Integrating activity spaces in health research: Comparing the VERITAS activity space questionnaire with 7-day GPS tracking and prompted recall

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Abstract 150 words

Background: Accounting for daily mobility allows assessment of multiple exposure to environments. This study compares spatial data obtained (i) from an interactive map-based questionnaire on regular activity locations (VERITAS) and (ii) from GPS tracking.

Methods: 234 participants of the RECORD GPS Study completed the VERITAS questionnaire and wore a GPS tracker for 7 days. Analyses illustrate the spatial match between both datasets.

Results: For half of the sample, 85.5% of GPS data fell within 500 meters of a VERITAS location. The median minimum distance between a VERITAS location and a GPS coordinate ranged from 0.4 m for home to slightly over 100 m for a recreational destination.

Conclusions: There is a spatial correspondence between destinations collected through VERITAS and 7-day GPS tracking. Both collection methods offer complementary ways to assess daily mobilities, useful to study environmental determinants of health and health inequities.

Keywords: GPS, VERITAS, Activity locations, Activity space, multiple exposures

1. Introduction

The notoriety of the “local” [1] or “residential trap”[2] within the discipline of place and health research has led to an increasing interest in the role of spatial mobility for disentangling the complex relationships linking environmental contexts to health. Because individuals, through daily mobility, access locations lying exterior to the boundaries of their residential neighborhood, an exclusive focus on local residential neighbourhoods leads to a misrepresentation of daily environmental exposure [3]. Accounting for participants’ daily mobility may help explain previously elusive social and spatial variations in health behaviors, health status, and health inequalities [4]. This in turn may help to identify causal pathways linking environmental conditions to population health.

A variety of methods exist to collect spatial information on individual's mobility including qualitative methods [5-7], mobility surveys [8-10], activity space questionnaires [11-15], and global positioning systems (GPS) receivers [16-19].

GPS tracking is increasingly being used, sometimes in combination with accelerometers [16, 17, 20], heart rate, or other sensors [21]. GPS data can further be used to locate complementary qualitative data such as perceptions (momentary assessment) while providing an objective account of travel, activity locations [22], or, potentially, social connections [23]. Whereas GPS trackers generate fine-grained spatial and temporal location information, a number of limitations exist. For now, GPS has most often been used within relatively short time frames (7-10 days), although potential for much longer data collection periods exist, especially through the use of smartphone applications [24]. Missing data remains an issue – mainly due to limitations in battery life, loss of signal when inside buildings or underground, or simply compliance problems in wearing or recharging a GSP tracker. The sheer amount of GPS data makes it further relatively complex to process and it can also be difficult to collect GPS data for larger samples [25].

New novel map based electronic questionnaires have provided an alternative method of data collection that unlike the GPS target the identification of regular destinations that are visited by the individuals over longer periods of time, capturing notions of activity space. As an example, the VERITAS questionnaire [26] couples inquiries about activity locations with interactive mapping tools, allowing rapid geolocation of regularly visited places by participants. Such questionnaires can furthermore be adapted to specific research questions, and allow qualitative assessment of places, or delimitation of areas of significance such as perceived residential neighborhoods [27, 28]. Complementary questions regarding with whom people visit places further allows to generate participants' spatialized social network [23].

Whereas the interest and use of both interactive map-based questionnaire and GPS tracking are rising, no study has compared the spatial information obtained from both types of sources. Whereas the former is self-reported and mainly collects information on regular destinations, the latter is generally considered 'objective' (i.e. bias-free), and provides detailed daily mobility information. While both data sources are different in nature, they both provide rich information on daily mobility patterns and are increasingly being used in studies interested in health and place. . This study analyses how spatial information obtained from such a map-based questionnaire, VERITAS, compares with 7-day GPS tracking.

2. Methods

2.1. Study design and sample: the RECORD GPS Study

Some 234 participants were recruited for the RECORD GPS study. This sample is a subsample of the second wave of the RECORD study, a study designed to investigate environmental determinants of territorial disparities in health, in the Paris region. The RECORD study included adults aged 30 to 79 at baseline (2007-2008) that had received a free preventive medical check-up offered by the French National Health Insurance System every five years, in four centers of the Centre IPC, in the Ile-de-France region [29]. Some 410 participants responding to the questionnaire during wave two of the RECORD cohort study (2011-12), were invited to participate in the GPS Study, and 234 accepted and completed the data collection. No compensation was provided for participation.

