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A comparative analysis of mobile phone data and travel surveys in understanding travel behaviour

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Abstract
This study evaluates the comparability of aggregated mobile phone data (MPD) derived from passive network signalling events and traditional travel survey data for urban transport planning, using the province of Liège as a case study. Our analysis demonstrates that while MPD captures a higher density of origin–destination (OD) connections, it cannot fully replicate all flows observed in surveys, underscoring the need for a complementary approach between the two data sources. Key mobility indicators, including average trip rates, hourly trip volumes, and structural patterns in daily OD matrices, show strong alignment. This structural similarity is rigorously quantified using a Mean Structural Similarity Index with a distance decay effect. Furthermore, Kolmogorov-Smirnov tests confirm comparable trip length distributions between the sources. While MPD-based population estimates closely match official 3:00 AM census counts, discrepancies in specific zones highlight potential pitfalls for real-time population mapping. Our findings confirm that MPD provides a robust and valuable complement to traditional surveys, particularly in contexts with limited or infrequent survey data. The study offers critical insights for integrating MPD into urban policy planning, emphasizing its utility for validation and its caveats for population estimation.

Keywords Travel survey data · Mobile phone data · Origin–destination matrices · Population counts · Trip length distributions

Introduction

Traditional urban transport planning relies heavily on household travel survey (HTS) data, a method long hampered by fundamental methodological constraints. Although these conventional surveys are relatively detailed, they are not only updated infrequently due to high costs, but their expense also results in low sampling rates. While early efforts could achieve sample sizes of 1–3% through face-to-face interviews (Stopher and Greaves 2007), even these rates are compromised by declining response rates across all survey modes, including postal, telephone, and face-to-face methods (Mohammadian et al. 2010). The pursuit of

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larger samples is riddled with challenges: diary surveys rarely exceed 10% sampling rate, and expansive censuses face systematic issues related to privacy and confidentiality (Saadi et al. 2018). Furthermore, the data collection process itself is tedious and time-consuming. Consequently, even a modest 1–2% sample of households in a large urban population requires surveying several thousand people through household interviews (Chandrasekar 2015), and the resulting data remain susceptible to sampling bias and reporting errors (Bwambale et al. 2021). Given these inherent limitations, a consensus has emerged that traditional surveys must evolve to ensure temporal and spatial comparability in the era of big data (Bonnel and Munizaga 2018; Cottrill et al. 2013; Kamenjuk et al. 2017). In this context, mobile phone-based measures represent a promising alternative, offering a reasonable proxy for individual mobility and enormous potential for urban transport modelling (Calabrese et al. 2013). As they are less costly and have a high penetration rate compared with conventional survey methods, mobile phone data (MPD) have been increasingly applied to measure the spatio-temporal changes in the population (Calabrese et al. 2011; Demissie et al. 2015; Ahas et al. 2015; Kamenjuk et al. 2017). However, unlike travel surveys' enriched sociodemographics or contextual information, MPD lacks ground truth to be validated against, which remains unresolved (Bonnel and Munizaga 2018).

In addition to data obtained from mobile phone network operators and passive data collected from third-party smartphone applications, numerous trials of novel travel survey techniques have been conducted, including surveys facilitated by smartphones, GPS, WiFi, Bluetooth, or the Internet. However, there is no single data source or collection method that can meet all of the needs for determining mobility in the field of public travel policies; digital data sources and new data collection technologies cannot replace the conventional techniques of the survey by telephone or face-to-face in the short or medium term (five years hence) (Richard and Rabaud 2018). Harding et al. (2021) indicated that until significant improvements in mode inference algorithms arise, purely passive location-logging smartphone apps cannot serve as full-fledged automated travel survey instruments. In reality, operational surveys with substantial sampling combined with smartphone and internet techniques, such as the Future Mobility Sensing system in Singapore (Zhao et al. 2015) in 2012/2013 and MOBIS, a national-scale transport pricing survey combining traditional survey methods and active GPS tracking (Molloy et al. 2023) in Switzerland, are valuable and have gained increased attention. Besides, data fusion has a great potential to contribute to higher travel survey data quality as it may reduce respondent burden and make the fieldwork of data production leaner (Kuhnimhof et al. 2024). Some data fusion approaches are observed to get the best of both traditional survey and MPD for transportation planning applications (Caceres et al. 2020a; Bwambale et al. 2021).

In particular, Kuhnimhof et al. (2024) elaborated two types of MPD that are specifically interesting in the context of travel survey data production: (**i**) long-term individual smartphone location history data (i.e., GPS-based smartphone tracks) and (**ii**) aggregate mobile phone movement data (i.e., the number of mobile phones or SIM-cards moving between GSM-calls). The first MPD type (**i**) is very rich on the individual level but may yield insights into the mobility of a small and selective proportion of the population, as it seems unlikely that more than just a tiny fraction of respondents would be willing to share their timeline data. The second MPD type (**ii**) can be derived from billing (call detail records, CDR) or network signalling data offered by mobile phone providers. Similarly, Calabrese et al. (2014) classified MPD type (**ii**) as cellular network-based data and further subdivided them into event-driven data and network-driven data. Event-driven data are collected when mobile communication (i.e., calls and SMS) or internet usage (e.g., browsing the web, or checking the mail server) takes place. Di Lorenzo et al. (2011) called these events *network connections* and demonstrated that they constitute a superset of the ones contained in the call details records. The definition of network-driven MPD has been refined across several key studies. The network-driven data (including periodic location updates, handover, and mobility location updates) given in Calabrese et al. (2014) are based on the Location Area (LA), which is a set of base stations that are grouped to optimize signalling. Wang et al. (2018) characterized network-driven data as information collected on a periodic basis without the trigger of events or when mobile phones move from one cell to another. Bonnel et al. (2018) then provided a more detailed taxonomy, classifying the handover and LA update as itinerancy events, and offering the inventory of the signalling data stream, noting that it contains various event types. Critically, they highlighted that active user actions, including communication events and internet usage, also generate digital traces within this network signalling data.

In addition, Wang et al. (2018) noted that their taxonomy aligns with empirical observations that network-driven data offer higher temporal resolution and are more stable, as they capture passive movements absent in event-driven records. This binary classification is consistently used; for instance, Huang et al. (2019) adopted the event-driven and network-driven definitions from Calabrese et al. (2014). However, Huang et al. (2019) further clarified the field's terminological landscape, observing that terms like "mobile phone data", "mobile network data", and "mobile positioning data" are similar terms used in the literature to denote mobile phone network data, while particularly differentiating these from GPS data. They also confirmed that network-driven data generally possess superior spatio-temporal granularity. Crucially, Huang et al. (2019) provided a comprehensive and detailed inventory of network-driven data (which they also term signalling or sightings data), specifying that it captures location updates triggered by a wide range of network events. These include: phone power cycles (on/off); LA updates; handovers during calls or data sessions; making/receiving calls, SMS, or accessing internet services (recording the user's location without communication details); periodic location updates when a phone is idle. Event-driven mobile data include Internet Protocol Detail Records (IPDR), which are also known as internet access logs, and CDR, which typically consist of the communication details such as phone number, type (calls or SMS), ID, a timestamp, and call duration, etc.

This paper adopts a clear, two-level taxonomy for MPD to resolve terminological inconsistencies. At the highest level, we employ the classification by Kuhnimhof et al. (2024). Our research focuses specifically on the second MPD type (**ii**). To further refine this category, we apply the established sub-classification from Calabrese et al. (2014), which divides cellular network-based data into event-driven and network-driven data. This integrated framework allows for precise discussion, acknowledging that "mobile phone data" is an umbrella term encompassing both high-resolution GPS from smartphones and aggregate data from cellular networks, which are distinct in their generation, applications, and biases.

MPD type (**ii**) is of primary concern in the context of data fusion as it can provide large amounts of origin–destination (OD) matrices but lacks individual sociodemographics. Although deriving complete trip characteristics (including modes, purposes, and temporal patterns) from MPD remains challenging due to both the lack of sociodemographic attributes and restricted raw data access (as cellular network-based data are typically licensable only from telecom operators under strict privacy safeguards), their derived OD matrices remain indispensable for four-step and activity-based models, even when working with pre-aggregated or anonymized datasets. In addition, MPD can provide relevant information in the context of population mapping, overcoming the limitations of traditional data sources such as censuses and surveys (Khodabandelou et al. 2016). Consequently, rigorously assessing the comparability and reliability of MPD against conventional travel demand data sources becomes critical for informing transport planning practice. This necessity is evidenced by the growing research efforts to benchmark MPD against established surveys. Our work contributes to this effort by demonstrating how the passive, network-driven MPD can complement and validate traditional surveys. Such validation is essential for policymakers and planners who increasingly utilise MPD, as it ensures the validity of these new data sources against established standards before they are integrated into urban planning practice.

