interviews to document the time-location patterns of a low socioeconomic status (SES) immigrant group in a major goods movement corridor. This focus is particularly important given that available national and regional time-activity data provide limited insights into the activity and travel patterns of low SES populations and residents of disadvantaged neighborhoods. Participants were largely Hispanic women and homemakers who spent about 89% of their time indoors, about 5% of their time in enclosed vehicles, and about 6% of their time outdoors. Using these broad location categories, participant time-location patterns were fairly consistent with those of adult respondents to previous national random telephone recall surveys (Klepeis et al., 2001). Although many HCTLS participants were active volunteers and/or attended community education classes, they spent a significantly higher proportion of their time indoors at home than NHAPS respondents (78% vs. 66%). In this regard, HCTLS participants were most similar to unemployed adult respondents in the national NHAPS sample.

Unlike previous location-based studies which assessed traffic exposure for one location type such as home, school, and childcare centers (Appatova et al., 2008; Green et al., 2004; Gunier et al., 2003; Houston et al., 2006, 2004), we used 15-s interval GPS-enhanced time-location data to assess traffic exposure across daily locations and results suggest facility, roadway, and land use types which are of the greatest concern for mitigation efforts. Of the 5 h that HCTLS participants spent in high traffic areas on average, about 3 h/day were inside a residence and about 1 h/day was inside a public, service, retail, or workplace location. Potential exposures in these locations could be of particular concern given that 50–70% of participants were inside a residence and 20–40% of participants were within a public, service, school, or workplace location in the morning, mid-day, and early evening periods when traffic on arterials and freeways tend to be at their highest levels. Smaller retail, commercial, and public land uses tend to be located along major arterials in the study area and could potentially be important microenvironments for overall exposure to vehicle-related air pollution. Previous estimates suggest that spending 1.5 h/day in-vehicle, an amount consistent with the average in-vehicle time of the NHAPS sample in the current study, could be associated with about 33–45% of total daily exposure to ultrafine particles (Fruin et al., 2008) and about 30–55% of total daily exposure to diesel exhaust particulate matter (Fruin et al., 2004).

Although HCTLS participants spent only about 1.2 h/day on average in-vehicle, their in-vehicle time could potentially be an important microenvironment for overall exposure to vehicle-related pollutants since they spent 40 min/day of in-vehicle time in high-traffic areas.

We found that GPS activity databases when enhanced by participant diary and follow-up data offer improvements over conventional time-location surveys by providing a nearly continuous spatial database that can be used to estimate exposure on smaller time intervals based on proximity to pollution sources and concentrations over the course of the day. Although it was beyond the scope of our study to measure or model individual air pollution exposure, we demonstrated the benefit of highly resolved diurnal location-exposure data by using proximity-based measures of traffic exposure. Given our small sample size, we were unable to assess how comparable the time-location and traffic exposure patterns of our participants were to those of the larger community. Our sample of largely unemployed or partially employed women with daily childcare, household, and volunteer obligations likely spend more time within the study communities than residents who commute elsewhere for full-time jobs. In this sense, our sample may represent residents who are among the most adversely impacted by traffic exposures during peak traffic and container movement periods in this port-adjacent community. Our findings are also limited in that we analyze only 2–3 days of time-location patterns for each participant and our results may only partially represent participant routine activities and travel.

Despite our limited sample size and monitoring period, our analysis of unreported locations and trips on exposure estimates has important implications. Unlike traditional time activity studies which require participants to report activities every 15 or 30 min (Klepeis et al., 2001) and traditional travel surveys which require participants to record details of every trip (Bricka and Bhat, 2006; California Department of Transportation, 2002), our participant activity diary required participants to record activities every time they moved between microenvironments. Although this approach provided greater temporal resolution necessary for syncing reported activities with our 15-s GPS data, our results may not be directly comparable to previous studies. Analysis of travel surveys from four California counties compared GPS vehicle tracking to travel diaries and suggested that respondents did not report 18–40% of vehicle trips (California Department of Transportation, 2002). To our knowledge, only two studies in the exposure assessment literature have used GPS tracking to evaluate participant-reported activities. Phillips et al., 2001 identified short unreported trips on activity logs during 16 GPS trials with participants aged 21–55 years old in the Oklahoma Urban Air Toxics Study. Elgethun et al., 2007 used GPS tracking to determine that parents of 31 children aged 3–5 years in Seattle, Washington misclassified time location patterns on diary timeline about 48% of the time, and that parents in Spanish-speaking households were more likely to misreport time-locations. Even though our methods and study population differed in significant ways, this rate is very similar to the underreporting rate among HCTLS participants (49%).

Participants did not report nearly half of the location/trips identified in the GPS-enhanced data on their activity diaries, resulting in about 3 h/day in unreported locations and 0.6 h/day on unreported trips. Self-reported data missed about 50 min of heightened air pollution exposures during the 5 h/day on average participants spent in high-traffic areas and about 30 min during the 4 h/day near truck routes. Consistent with previous findings (Bricka and Bhat, 2006), results of our multivariate analysis indicate that the probability of a location/trip being underreported was systematically correlated with participant and location/trip characteristics. The probability of a location being unreported was higher for community-oriented and non-home residential locations, and for

female participants, participants in a household with under \$25,000 annual income, and participants in a household with more vehicles. The probability of a trip being unreported was higher for walking trips and trips to school, service, and recreational locations, and for participants with less than a high school education. The level of the unreported locations and trips in our sample was surprisingly high, and the non-randomness of this phenomenon was statistically significant. Given that the level of the unreported locations and trips in our sample was surprisingly high and the non-randomness of this phenomenon was statistically significant, current methods of estimating traffic exposure could be downwardly biased. This bias cannot be corrected by a simple adjustment factor because it varies by trip, location, and individual characteristics.

Findings provide a refined perspective on the impacts of traffic in near-port communities and inform transportation and land use strategies to mitigate air pollution impacts in goods movement corridors. Future assessments of traffic exposure in these communities should consider the impact of the PierPass program, which provides incentives to shift container traffic to nights and weekends through a traffic mitigation fee during peak hours (Houston et al., 2008). This program could have significant impacts on the timing and duration of HDDT traffic exposure patterns given we found that the time-location patterns of near-port residents vary substantially across the day. Although our proximity-based traffic exposure measure did not directly account for near-roadway pollution concentrations, the Clean Truck Program adopted as part of the San Pedro Bay Ports Clean Air Action Plan could significantly alter the level and composition of near-roadway HDDT-related air pollution if it is successful in ensuring that all HDDTs entering the port complex by 2012 comply with “cleaner” 2007 HDDT emission standards (Port of Long Beach and Port of Los Angeles, 2006). Although less than 20% of containers leave the port complex by rail and per-container rail air pollution emissions are lower than per-container HDDT emissions (Houston et al., 2008; Lee et al., 2010), railroad sector air pollution also raises concerns over community impacts (Rahai, 2008; You et al., 2010). Understanding the intersection of time-location patterns and exposure to rail-related air pollution could be particularly important if the proportion of containers traveling to-from the port complex on rail increases (Lee et al., 2010).

Our experiences with participants reiterated that residents of port-adjacent communities are very concerned over the potential health effects of port- and truck-related air pollution, but most seemed to have only general knowledge about the potential sources, dispersion patterns, and harmful impacts of air pollution. Effective interventions to reduce exposure in these communities will require more pollution and activity monitoring as well as more extensive public outreach so that residents of goods movement corridors can be more effective partners in developing solutions to air pollution problems in their community.

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