2.2. Data collection

VERITAS questionnaire: RECORD participants completed the VERITAS questionnaire [26], an interactive map survey designed to collect data on the destinations they regularly visit. The questionnaire was administered by interviewers in front of a computer where the respondent could see the screen – and map. Participants were asked to identify the locations of places where they performed regular activities in a fixed order (e.g. home, work, shopping, recreation, restaurant, etc.). For most activity types, participants were invited to report destinations they visit at least once a week. Exact visiting frequency was further provided (n times per day, week or month). No particular recall period, such as “over the past 6 months,” was specified. The once-a-week minimum frequency did not apply to: workplaces, for which participants were asked to geolocate locations they would spend at least one third of their working time; supermarkets, for which a minimal frequency of once a month was asked; and no minimal frequency was required for regular bank, post office, and hair salon/barber. VERITAS allows to identify the same location for different purposes (e.g. work location can be home). Further details on the VERITAS questionnaire applied in the RECORD cohort study can be found in Chaix et al. 2012.

GPS data: Participants were instructed to wear a GPS receiver (QStarz BT-1000X, company-reported spatial accuracy: 3 meters) and a tri-axial accelerometer (Actigraph GT3X) at the hip at all times, except when sleeping or when in contact with water, for a continuous period of seven days. They were also given a USB cord with a charger and asked to recharge the device while they slept. GPS sampling frequency was set to 1 location every 5 seconds. On the second day of data collection, a phone call was made for quality control purposes and to encourage compliance. A second follow-up call was made during the last day of data collection to remind participants to return the device using a prepaid postage box.

Upon reception of the GPS devices, raw GPS data were processed using a kernel-based algorithm [30]. Resulting locations, trips and timetables for each day were sent to the participant and uploaded to an in-house developed online MWM (Mobility, Web, Mapping) application, which was used for the prompted recall survey.

Prompted recall survey: Participants received paper copies of maps depicting GPS tracks, detected activity locations, and corresponding timetables, for each of the seven days of tracking a few days after returning the device. A prompted recall computer-assisted phone interview asked them to a) confirm/infirm detected activity locations and trip segments or add missing visited locations or trips; b) correct corresponding beginning and end times, and c) indicate trip modes. Corrections were directly entered in the MWM application.

2.3. Measures

VERITAS questionnaire: The VERITAS locations were classified into 6 categories: home, work, transport, and shopping, social, and recreational activities. The work category can include multiple work places. Transport designates the public transportation hubs or stations regularly visited by a participant. The shopping category is composed of retail food stores (e.g. bakery, supermarket, meat market), and services (e.g. banks, post offices, hairdressing salons). The social category includes locations where participants visited friends, and locations where they accompanied dependents. Finally, the recreational category included sports, cultural and/or other community activities.

GPS tracks: Raw 7-day GPS tracks were split into seven 24-hour tracks (split time = 03:00 in the morning) and processed using a validated kernel-based algorithm [30, 31]. The algorithm generates a kernel density surface from all GPS data points and detects ‘peaks’ as activity locations for which time-tables of presence are then generated. Linear interpolation of missing data is performed between consecutive GPS points if less than an hour has passed between the collections of both points, or if the points are not more than 100 meters apart. Output data includes identification of activity locations, trips, and corresponding timetables. The following algorithm parameters were applied: kernel bandwidth of 100 m and elimination of data points with HDOP (Horizontal Dilution of Precision) value higher than 6.. Full details of the processing algorithm and validation can be found in Thierry et al. 2013.

Total GPS time was evaluated by summing the time elapsing between each GPS fix and its immediate follower, which, in most of the cases, amounted to the sampling rate (1 fix every 5 seconds). However, longer time periods were obtained when the GPS signal had dropped, often due to participants entering an indoor location. In these cases, as explained above, missing data was imputed using the last valid GPS fix.

2.4. Analyses

Temporal analyses: We computed the participant’s proportion of GPS time spent within 100, 250, 500 and 1000 meters buffers of their VERITAS locations. Such buffer sizes have been used before in the literature. Using the same buffer distances, the amount of time spent within (1) home range, and, if not within home range, within (2) work range, and if not within work range, within (3) other locations range. Statistics were computed separately for participants with (n=124) and without (n=110) employment, because people who work may display more regular mobility patterns. Furthermore, computation of the proportion of total tracking time spent within the buffer distances and closest to each VERITAS location allowed providing proportion of time spent within the defined range and either being closer to home or to a non-home activity location.