The remainder of this paper is structured as follows: Sect. 2 provides a review of the relevant literature. Section 3 details the data and methodology employed. Section 4 presents the findings of the comparative analysis, and Sect. 5 discusses their implications. Finally, Sect. 6 concludes the study by summarizing the key findings and outlining directions for future research.

Literature review

To contextualise our research, this section synthesises existing studies that have compared MPD (Type **ii**) with traditional surveys. Di Lorenzo et al. (2011) aggregated trips from millions of individual mobile phone users (with *network connections*) in the Boston Metropolitan area and obtained an average of 5.0 one-way trips per day during the weekday and 4.5 during the weekend. They compared them with the US National HTS, which evaluated this number as 4.2 during weekdays and 3.9 during weekends. Furthermore, when trips were aggregated at the census tract and county levels, the OD flows measured using MPD exhibited a strong correlation with the estimates from the US census.

Deville et al. (2014) applied phone call activity aggregated by towers from more than 1 billion mobile phone call records from Portugal and France to estimate population densities at national scales. They then compared these outputs from MPD and remote sensing methods at night with baseline census-derived population densities. Pearson correlation coefficients of 0.89 and 0.92 were found for MPD and remote sensing methods, respectively.

Alexander et al. (2015) inferred users' homes and workplaces from CDR data for the Boston metropolitan area and benchmarked against the NHTS (National Household Travel Survey) departure time distribution. Additionally, they found that the CDR trips compared well with trips from two local household travel surveys by the time of day and purpose. The relative share of average weekday trips for each trip purpose is comparable for the CDR and survey data. Moreover, the total CDR and local survey trips implied comparable average weekday trips per person, namely, 3.50 and 4.24, respectively. Lastly, the correlation coefficients of the trip matrices improved significantly with aggregation to the town level compared with the tract level.

Çolak et al. (2015) discussed how cell phone data can be processed to inform a four-step transportation model. The illustrated data treatment approach used only CDR and population density to generate trip matrices in two metropolitan areas: Boston, Massachusetts, and Rio de Janeiro, Brazil. It is worth noting that the spatial resolution of these datasets differs: Rio de Janeiro are provided at tower-level resolution, while Boston's coordinates derive from a triangulation algorithm applied by the data provider. Furthermore, the validation sources differ. For Boston, census and travel diary survey commuting data were used, whereas for Rio de Janeiro, OD estimates by purpose and time of day were used. Consequently, a high correlation between the CDR and survey data based on the total number of trip productions and attractions was found in Boston, approaching a correlation coefficient of 1. In comparing home-based work trips for each OD pair during the morning peak, a correlation of 0.84 was observed for Rio de Janeiro, whereas Boston exhibited a correlation of 0.99.

Phithakkitnukoon et al. (2022) inferred large-scale temporary migration trips from CDR of mobile phone users in Portugal, and analyzed their spatial determinants based on urban assets derived from Google Places data. Trips that involve a temporary change of the place of residence and are potentially long-distance trips, such as annual holiday travel, business trips, and long-holiday travel, can be considered as temporary migration in this study. Information about text messages and data usage (Internet) were not included in this anonymized CDR data. Statistically, the CDR-based population was highly comparable with the actual census data, with a relatively high correlation coefficient (R-value) of 0.94.

Bonnel et al. (2018) compared the trip matrices obtained from MPD with those obtained from the travel survey collected by phone using a representative sample of the Rhône-Alpes region population. The signalling data contain several types of events: communication events (calls and SMS), handover and LA update, attach/detach events, and obviously data/internet connections. First, to be comparable to survey data, they chose their cellular data from 3:00 AM to the next working day, 3:00 AM, and aggregated the 77 traffic sectors into 14 macro zones so that most of the OD pairs have a sufficient number of trips. Then, they regressed the number of mobile phone trips by the number of survey trips and showed that the structure of the two matrices was very similar, with a coefficient of determination (R^2) of 0.96 and a slope very close to 1. However, these very encouraging results were accompanied by other less satisfactory results in the case of some OD pairs for which the disparities attained 70 to 80%.

Caceres et al. (2020a, b) provided the main qualitative and quantitative findings derived from comparative analysis for MPD and HTS mobility matrices for the urban agglomeration of Malaga, Spain. The data used for this study are based on aggregated and anonymised phone events collected, which consist of active interactions related to phone calls and text messages, as well as passive interactions that occur in the background (or idle status). Their qualitative discussions involved cost and time consumption, sample design, feasibility and timeliness, and level of detail. The quantitative findings highlighted demonstrations of similarities between the two kinds of OD matrices based on Pearson's coefficient and the Mean Structural SIMilarity (MSSIM) index. They concluded that the comparative analysis of sources was more consistent at the macro-zone level than at the transport zone level.

Landmark et al. (2021) compared the MPD-based OD matrices constructed using public transport data, turnpike logs, and traditional travel surveys for the region of the Oslo metropolitan area. They aggregated data from a finer spatial level to a macro spatial level for comparison with travel surveys. Their phone data are based on CDR, IPDR, as well as cell tower switches (which occur when a device is moving and leads to a shift in the cell tower channelling the activity). They constructed an OD trip distribution difference matrix and conducted a correlation analysis, finding a match with an R^2 of 0.82. Additionally, they validated the population counts estimated with MPD against official population statistics. In most districts, the number of residents exceeded the number of mobile signals, which can be explained by the fact that not all residents own mobile phones.

Fekih et al. (2022) used the same MPD and travel survey source data as Bonnel et al. (2018). However, their comparison focused on analyzing travel demand differences at the temporal level and emitted trips from each geographical zone. They concluded that MPD could not correctly capture trips performed during the morning rush hours, leading to an underestimation of the total trip volume observed from MPD. However, the hourly global demand profiles and the total number of trips emitted by each zone, estimated from both data sources, were highly correlated.

Existing research demonstrates a progression in the types of MPD used for mapping population and trips. Early approaches often relied solely on CDR from event-driven data (where data are recorded only during the active phone use), as seen in Deville et al. (2014); Alexander et al. (2015); Çolak et al. (2015), and Phithakkitnukoon et al. (2022). Subsequently, researchers began integrating broader MPD datasets; for instance, Di Lorenzo et al. (2011), combined CDR with events triggered by internet usage, while Landmark et al. (2021) utilized a mix of CDR, IPDR, and cell tower switches. Finally, a more recent and advanced category employs network-driven MPD derived from passive network signalling events, which offers a more comprehensive data stream for enhancing trip mapping, as demonstrated by Bonnel and Munizaga (2018) and Caceres et al. (2020a).

The literature on MPD for transport planning is characterised by inconsistent terminology, which hinders comparability across studies. While foundational work like that of Calabrese et al. (2014) provided a clear classification of MPD, it appears that various literature may use different synonyms to refer to these data types. This ambiguity necessitates a clarification of existing typologies. In response, our work provides a consolidated overview of MPD classifications to resolve synonymy and enhance cross-study comparability. To further clarify this landscape, we focus on network-driven MPD, which are generated from passive signalling transactions. Unlike CDR, which only log billable events, this data stream captures a phone's interactions with the network simply by being powered on, including events like unanswered calls, switching the phone on and off, and location updates as noted by Bonnel et al. (2018). This results in a more continuous and comprehensive data source.

Empirical evidence demonstrates both the promise and limitations of MPD. Comparative studies demonstrate strong correlations between MPD-derived OD flows and conventional survey/census estimates, particularly when data are aggregated spatially (e.g., to census tracts or macro-zones) or temporally (e.g., daily trips). However, significant challenges remain. CDR-based studies, for instance, are dependent on users' calling plans, making them less reliable for analysing specific periods like morning commutes (Gundlegård et al. 2016; Çolak et al. 2015). More fundamentally, network-driven MPD also reveals persistent issues, including significant disparities in specific OD pairs and systematic underestimation of total trip volumes, especially during peak hours introduced by (Fekih et al. 2022). Furthermore, as noted by Landmark et al. (2021), the validation of MPD is inherently limited by the lack of comprehensive ground-truth data. Given these considerations, it is essential to continue evaluating the degree of concordance between travel surveys and network-driven mobile phone-based measures.

This paper compares network-driven MPD with the web-based household travel surveys. Specifically, the MPD used in this study is derived from passive network signalling records, which are distinct from mobile event-driven data. We do not employ CDR data in our analysis. The results of this study can broaden our comprehension of aggregate MPD compared to a diary survey conducted over compatible periods. This study's strength lies in directly comparing MPD and a web-based travel survey conducted within a compatible timeframe and geographical area. A key strength of this research lies in leveraging the compatible collection of MPD and web-based travel surveys, providing a unique opportunity to assess their comparability more accurately. The main contributions of this paper are as follows:

1. Our study uniquely compares network-driven MPD and web-based travel surveys conducted concurrently in Liège, a combination previously underrepresented in transportation literature.
2. We introduce an innovative methodological framework employing MSSIM, significantly enhancing the structural comparison accuracy of OD matrices compared to traditional statistical metrics.
3. We demonstrate that MPD can robustly validate and complement traditional travel surveys, especially valuable in contexts where survey samples are small or infrequent.
4. We highlight the importance and potential pitfalls of using MPD for real-time urban population estimates, with direct implications for urban policy planning, validating MPD against official census benchmarks.

These contributions demonstrate the potential of MPD to complement and enhance traditional travel surveys, offering new insights for transport policy and planning.

Data and methods

Data

We used three primary data sources (Table 1) to explain the comparability. The first source is MPD, including aggregated hourly mean OD matrices and extrapolated population present in each mobile phone cell for the province of Liège. OD matrices were provided by the regional government (SPW Mobilité et Infrastructures) in the form of hourly mean matrices (7 days × 24 h × 2 periods).

The MPD originates from the network operator Proximus, which holds about 40% of the market share in 2022 mobile phone operations in Belgium. Proximus processes over a billion transactions daily to derive the OD matrices. Each transaction of an individual Proximus user is geolocated using the coordinates of the antenna segment where it occurs, creating a Voronoi diagram representing Proximus' cellular coverage in Belgium. Therefore, data

Table 1 Comparison of three data sources

Data	Spatial resolution of the finest granularity	Geographical coverage	Timeframe
MPD	NSI6 (sub-commune)	Province of Liège in Belgium	15.01.2018–08.02.2018, 23.02.2018–18.03.2018
MONITOR	Household postal code	Belgium	03.2016 to 09. 2017
STATBEL population	100 m by 100 m grid	Belgium	2016

is not stored per transaction per user, but as registration by cellular location per user with a time stamp of start (first appearance of the user on this cellular location) and a time stamp end (last appearance of the user on this cellular location). When a user performs several consecutive transactions on the same cell location, these transactions are grouped together. To comply with privacy regulations, reports resulting from this Proximus contract can only contain data relating to groups of at least 30 people, to exclude any risk identification.

Transactions are classified into ‘staying points’, where an individual remains for more than an hour. This means that the individual must perform two or more transactions on this cell location with at least one hour between the first and the latest. Other transactions where the individual stays for less than an hour are defined as ‘transit points’. These movements are mapped to generate flow trajectories from origins to destinations.

Aggregation of this data is conducted in both space and time, allowing data to be reported hourly, daily, or averaged over several days. This method provides detailed insights into user movements and enables the creation of comprehensive OD matrices that reflect the travel behaviour of the entire user base. The two periods for which the hourly means were tabulated concern regular and holiday weeks (the Carnival and Easter holidays). Besides, SPW provides population data in the form of half-hourly changes in population in each cell derived from MPD for the day considered (7 days × 48 half-hours × 2 periods). The extrapolation takes into account factors, including the level of activity of users observed, Proximus market share, GSM penetration, and number of inhabitants in the research area. The province of Liège has been split into 310 zones (Fig. 1 provided by SPW) representing the unions of polygons built from the Voronoi diagram. The black delineations in Fig. 1 show the 84 municipalities in the province of Liège; the coloured ones are the 310 mobile phone cells.

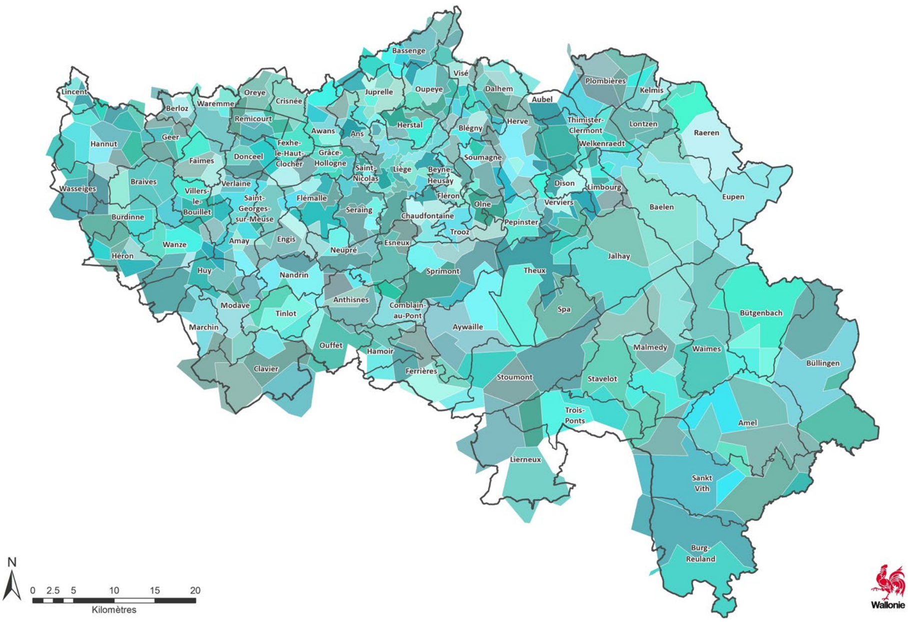


Fig. 1 Delineation of floating mobile data Proximus cells in the province of Liège

Due to privacy legislation, we were only provided with the aggregate OD matrices and could not access the raw MPD with individuals' trip information. Notwithstanding, we can compare the mobile phone-based origin–destinations with the locations described by STATBEL (Belgian Statistical Office). We used STATBEL's NSI coding system, which assigns a numeric code to each administrative unit, to check how closely they match. As a result, 270 out of 310 mobile phone zones have the same NSI6 codes as STATBEL's sub-communes (360 in the province of Liège). However, when we spatially aggregated the 310 mobile phone zones back to the municipality level, we made a comparable visualization with 84 municipalities (NSI5) from STATBEL (Fig. 2). After that, we computed the spatial intersection ratios of Fig. 2. The result shows that around 75% of zone pairs have at least 70% spatial matches. A more elaborate comparison discussion can be found in Gong et al. (2021).

The second data is from a Belgian national mobility survey called MONITOR, conducted entirely online from March 2016 to September 2017. A sample of 10,632 Belgians was interviewed to reflect the Belgian population based on age, gender, activity, and region of residence. To compare with mobile phone-based OD matrices, we derived OD matrices obtained from MONITOR. Since we focused on the province of Liège, trips whose origins

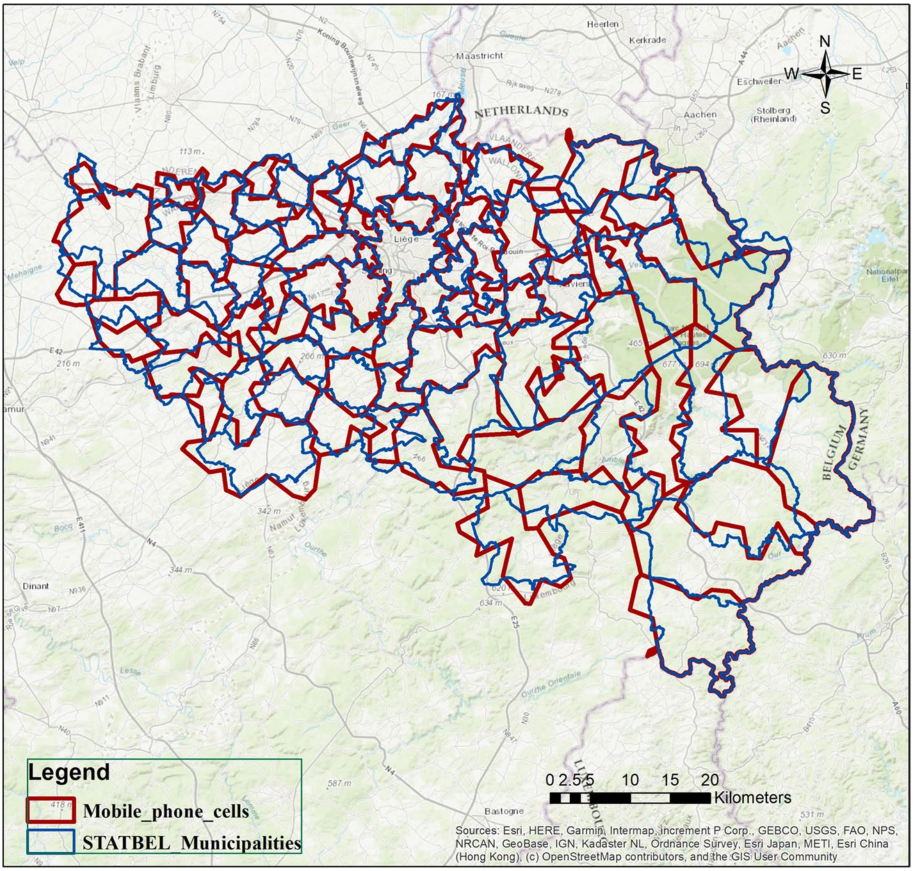


Fig. 2 Mobile phone cells compared with STATBEL (Belgian Statistical Office) zones at the municipality level

or destinations are not inside the research area have been filtered out. After the data cleaning and preprocessing, MONITOR daily trips were prepared, including 1167 trips from 410 participants throughout the province. The population sample represents 0.037% of the province's total population. We applied weights of MONITOR to scale the sample population up to the true population level and presented the weighted percentage by age group in Table 2. Since MONITOR begins tracking at age six, we compared its age groups to the actual population starting from six years old as well. Kolmogorov–Smirnov (K–S) tests were performed to examine whether populations are drawn from the same age distribution. Consequently, the *p*-value is 0.963, showing that there is no significant difference between the official distribution and the MONITOR distribution. Although the K-S test indicates that the observed differences are statistically non-significant, they may still reflect underlying disparities caused by survey sampling procedures and potential selection biases inherent in web-based approaches, particularly among younger and older demographic groups.