Proximity analyses: Proximity computations were done by calculating the shortest distance between each of the participants' VERITAS locations and their GPS track, and the shortest distance between each VERITAS location and the closest activity location detected by the GPS algorithm and further categorized through prompted recall.

Activity space overlap analyses: We compared activity spaces derived from VERITAS and GPS locations using two spatial metrics that have been used before to describe activity spaces [3, 32, 33]: a convex hull – providing the minimal convex polygon covering all locations, and a two standard deviational ellipse – providing a more general overview of the spatial distribution and orientation of data points. We compared the size and spatial overlap each of these metrics using (1) all VERITAS locations, and (2) all valid GPS fixes. Standard deviational ellipses were further weighted by the frequency of visit for the VERITAS locations and by time for the GPS coordinates.

3. Results

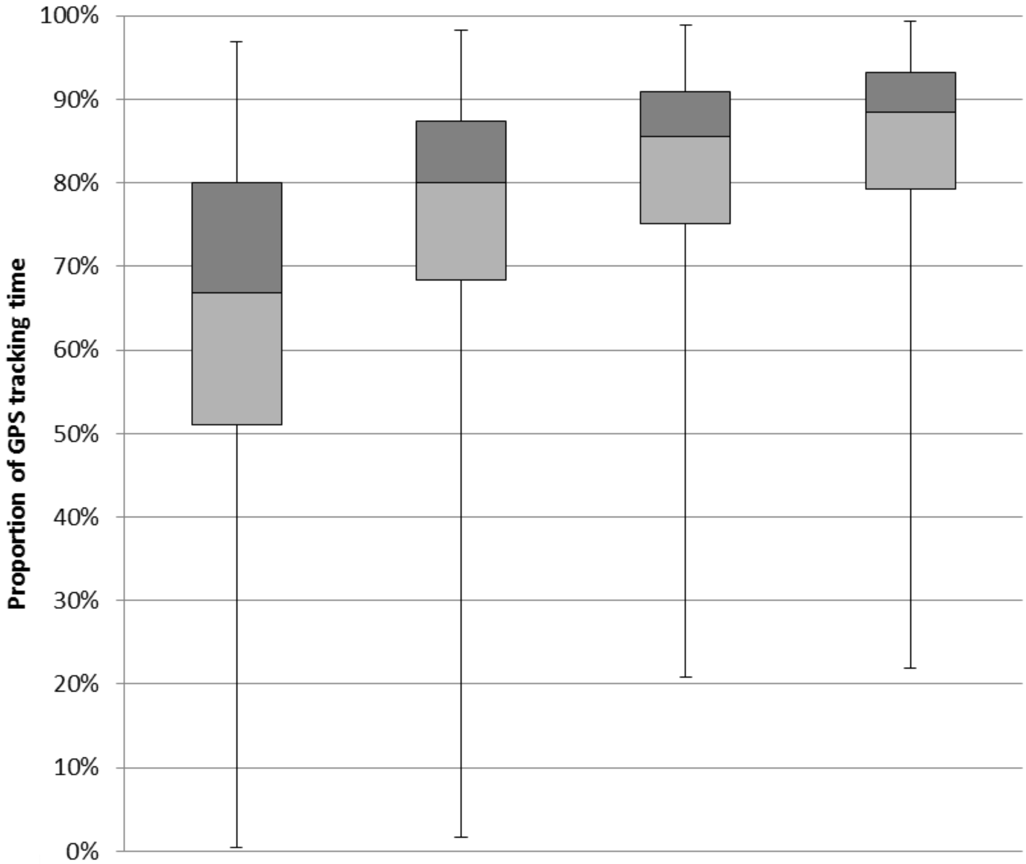
3.1. Sample description

Of the 410 RECORD cohort participants invited to take part in the RECORD GPS study, 234 agreed. There was no difference between those who refused and those who agreed, except for employment status, unemployed people being over-represented among those who refused to participate (8.1%, CI 4.5-13.3 vs 2.1%, CI 0.7-4.8 who agreed), as for people living alone (31.4% refused, CI 24.6-38.9, 22.7% agreed, CI 17.5-28.5). The sample was 62.8% male with a mean age of 57.8 years (SD=11.6, range: 35-83) and 42.7% of participants had post-secondary educational attainment. Table 1 provides descriptive statistics for VERITAS and GPS data. Each participant reported between 4 and 32 regular destinations in the VERITAS questionnaire for a total of 3,548 locations (mean of 15.1 destinations, SD: 5.3). Among the 234 participants, 124 (29%) reported having at least one work destination where they spend 30% or more of their working time. The median total collection time of valid GPS data (excluding interpolated data) covered 71.4% of the total survey time, with a maximum of 99.2% and a minimum of 4.4%. In average, participants had 67.8 data gaps of 2 minutes and more, with an average time of 52 minutes and 48 seconds for which participants GPS data was not available.