The last source is the official population data that can be downloaded from STATBEL. We chose a vector file of the population according to the km^2 grid showing the population residing in Belgium in 2016 on a grid of a square area with sides of 1 km. We cut the grid into a smaller (100 m by 100 m) one and retained the value of the larger grid that it was associated with using the ArcGIS Create Fishnet tool. As mobile phone cells differ from boroughs, we approximated the official population at a spatial level of mobile phone cells based on the new grid data. After that, MPD can be validated against official population statistics.

Methods

To address the lack of detailed insight into the compilation of mobile phone-based OD matrices and population extrapolation, we undertook additional comparative analyses. These were based on data aggregation into comparable statistics at the municipality level for three reasons. First, spatially, mobile phone cells can find the main match at the municipality level instead of the sub-commune level. Second, OD matrices derived from both MPD and MONITOR are overdispersed at their collected spatial granularity. Moreover, the online survey data is not as temporally precise as the MPD. The finer the spatial resolution, the higher the probability that the number of trips will fall below the required threshold, such as a non-zero value. Aggregation at the macro level can improve the correlation between MPD and travel surveys that align with existing related works.

Thus, we started by comparing mobile phone-based OD matrices in the regular week with those constructed using MONITOR. The departure time from the origin and the arrival time at the destination have been considered in the study. First, we compared the ongoing hourly number of trips (departures minus arrivals). Next, we demonstrated the sparsity of OD matrices, detected the level of similarity, and constructed a distribution difference matrix to quantify the discrepancies between the two OD matrices. We used the structural similarity index (MSSIM) (Djukic et al. 2013), including distance decay effect (Caceres et al. 2020b), to capture the underlying structural similarity between two OD matrices:

Table 2 Sample population by age groups in MONITOR

Group	1	2	3	4	5	6	7
Age	6–11	12–14	15–17	18–34	35–49	50–64	65+
MONITOR percentage (%)	8.97	2.07	3.20	31.45	21.44	20.60	12.26
STATBEL Percentage (%)	2.76	1.39	1.46	16.27	21.47	23.18	33.47

$$MSSIM(A,B) = \frac{1}{M}\sum_{j=1}^{M} SSIM(a_j, b_j) \tag{1}$$

Here we compared the similarity between MPD and MONITOR OD matrices by considering the OD pairs (trip flows between zones) at the municipality level. The MSSIM index ranges from − 1 to 1, with a value of 1 indicating a perfect match. Let us consider two square matrices A and B of size $n \times n$, and a (window/kernel) square box *a* (and *b*) of size $k \times k$ that slides over the full matrix.

$$SSIM(a,b) = \frac{2 \cdot \mu_a \cdot \mu_b + C_1}{\mu_a^2 + \mu_b^2 + C_1} \cdot \frac{2 \cdot \sigma_{ab} + C_2}{\sigma_a^2 + \sigma_b^2 + C_2} \tag{2}$$

At each step, we can compute Equ. 2, which includes three statistical metrics $\mu_{a(b)}$, $\sigma_{a(b)}$ and σ_{ab} to obtain *SSIM*(*a*, *b*). C_1 and C_2 are constants estimated from the literature. They ensure enough stability when the moments are close to 0.

$$\mu_j^a = \frac{\sum_{l=1}^{k\times k} a_j^l w_j^l}{\sum_{l=1}^{k\times k} w_j^l}, \quad \forall j \in \{1,\ldots,M\} \tag{3}$$

$$(\sigma_j^2)^a = \frac{\sum_{l=1}^{k\times k} w_j^l (a_j^l - \mu_j^a)^2}{\sum_{l=1}^{k\times k} w_j^l}, \quad \forall j \in \{1,\ldots,M\} \tag{4}$$

$$\sigma_j^{ab} = \frac{\sum_{l=1}^{k\times k} w_j^l (a_j^l - \mu_j^a)(b_j^l - \mu_j^b)}{\sum_{l=1}^{k\times k} w_j^l}, \quad \forall j \in \{1,\ldots,M\} \tag{5}$$

where μ_j is the weighted average of the j^{th} window, w_j^l is the weight of cell *l* of the j_{th} window, a_j^l is the element *l* of the j_{th} window, d_l is the Euclidean distance between the central cell and the l_{th} cell, σ is the variance of the distances between the central cell and all the other cells.

$$w_j^l = \exp\left(\frac{d_l^2}{\sigma}\right) \tag{6}$$

The distance between two OD pairs is given by

$$d(ODpair_i, ODpair_k) = \sqrt{(x_{Oi} - x_{Ok})^2 + (y_{Oi} - y_{Ok})^2 + (x_{Di} - x_{Dk})^2 + (y_{Di} - y_{Dk})^2} \tag{7}$$

where *x* and *y* indicate geographic coordinates of the controids of origin and destination cell towers.

Moreover, we performed correlation analyses for OD trips, origins and destinations from two data sources. Results are explained in the “Measuring (dis)similarity between MPD and MONITOR OD matrices” subsection. After that, we examined the comparability of trip length distributions between two data sources in the “Trip length distributions” subsection. Finally, we validated mobile phone-based extrapolated population presence using the official population statistics from STATBEL for the 84 municipalities (in the "Validation of MPD against population statistics" subsection).

Comparative analysis

Overall trip rate

Based on MPD collected during regular weeks, we derived an average of 1.9 trips per day per inhabitant in the province of Liège. Excluding inhabitants under 12 years old, the derived trip rate is 2.2, which aligns with the population carrying mobile phones with SIM cards. The trip rate was calculated by dividing the total number of trips in MPD-based OD matrices by the province's actual population size. In the corresponding year, the province of Liège had a registered population of 1,102,531. According to the national mobility survey MONITOR, Belgians make an average of 2.2 daily trips, comparable with the average trip rate derived from MPD. We compared the two OD matrices based on a two-sample t-test (t-statistic= − 0.42, p-value=0.67), indicating that the average trip rate of the travel survey data does not significantly differ from the MPD trip rate.

Hourly ongoing trips

Figure 3 (left) presents the normalized cumulative trip departures and arrivals derived from both MPD and MONITOR. Normalization was performed using the hourly cumulative value divided by the maximum value. Slight deviations are observed between departures and arrivals since not all travellers return to their origins at the end of a 24-hour period. Unlike other times of the day, the MPD-based OD matrices provide a total trip value for the period from midnight to 5:00 AM. To obtain the hourly mean values for this period, we divided the total trip value by five. The number of trips during this period is relatively small for the travel survey data, starting from 5:00 AM, when the first trip departures are captured in the travel survey data (see Fig. 3).

Figure 3 (right) presents the net difference between hourly cumulative trip departures and arrivals over a full day for both MPD and MONITOR. In general, the two curves have a similar pattern. However, the variability in travel survey data during the daytime is more significant than in MPD. In particular, there are more departures than arrivals at 7:00 AM

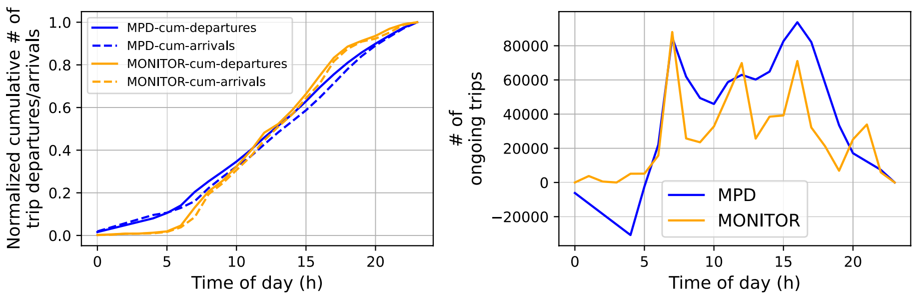


Fig. 3 Cumulative inbound and outbound trips (left) and ongoing trips (right) in the province of Liège

and 4:00 PM, whereas there are more arrivals than departures from 0:00 AM to 5:00 AM in MPD. We can observe that MPD exhibits a clear bimodal distribution of trips, aligning with conventional morning and afternoon peak periods observed in urban mobility studies. In contrast, the travel survey data show greater variability throughout the day, potentially reflecting reporting errors (e.g., respondents omitting short/regular trips) and sampling limitations. This difference can be explained by the sparsity in OD matrices. From 0:00 AM to 5:00 AM, ongoing trips derived from MPD are negative, showing that the number of arrivals (from the previous day) is much higher than departures during this period, while ongoing trips derived from MONITOR do not have any negative values and have one more peak at noon than MPD during the day. Since our MPD is derived from network signalling records, idle mobile devices periodically pinging towers when stationary (e.g., at homes/hotels) could inflate arrival counts. In addition, the MPD's higher arrival-to-departure ratio during late-night/early-morning hours may stem from night-shift workers returning home or travelers arriving via late-night transit, which is often underreported in surveys. Furthermore, MPD undersamples short-duration trips (e.g., lunch breaks, errands) due to technical thresholds for trip detection while travel surveys explicitly capture short, purpose-driven trips (e.g., lunch breaks, school pickups, errands) that dominate midday.

Sparsity of OD matrices

An absence of trips between an OD pair indicates that these two zones are not generating or attracting trips from each other. The sparsity in OD matrices is due to a combination of several factors, including localised travel patterns where most trips occur within nearby zones rather than between distant ones, the distribution of residential, commercial, and industrial areas, varying transportation infrastructure capabilities, and typical travel distances by different modes. The data collection methods also play a role in shaping the sparsity of an OD matrix, and this factor is of interest in this comparative analysis. Figure 4 presents the ratio between the number of reported trips in MONITOR by residents of a zone and the population living in the corresponding zone, expressed as the number of reported trips per 1k inhabitants. It is evident that several zones have missing values and that this ratio varies across space. Few zones exhibit a ratio of 5 or more.

If we identify either null (missing values) or zero ones as zero number of trips in OD matrices, MPD has 2088 OD pairs with non-zero daily mean trip flows, while MONITOR has 433. By comparing MPD and MONITOR OD matrices cell by cell, we found that only 388 non-zero cells in the survey-based matrix correspond to non-zero cells in the MPD-based matrix. Despite the impression that MPD captures mobility in a higher percentage of OD connections, MPD cannot cover all possible OD flows either ($388 < 433$), indicating that MPD and travel survey data should complement each other. If we define the sparsity of an OD matrix as the number of zero-value pairs divided by the total number of pairs, then the sparsity of the survey-based matrix (0.94) is higher than that of the mobile phone-based matrix (0.70), which can be seen in Fig. 5. Blue cells (logarithmic scale) of matrices represent OD pairs with non-zero trips, the rest are OD pairs with zero trips.

Next, we normalized daily trip values by origin so that the sum along the columns (destinations) equals 1. The same was applied to trips by destination. To quantify the discrepancies in cellwise trips with respect to origins and destinations between the two data sources, we constructed distribution difference matrices. To know which zone originates/attracts no

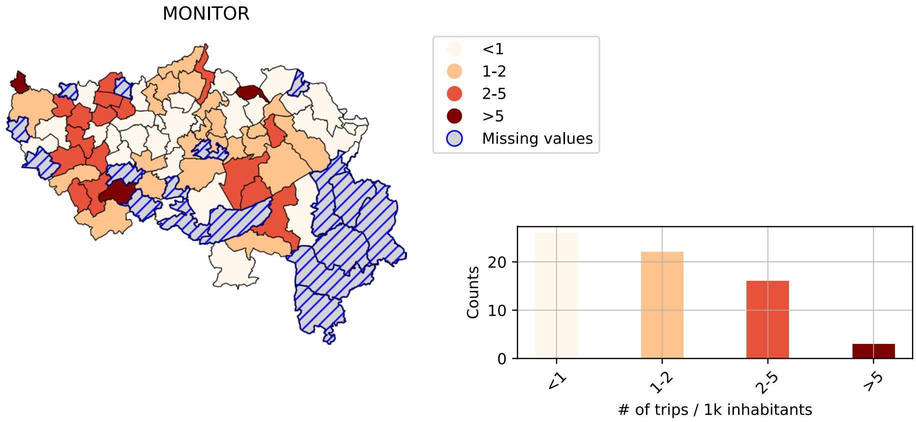


Fig. 4 Spatial sparsity: ratio of reported trips (MONITOR) to population

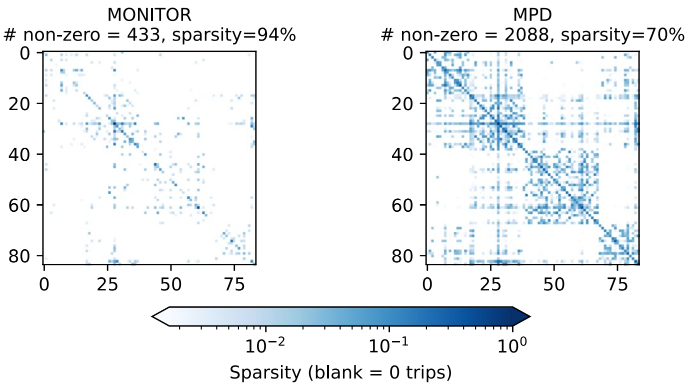


Fig. 5 Sparsity of matrices based on the 84 zones of MONITOR (left) and MPD (right)

trips, the trip number threshold was set as zero. As a result, 70 out of 84 municipalities were identified based on 388 non-zero OD pairs. Figure 6 shows the cellwise difference based on the difference between MPD and MONITOR. Blank cells represent OD pairs that have no matched trips observed for MPD and MONITOR. Deep green cells show that MPD has higher trip generation/attraction shares than MONITOR and are often found for intrazonal trips. Red cells demonstrate that MONITOR has higher trip generation/attraction shares than MPD. The analysis reveals systematic differences between MPD and survey trip patterns. MONITOR records a lower share for intrazonal OD pairs, as MPD's continuous tracking may capture short movements that surveys underreport. The presence of blank cells, indicating no trips recorded by either source, highlights the unique mobility patterns captured by each method. These divergences reflect fundamental differences in how each source operationalises "trips" rather than a matter of superiority–with MPD capturing physical tower connections and surveys recording perceived travel episodes. This suggests that the combined use of MPD and surveys could offer a more comprehensive understanding of mobility.

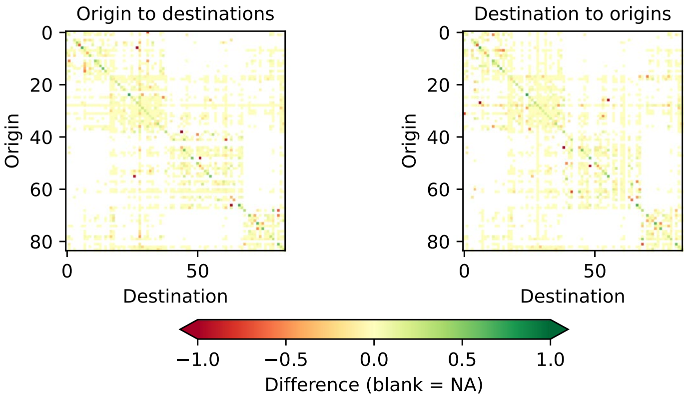


Fig. 6 Cellwise difference in trip generation shares (left) and trip attraction shares (right) between MPD and MONITOR

Measuring (dis-)similarity between MPD and MONITOR OD matrices

Evaluation using statistical metrics

First, we conducted a statistical comparison considering the 388 OD pairs with non-zero trip flows for both MPD and MONITOR. Trip flows from the two sources correlate with a coefficient of determination R^2 of 0.680 and a Pearson correlation coefficient of 0.893. To enhance readability, we represented each point in Fig. 7a on a logarithmic scale of the trip count. The blue line is the diagonal. We can observe more deviations between MPD and MONITOR for low trip counts, which is logical as MPD is based on signalling detection, and the derived trip flow in Fig. 7a is an average of daily trips during a week, while survey data is collected based on a stratified random sample and collects data continuously throughout the year.

Second, we compared total trip generation and attraction for the identified 70 municipalities. Each point represents a zone's total trip generation (Fig. 7b) and attraction (Fig. 7c) on a logarithmic scale. We derived R^2/Pearson correlation coefficient of 0.919/0.927 and 0.959/0.964 for trip generation and attraction, respectively. The size of each point is determined by the population of the municipality divided by 300. MONITOR tends to slightly underestimate trips that originated from/arrived in more populated zones (identified by larger dots), while MPD overestimates trips in less populated zones. Besides, MPD and MONITOR are less correlated based on trips that originated/arrived in sparsely populated zones.