Table 1 . Descriptive statistics, VERITAS and GPS data, by employment status

	TOTAL (234)		EMPLOYED (124)		UNEMPLOYED (110)	
VERITAS	Number of respondents reporting one or more activity destination as…	For those reporting one, average distinct number of destinations categorized as…	Number of respondents reporting one or more activity destination as…	For those reporting one, average distinct number of destinations categorized as…	Number of respondents reporting one or more activity destination as…	For those reporting one, average distinct number of destinations categorized as…
	n (%)	n (SD)		n (SD)		n (SD)
...Home	234 (100)	1 (0)	124 (100)	1 (0)	110 (100)	1 (0)
...Work	124 (29.0)	1.12 (0.45)	124 (100.0)	1.12 (0.45)	NA	NA
...Shopping	234 (100.0)	8.54 (3.88)	124 (100.0)	8.14 (3.96)	110 (100.0)	9.00 (3.75)
...Social	177 (75.6)	2.28 (1.58)	100 (80.6)	2.26 (1.54)	77 (70.0)	2.31 (1.64)
...Transport	163 (69.7)	1.95 (1.10)	88 (71.0)	1.81 (1.08)	75 (68.2)	2.12 (1.10)
...Recreation	170 (72.6)	2.21 (1.62)	85 (68.5)	2.25 (1.53)	85 (77.3)	2.16 (1.70)
...Other	68 (27.8)	1.16 (0.37)	27 (21.8)	1.15 (0.36)	41 (37.3)	1.17 (0.38)
Median number of destinations (inter-quartile range)	14 (12; 19)		14 (11; 19)		14 (12; 19)	
GPS tracking						
Median valid GPS tracking time before interpolation (interquartile range)	4 days 23:42:55 (3 days 04:00:00; 5 days 23:26:05)		4 days 18:09:35 (3 days 04:00:00; 5 days 15:25:50)		5 days 04:06:50 (2 days 23:53:25; 6 days 10:10:15)	
Median valid GPS tracking time after interpolation (Interquartile range)	5 days 19:16:18 (4 days 13:43:14; 6 days 14:31:37)		5 days 14:20:58 (4 days 13:42:08; 6 days 03:59:23)		6 days 08:16:58 (4 days 13:43:14; 6 days 18:06:42)	
Median number of activity locations (interquartile range)	25 (20; 32)		26 (21; 32)		25 (20; 32)	

3.2. Temporal analyses

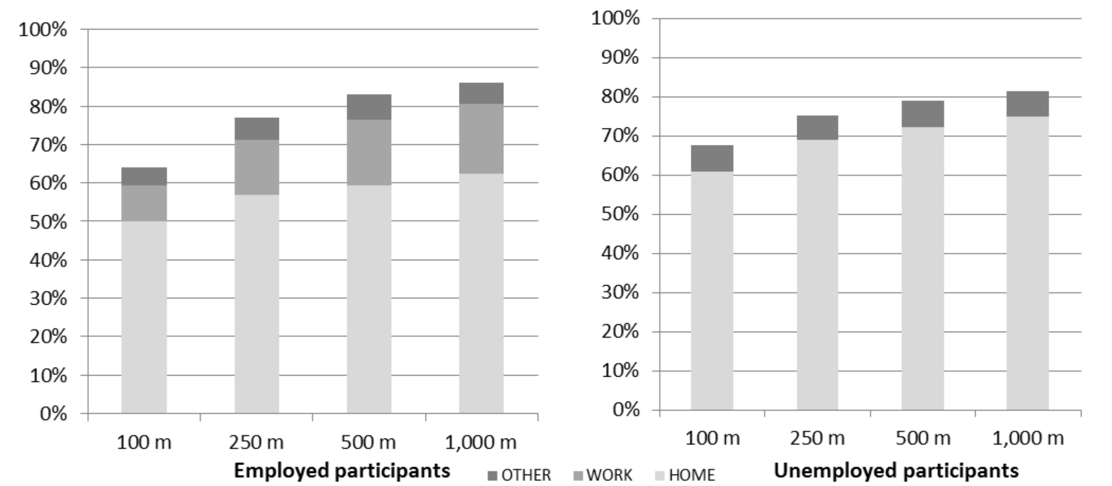


	Within 100 m	Within 250 m	Within 500 m	Within 1,000 m
Median	66.8 %	80.0 %	85.5 %	88.5 %
IQR	(51.1 %; 80.1 %)	(68.4 %; 87.3 %)	(75.1 %; 90.9 %)	(79.2 %; 93.3 %)
Min	0.4 %	1.7 %	20.9 %	21.9 %
Max	96.9 %	98.3 %	98.9 %	99.3 %

Figure 1 – Median proportion of GPS tracking time spent within 100, 250, 500 and 1000 meters from reported VERITAS locations

Figure 1 illustrates how the proportion of GPS tracking time spent within the specified ranges of VERITAS locations follows an asymptotic trend. Median values range from 66.8% to 88.5% for areas within 100 m to 1 km around VERITAS destinations.

Both employed and unemployed participants spent the majority of their total GPS time close to their residence. However, employed participants spent a larger proportion of their time outside of the home buffer ranges. Unemployed participants spent between 10.8 and 12.8 additional percentage points within their residential neighborhoods compared to working participants. However, they did also spent slightly more time outside the buffer reach of their regular destinations, when considering buffers of 250 meters and up. As an example, unemployed participants spent an additional 1 hour and 19 minutes on average beyond 250 meters of any VERITAS location compared to employed respondents.



	Employed participants				Unemployed participants			
	100 m	250 m	500 m	1,000 m	100 m	250 m	500 m	1,000 m
Home	50.0	57.0	59.4	62.4	60.8	69.1	72.2	74.8
Work	9.3	14.2	17.0	18.1	N.A	N.A	N.A	N.A
Other	4.8	5.9	6.7	5.4	6.8	6.1	6.7	6.6
Total %	64.2	77.0	83.2	86.0	67.7	75.2	78.9	81.4

Figure 2 : Average proportion of GPS survey time spent within distances from home, work and other VERITAS destinations, for employed (n=124) and unemployed participants (n=110) (buffers mutually exclusive)

Out of their total tracking time, employed (unemployed) participants spent 28.5% (8.5%) of their time within 500 m of an out-of-home activity location (Figure 2). Consequently, if one subtracts 7 hours of sleep French people get in average from the total time spent in the home buffer, 38.7% (57.1%) of the remaining tracked wake time is spent within 500 m and closer to home, and the remaining time, i.e. 61.3% (43.0%), outside of this area.

Proximity analyses

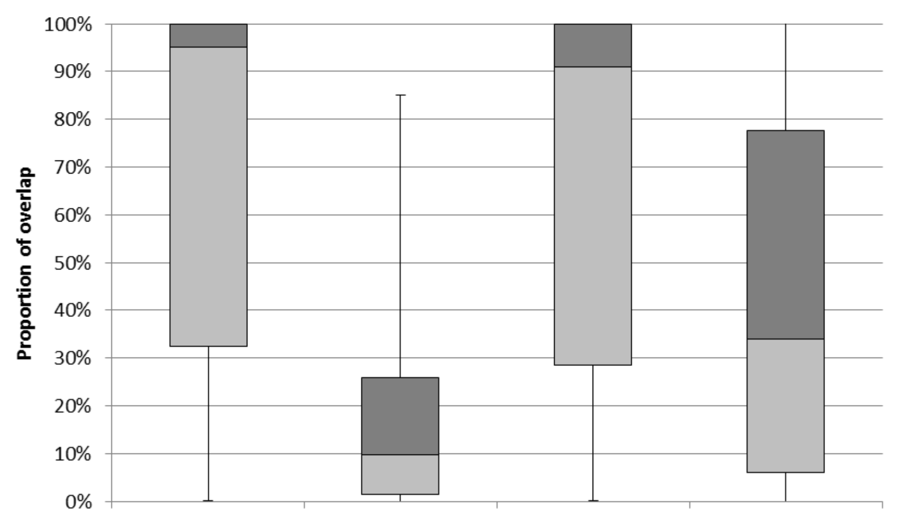
Table 2 shows the median shortest distances between a VERITAS location and either a GPS coordinate, or a GPS-derived location, by category of activity location. The median distance between VERITAS locations and GPS tracks ranged from 0.4 m for home to slightly over 100 m for a recreational destination. The median distance between locations detected from GPS tracks and belonging to the same category as the VERITAS obtained locations varied from 20.8 m for home, 74.4 m for work, 221.7 m for shopping, 256.0 m for transportation, 403.4 m for social and 438.1 m for recreation destinations.