Note that the derived R^2 measures are strongly driven by the largest number of flows if the sparsity of the OD matrix is relatively high. This is the case for the MPD and MONITOR OD matrices. Only two OD pairs out of 388 have intrazonal daily flows above 100k and one above 200k. They are Verviers and Liège, the municipalities with the most dense population in the province of Liège. Another interesting finding from survey-based OD trips is that we observed the shares of three OD flows are 100%, meaning that only one destination exists for the given origin at the municipality level. The reason behind this is the missing OD trips in travel survey data, which is not insignificant for an OD matrix. Among three OD flows,

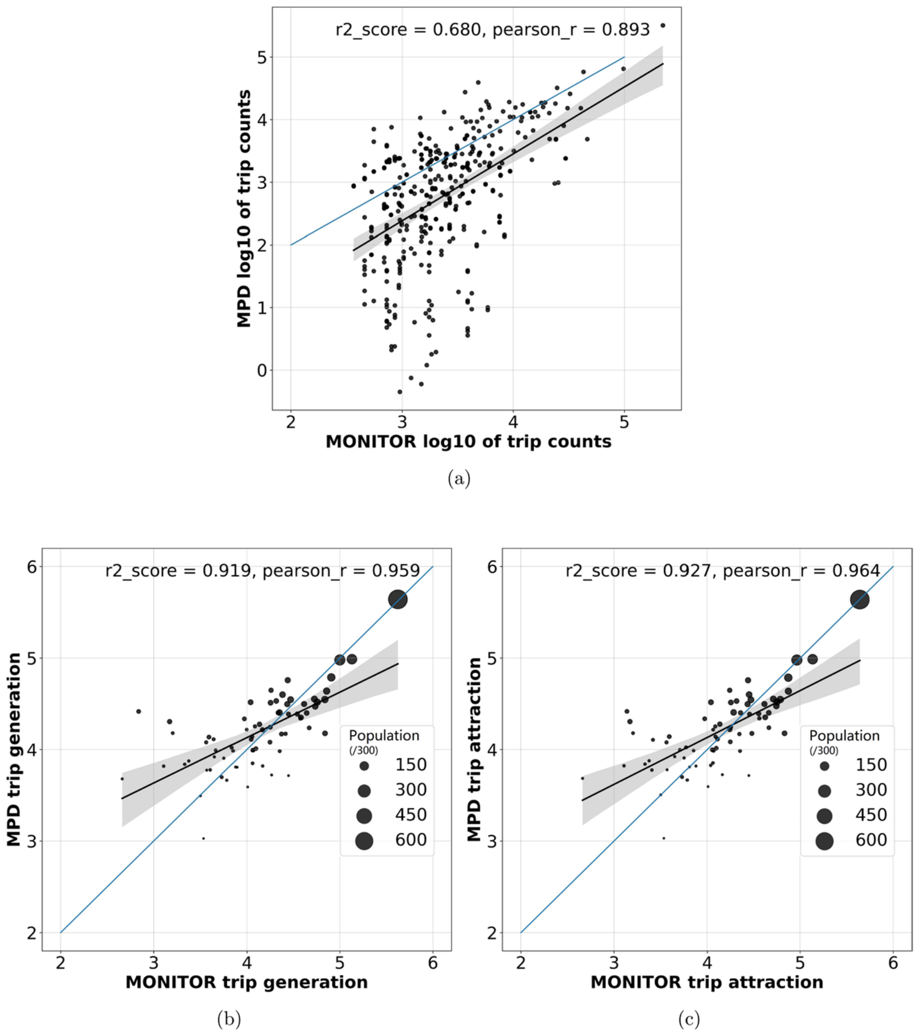


Fig. 7 Correlation of OD trip flows (**a**), trip generation (**b**), and trip attraction (**c**) between MPD and MONITOR

there are two interzonal flows. However, when we checked the complete mobile phone-based OD matrices, the top share of OD flows was always the intrazonal flow. Nevertheless, destinations in these two interzonal flows are still relatively more attractive to origins than other external destinations.

The structural similarity index (MSSIM)

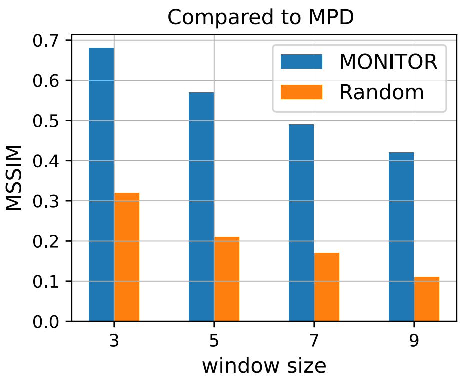
The conventional statistical metrics to measure similarity, such as the Pearson correlation coefficient and/or the coefficient of determination, may not fully capture the similarity in the presence of sparse matrices. To deepen the analysis, we used the structural similarity index (MSSIM), including distance decay effect, to capture the underlying structural similarity between two OD matrices. The MSSIM index ranges from − 1 to 1, with a value of 1 indicating a perfect match. We compared the MPD and MONITOR OD matrices using four different window sizes (3, 5, 7, and 9). To ensure that the observed similarity is due to an existing underlying similarity structure rather than chance, we also systematically compared random matrices with MPD. In Fig. 8, we observed that the MSSIM indicator clearly captures the underlying structure, as the metric is consistently more than double compared to random matrices. The MSSIM is 0.68 if k=3, which shows that MPD and MONITOR OD matrices are similar.

Trip length distributions

We compared trip length distributions between MPD and MONITOR. Although both data sources can provide trips that originate from the province of Liège and arrive in other provinces, and the trips that depart from other provinces eventually arrive in the province of Liège, the comparison requires more details to define a trip's length whose origin or destination is located outside the given zone. Therefore, we only chose trips with origins and destinations located in the province. In addition, travel survey data provides only one-day trip plans for each respondent, which makes it challenging to construct multi-day trip plans. To compare on an equal basis, we considered daily mean OD flows of MPD in the regular week and Euclidean distances between origin and destination centroids to compute trip length distributions. Figure 9 shows that MONITOR trip length distributions fit well with those of MPD. However, MONITOR has a lower proportion of short-distance trips (< 2 km) and a higher proportion of long-distance trips (>10 km). MONITOR records a lower share for intrazonal and short-distance OD pairs, as MPD's continuous tracking may capture short movements that surveys underreport. In contrast, MONITOR exhibits higher shares for certain longer OD pairs, which is likely because surveys explicitly record purpose-driven long trips, such as occasional leisure, while MPD may miss trips that lack tower handovers or occur in areas with sparse coverage. When using Euclidean distances between antenna cell centroids, MPD systematically overestimated short-distance trips (<2 km). This bias was substantially reduced by implementing network-based shortest path distances (derived from OSM), which better reflect actual travel routes (see Fig. 4 in Gong et al. (2021)).

In addition, K–S tests were performed to examine whether mobile phone-based and surveyed trip length distributions at the municipality level are drawn from the same distribution. For each municipality, the trip length distribution of trips originating in that

Fig. 8 Comparison of MSSIM between MPD and MONITOR, and between MPD and random data



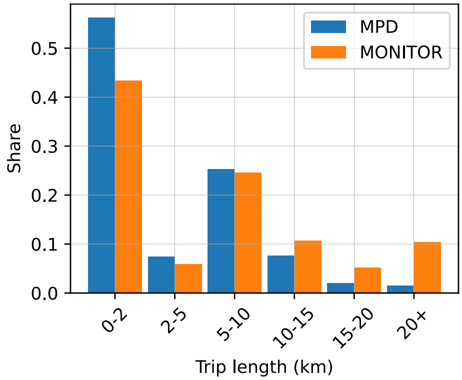


Fig. 9 Comparison of trip length distributions between MONITOR and MPD

municipality is computed. Most of the p-values (94.4%) vary from 0.357 to 1.0, indicating a similar distribution for municipalities between MPD and MONITOR trip lengths. There is only one zone with a p-value less than 0.05, which has only one interzonal destination reported in MONITOR.

Validation of MPD against population statistics

To further validate the MPD, we compared the population presence in traffic analysis zones to official population statistics from STATBEL. Population presence in traffic analysis zones fluctuates as people travel between different places during the day. However, we can assume that the count should correspond to national population statistics at some point in the day (Landmark et al. 2021). To validate this assumption, we compared the population from STATBEL and the extrapolated population based on MPD for different time slots (24 h of the day $\times$ 7 days) in a regular week. The absolute deviation is defined as the difference between the STATBEL and MPD population counts for each mobile phone cell. In particular, some time slots, such as 3:00 AM, were selected to present the difference and summarised in Table 3. Notably, the median population differences across all cells are smaller during nighttime hours compared to the daytime periods. This expected pattern reflects greater residential stability at night, as most individuals return to their primary residences during these hours, thereby improving the alignment between mobile phone-derived population estimates and official statistics.