Table 2: Median shortest distance between a VERITAS location and i) GPS tracks and ii) GPS detected activity location, by category

VERITAS Locations	**Median shortest distance between a VERITAS location and GPS tracks (m)**	**Median shortest distance between a VERITAS location and GPS detected activity location (m)**
Home	***0.4***	***20.8***
Work	***3.5***	***74.4***
Transport	***10.2***	***256.0***
Shopping	***15.4***	***221.7***
Social	***49.8***	***403.4***
Recreation	***102.9***	***438.1***

Activity space analyses

The convex hulls derived from the VERITAS and GPS datasets differed importantly in size (median size of 33.0km², IQR: 7.0-368.8 and 147.9km², IQR: 50.3-1348.6 respectively). The area difference was reduced when weighting datapoints by frequency of visit (VERITAS) or time spent (GPS), with median sizes of respectively 76.2km² (IQR: 12.5-519.9) and 110.9km² (IQR: 25.2-1057.5).



	VERITAS Convex Hull covered at ...% by GPS Convex Hull	GPS Convex Hull covered at ...% by VERITAS Convex Hull	VERITAS Deviation Ellipse covered at ...% by GPS Deviation Ellipse*	GPS Deviation Ellipse covered at ...% by VERITAS Deviation Ellipse*
Median	95.1 %	95.1 %	90.9 %	33.9 %
IQR	(32.5 %; 100 %)	(1.4 %; 25.9 %)	(28.5 %; 100 %)	(6.1 %; 77.6 %)
Min	0 %	0 %	0 %	0 %
Max	100 %	85 %	100 %	100 %

* 2 standard deviation ellipses weighted by frequency of visit (VERITAS) and time spent (GPS)

Figure 3: Spatial overlap of convex hulls and of 2 standard deviation weighted ellipses of VERITAS and GPS data.

Figure 3 shows the degree of spatial overlap between the VERITAS and GPS convex hulls and standard deviational ellipses. GPS-based areas being generally larger, they covered an important proportion of the VERITAS areas. For half of the participants, the GPS convex hull covered 94% or more of the VERITAS convex hull, and the weighted GPS deviational ellipse 90% or more of the VERITAS deviational ellipse. Inversely, the VERITAS convex hull covered only 12 % or less of their GPS convex hull, and the VERITAS deviational ellipse covered 40% or less of the GPS deviational ellipse. These median values do however not reveal the important inter-individual variations, as shown by large interquartile ranges.

4. Discussion

This study compared spatial data obtained from the VERITAS activity space questionnaire on regular destinations with spatial data obtained from 7-days continuous GPS tracking. A significant amount of participant's time – as documented by 7-day GPS tracking – was spent nearby self-reported VERITAS location. Half of the sample had 85.5% or more their

GPS data within 500 meters of a VERITAS location, three quarter of the sample 71.1% or more, and one quarter 90.9% or more. This shows that VERITAS provides a representative picture of participants' actual roaming spaces as measured objectively by GPS over 7 days. A closer look at GPS time does however also indicate that for a few participants the percentage was rather low, possibly indicating that they had not spent much time of their week neither at home nor in reported VERITAS locations. The sub-analysis looking at differences between employed and unemployed participants showed the latter spent greater lengths of time outside of their network of regular places. A significant proportion of wake time was spent around non-residential locations, and more so for participants that where employed. This finding supports previous claims suggesting that a focus on the sole residential location can be problematic [2], possibly misspecifying true environmental exposure.

Proximity analyses revealed participants' GPS tracks fell close but within increasing distances from home, work, transport, shopping, social, and recreational destinations. Increasing median distances across these categories are probably linked to an increased inverse probability to actually visit one of these destinations during an 'accute' seven-day GPS survey period. Furthermore, visited workplace, shopping, and transportation destinations are probably more fixed in space than recreational and social places - for which VERITAS-GPS distances were larger[23]. Furthermore, longer times spent at home or workplace may also translate into better spatial precision in GPS location detection. Part of the spatial discrepancies observed, although relatively minor, are also linked to the approximation of individuals' precise location within a given setting. In VERITAS, work location may be geocoded at the address level, which is of course an approximation of the individual's precise location. If a given address encompasses several buildings, such as in some institutional work locations, the individual may actually be sitting in an office relatively far away from the official address location documented in VERITAS. Further micro-scale analysis to be run on GPS data could be of interest to identify if algorithm-derived locations are able to pinpoint exact buildings or relative positions within a building.

Activity space analyses indicated that GPS derived areas were larger, and strongly covering the VERITAS derived areas. Congruent with the results of another study comparing GPS tracks with self-reported regular destinations [34], these spatial overlap analyses suggest that although activity location questionnaires may provide a sound representation of regularly visited places, they do not encompass the full spatial extent of the participant's daily mobility. This is partly due to the fact that actual routes between destinations had not bee collected in VERITAS in this study, but more convincingly, it questions the regularity in participants' spatio-temporal behaviours. Previous studies, mostly based on cellphone location data, have demonstrated a high level of regularity in peoples' spatio-temporal behavior [35-37], both outside but even inside homes[38]. Yet, whereas most people have highly routinized activities, schedules, and destinations, some have less regular roaming spaces. For those, both spatial data collection methods somehow fall short: with VERITAS, mostly regular destinations will be collected and consequently capture only part of participants' more 'flexible' activity spaces. Conversely, with a relatively short 7-day GPS tracking period, only part of the activity space of a person with highly changing mobility patterns would be captured. Access to longer-term location information, for example obtained from people's cellphones, could be used to more fully describe participants' daily mobilities, and help estimate exposure to environments, or model social contacts and disease spread [39].

4.1. Limitations

Although participants were instructed to wear the GPS tracker for the full 7 day period except while in contact with water or while sleeping, GPS data contains missing periods. These are generally due to weak or absence of GPS signals inside buildings, but also possibly to human errors, either forgetting to wear the GPS device, to recharge it, or turning it off. Consequently, although this study relies on a 7-day tracking period, the actual period with data that can be analyzed is shorter, meaning some visited destinations or trips being missed. Spatial imprecision is also inherent to online mapping. As mentioned, VERITAS identified locations may not be geographically accurate. Geocoding is associated with spatial imprecisions, often dependent on density, with larger positional errors observed in rural and suburban compared to urban areas [40, 41]. Finally, this study was conducted in a specific setting – Paris region – with a specific population – adults aged 35 and up. Differences between regular patterns as collected through VERITAS and 'acute' 7-day mobility as captured through GPS might be larger or smaller in other contexts, calling for repeated analyses like this one.

5. Conclusion

Beyond these limitations, both GPS and map-based activity space questionnaires offer interesting ways to collect daily mobility information for health research. On one hand, GPS tracking offers the advantage of including both spatial and temporal data, making it possible to locate other time-stamped sensor-based measures such as physical activity obtained from accelerometers. On the other hand, map-based questionnaires such as VERITAS offer efficient ways to document regular activities and destinations, beyond a short 7-day window frame, and can include questions about places, transportation modes, or social networks members met at those locations. VERITAS being a relatively generic survey instrument, it may include questions that may be more population specific – e.g. asking 'where do you hang out with friends?' when surveying adolescents – or outcome specific – e.g. asking 'where do you generally smoke pot?' when studying marijuana use. Overall, both methods provide richer data on daily mobility allowing to increase specificity in exposure assessment while allowing to document part of the 'why' and 'with whom' that can help 'contextualise context' and improve our understanding of mechanisms linking places to health. [23, 42].

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