Figure 10 presents the absolute population differences at 3:00 AM for all mobile phone cells. In this visualization, the positive difference represents the number of residents exceeding the population present in the zone extracted from MPD, and a negative difference indicates that the MPD-estimated population is smaller than the census-based resident population. While a majority of cells show close alignment, systematic biases emerge in specific zones: some cells have persistent positive differences (dark green in Fig. 10) indicating underestimation of the population by MPD relative to official STATBEL census data, and some have persistent negative ones (dark pink in Fig. 10) indicating overestimation.

We chose two representative cells called Bruyeres (darkest green) and Eupen (darkest pink), respectively, to further evaluate the mobile phone-based population during the nighttime hours. Figure 11a and b shows the percentage of population difference, normalised by population figures from STATBEL, for these two cells from 7:00 PM to 4:30 AM over

Table 3 Statistics of population differences for all cells in the province of Liège

Hour	Median	Mean	Std. Dev.
0:00	− 23	148	1812
3:00	8	250	1855
9:00	149	238	1886
14:00	190	210	2187
19:00	− 37	117	1797

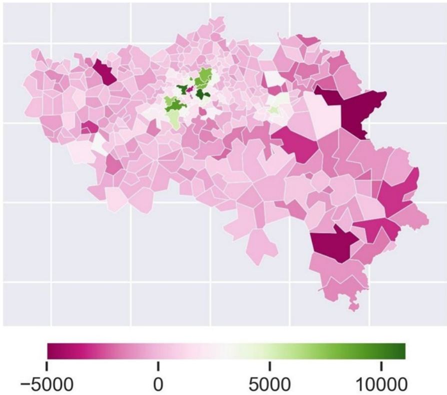


Fig. 10 Absolute population difference between STATBEL and MPD at 3:00 AM

the course of a week. We can see that the extrapolated population based on MPD for these two cells has a 40 to 50% bias to the population estimated from STATBEL. The former cell is one of the residential areas in the province's capital city, Liège. The latter is the whole capital of the German-speaking Community of Belgium. Regarding the population density, the former is much higher than the latter. The population is underestimated by MPD in Fig. 11a and overestimated in Fig. 11b.

In addition, we plotted the normalised hourly population difference for all mobile phone cells from 7:00 PM to 4:30 AM over the course of a week as 11c. Most of them lie between − 0.5 and 0.5. The red dashed line is the median value. Values smaller than − 1 mean that the STATBEL population is much smaller than the mobile phone-based extrapolated population, which takes a smaller proportion in this study.

Discussion

Comparing MPD and travel surveys is challenging as the definition of a "trip" differs between the two data sources. Trips reported in the travel survey have the respondents' self-reported departure and arrival times and locations. Mobile phone users' trip properties have to be characterised by various methodologies based on mobile devices connecting to cell towers and the inference of mobility patterns. In this study, we discuss aggregated MPD and travel surveys through a systematic comparative analysis. The methods we used to evaluate mobile phone-based OD matrices are robust and can be employed to derive similar results from other travel surveys. We assess the similarities and differences between MPD and MONITOR and between MPD and the population census as discussed below.

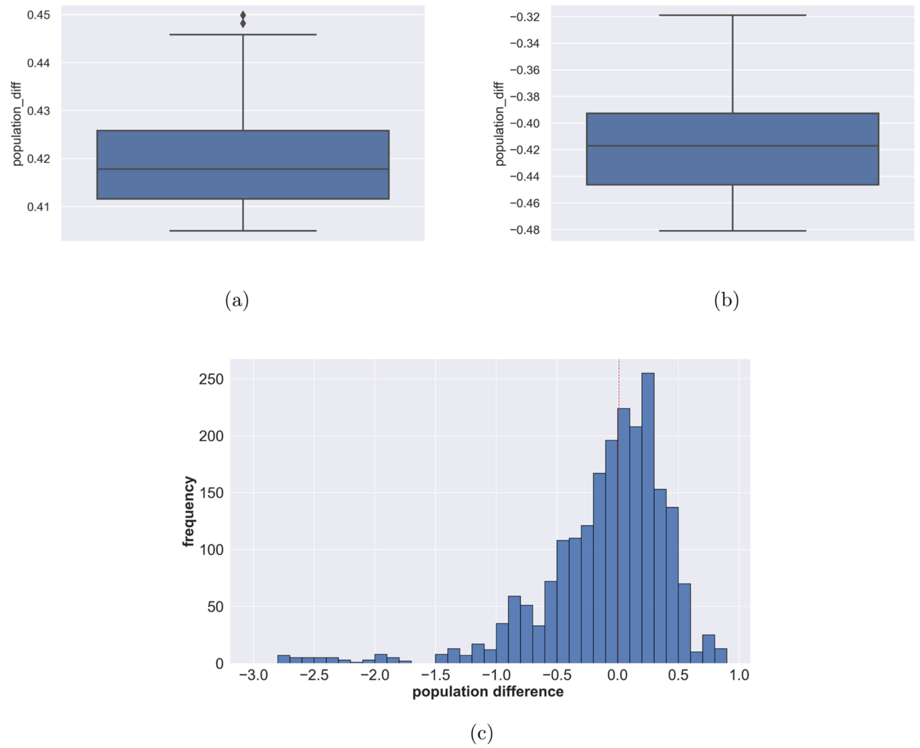


Fig. 11 Nighttime-only population differences from 7:00 to 4:30 AM for a week: **a** in Bruyeres, **b** in Eupen, and **c** for all mobile phone cells

The web-based travel survey has a relatively small number of respondents for the province of Liège, which is less than 0.04% of the population. Therefore, the sparsity of the survey-based OD matrix is relatively high and will increase if we expand the analysis to an hourly level. That's why we focused on the comparison of OD matrices at the daily level. In general, Fig. 6 shows that MPD and MONITOR have a similar trip generation/attraction share looking into OD matrices, apart from intrazonal trips and OD cells with possibly missing values. About 85% of OD pairs have differences (MPD minus MONITOR) in trip generation/attraction, the relative differences lying in the range of [− 20%, 20%]. The extremely high difference with respect to origins and destinations happened in intrazonal trips or interzonal trips from MONITOR with only one destination existing for the given origin. This can be explained by the effect that travel survey data cannot observe all possible OD pairs. Nevertheless, we can see OD trip flows from MPD strongly correlate with travel survey data, especially with respect to aggregate departures from origins and arrivals in destinations. Moreover, unlike the linear correlation coefficient, which is more influenced by the sparsity of matrices, Fig. 8 shows that the MSSIM index captures the similar structural aspects of MPD OD pairs related to MONITOR OD pairs at a daily level.

The MPD given in this study is aggregated by transactions of individual Proximus users defined by a time stamp and cellular localisation. Only when an individual remains for more than an hour will the transaction be classified into ‘staying points'; otherwise, the transaction will be classified into ‘transition points’. Theoretically, MPD does not represent short-duration trips well such as going out for a walk, due to the definition of trips less than a relatively small time threshold. However, from Figs. 6 and 9, we can see that trips stemming from MPD present higher proportions of short-distance trips than the travel survey. Another reason for more short-distance trips shown in Fig. 9 may be our decision to compute the trip length based on municipalities’ centroids. This approach allows us to compare trip length distributions on an equally spatial basis. The observed levels of spatial granularity for MPD and MONITOR given in Table 1 are not the same. If we switch to a finer level of zoning-system granularity instead of the municipality level, the results of trip length distributions can be slightly improved.

MPD offers additional benefits in terms of measuring population dynamics. Usually, the census population will be used to upscale the mobile phone estimation, which is unknown to us in this research. By contrast, we can observe a better match at night when comparing the mobile phone-extrapolated population with official population statistics. However, for most of the cells, the number of residents exceeds the number estimated by MPD during the day, which can be explained by the fact that not all residents own mobile phones and are active at home during the day. One of the exceptions is the biggest conurbation area for the province (deep green in Fig. 10), with a strong underestimation of the population from MPD during a whole week, while MPD always overestimates the other less populated but important cultural city (deep pink in Fig. 10). The place of the largest conurbation area at the municipality level is the capital city of the province of Liège, which has the most dominant effect on trip generation and attraction shown in Fig. 7.

The comparison results indicate that the variability in the survey-based OD matrices is extremely large, which aligns with findings of Cools et al. (2010a) that accurate OD matrices are not attainable from travel surveys. Only when half of the population is required is an acceptable OD matrix obtained at the provincial level. Clearly, the development of the web-based travel survey MONITOR was influenced by human, material, and financial considerations; however, it also led to a significantly increased variability in the survey. Therefore, it is imperative to incorporate additional data sources and methods, such as GPS-based smartphone tracking, machine learning-based data fusion, and mode inference algorithms, which could complement traditional surveys and MPD, enhancing realism and accuracy in capturing mobility behavior shifts. Cools et al. (2010b) offer an overview of potential methods for calibrating transport planning tools at the data level, model level, OD matrix level and assignment level by utilizing MPD. This example illustrates the approach of fusing MPD into travel demand models based on travel surveys. A direct combination of travel survey data with MPD is given in Gregg et al. (2024), who employ a machine learning approach calibrated with passenger survey data to infer the air travel purpose and airport access mode for MPD. Notwithstanding, this research assumes that features available from the surveys can also be observed or inferred through mobile network data. Besides, their MPD includes passengers’ and trips’ details such as passenger sociodemographics. Although our current MPD lacks sociodemographic detail, our validation demonstrates that caution is warranted when inferring detailed sociodemographics from aggregated MPD alone, emphasising that our validation highlights potential inaccuracies or biases in MPD extrapolation to individual characteristics. The MPD validation analysis in this research also demonstrates that we cannot fully trust the inferences derived from MPD. Moreover, data transparency remains one of the barriers preventing the broader application of MPD in conjunction with travel surveys. These challenges highlight the necessity of setting standards regarding the suitability of auxiliary data that give enough information to be able to formulate strong hypotheses about people's travel (Kuhnimhof et al. 2024).

Conclusion

This work evaluates the comparability of MPD and travel survey-based OD matrices by highlighting their underlying strengths and drawbacks. The novelty is the comprehensive comparison of OD trips between the web-based travel survey and MPD, and these two data sets are collected within a compatible year and area.

Comparable average trip rates, hourly ongoing trips, and trip length distributions were found. More uncertainties lie in the difference of OD matrices normalized by origin and dynamics of population estimation by MPD. We hope to improve the robustness of validation by learning the procedure of mobile phone estimations and improving the temporal resolution, which is unfortunately impossible due to the mobile data legacy. In addition, the quality of data collection and sampling rate for web-based travel surveys should be enhanced.

The findings suggest that MPD can effectively complement traditional travel surveys for urban transport planning. The strong correlations and similar patterns observed in the comparisons validate the potential of MPD to provide rich and timely insights into travel behaviour and population dynamics.

Future research should address the identified discrepancies, improve data integration methods, and explore the potential of combining multiple data sources for a more comprehensive understanding of urban mobility.

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Author contributions S.G. conceived and designed the study. S.G. and J.T. collected the data. S.G. and I.S. conducted the investigation, software, and analysis. S.G., I.S., J.T., and M.C. interpreted the results. S.G., I.S., and M.C. prepared the draft manuscript. All authors reviewed and approved the final version of the manuscript.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare no conflict of interest.

References

Ahas, R., Aasa, A., Yuan, Y., Raubal, M., Smoreda, Z., Liu, Y., Ziemlicki, C., Tiru, M., Zook, M.: Everyday space–time geographies: using mobile phone-based sensor data to monitor urban activity in Harbin, Paris, and Tallinn. Int. J. Geogr. Inf. Sci. **29**(11), 2017–2039 (2015)

Alexander, L., Jiang, S., Murga, M., González, M.C.: Origin-destination trips by purpose and time of day inferred from mobile phone data. Transp. Res. Part C Emerg. Technol. **58**, 240–250 (2015)

Bonnel, P., Fekih, M., Smoreda, Z.: Origin-destination estimation using mobile network probe data. Transp. Res. Procedia **32**, 69–81 (2018)

Bonnel, P., Munizaga, M.A.: Transport survey methods-in the era of big data facing new and old challenges. Transp. Res. Procedia **32**, 1–15 (2018)

Bwambale, A., Choudhury, C.F., Hess, S., Iqbal, M.S.: Getting the best of both worlds: a framework for combining disaggregate travel survey data and aggregate mobile phone data for trip generation modelling. Transportation **48**(5), 2287–2314 (2021)

Caceres, N., Benítez, F.G., Romero, L.M.: Land use inference from mobility mobile phone data and household travel surveys. Transp. Res. Procedia **47**(2019), 417–424 (2020)

Caceres, N., Romero, L.M., Benitez, F.G.: Exploring strengths and weaknesses of mobility inference from mobile phone data verses travel surveys. Transp. A Transp. Sci. **16**(3), 574–601 (2020)

Calabrese, F., Colonna, M., Lovisolo, P., Parata, D., Ratti, C.: Real-time urban monitoring using cell phones: a case study in rome. IEEE Trans. Intell. Transp. Syst. **12**(1), 141–151 (2011)

Calabrese, F., Diao, M., Di Lorenzo, G., Ferreira, J., Ratti, C.: Understanding individual mobility patterns from urban sensing data: a mobile phone trace example. Transp. Res. Part C Emerg. Technol. **26**, 301–313 (2013)

Calabrese, F., Ferrari, L., Blondel, V.D.: Urban sensing using mobile phone network data: a survey of research. ACM Comput. Surv. **47**(2), 1–20 (2014)

Chandrasekar, P.: Big data and transport modelling: opportunities and challenges. Int. J. Appl. Eng. Res. **10**(17), 38038–38044 (2015)

Çolak, S., Alexander, L.P., Alvim, B.G., Mehndiratta, S.R., González, M.C.: Analyzing cell phone location data for urban travel: current methods, limitations, and opportunities. Transp. Res. Rec. **2526**(1), 126–135 (2015)

Cools, M., Moons, E., Wets, G.: Assessing the quality of origin-destination matrices derived from activity travel surveys: results from a Monte Carlo experiment. Transp. Res. Rec. **2183**(1), 49–59 (2010)

Cools, M., Moons, E., Wets, G.: Calibrating activity-based models with external od information: Overview of different possibilities. In: *89th annual meeting of the transportation research board*. Transportation research board of the National Academies, Washington, United ... (2010)

Cottrill, C.D., Pereira, F.C., Zhao, F., Dias, I.F., Lim, H.B., Ben-Akiva, M.E., Zegras, P.C.: Future mobility survey. Transp. Res. Rec. **2354**, 59–67 (2013)

Demissie, M.G., Correia, G., Bento, C.: Analysis of the pattern and intensity of urban activities through aggregate cellphone usage. Transp. A Transport Sci. **11**(6), 502–524 (2015)

Deville, P., Linard, C., Martin, S., Gilbert, M., Stevens, F.R., Gaughan, A.E., Blondel, V.D., Tatem, A.J.: Dynamic population mapping using mobile phone data. Proc. Natl. Acad. Sci. U.S.A. **111**(45), 15888–15893 (2014)

Di Lorenzo, G., Liu, L., Ratti, C., Calabrese, F.: Estimating origin-destination flows using mobile phone location data. IEEE Pervasive Comput. **10**(4), 36–44 (2011)

Djukic, T., Hoogendoorn, S., Van Lint, H.: Reliability Assessment of Dynamic OD Estimation Methods Based on Structural Similarity Index. In: Transportation research board annual meeting, Washington, DC. pp. 13–4851. National, Academies. Number (2013)

Fekih, M., Bonnetain, L., Furno, A., Bonnel, P., Smoreda, Z., Galland, S., Bellemans, T.: Potential of cellular signaling data for time-of-day estimation and spatial classification of travel demand: a large-scale comparative study with travel survey and land use data. Transp. Lett. **14**(7), 787–805 (2022)

Gong, S., Saadi, I., Teller, J., Cools, M.: Validation of MCMC-based travel simulation framework using mobile phone data. Front. Future Transp. **2**, 10 (2021)

Gregg, A., Blasco-Puyuelo, J., Jordá-Muñoz, R., Martínez, I.M., Burrieza-Galán, J., Ros, O.C.: Airport accessibility surveys and mobile phone records data fusion for the analysis of air travel behaviour. Transp. Res. Procedia **76**, 269–282 (2024)

Gundlegård, D., Rydergren, C., Breyer, N., Rajna, B.: Travel demand estimation and network assignment based on cellular network data. Comput. Commun. **95**, 29–42 (2016). Mobile Traffic Analytics

Harding, C., Faghih Imani, A., Srikukenthiran, S., Miller, E.J., Nurul Habib, K.: Are we there yet? Assessing smartphone apps as full-fledged tools for activity-travel surveys. Transportation **48**(5), 2433–2460 (2021)

Huang, H., Cheng, Y., Weibel, R.: Transport mode detection based on mobile phone network data: a systematic review. Transp. Res. Part C Emerg. Technol. **101**, 297–312 (2019)

Kamenjuk, P., Aasa, A., Sellin, J.: Mapping changes of residence with passive mobile positioning data: the case of Estonia. Int. J. Geogr. Inf. Sci. **31**(7), 1425–1447 (2017)

Khodabandelou, G., Gauthier, V., El-Yacoubi, M., Fiore, M.: Population estimation from mobile network traffic metadata. In: *2016 IEEE 17th International symposium on a world of wireless, mobile and multimedia networks (WoWMoM)*, pages 1–9. IEEE (2016)

Kuhnimhof, T., Fabre, L., Cools, M.: Workshop synthesis: data fusion-generating more than a sum of parts. Transp. Res. Procedia **76**, 670–677 (2024)

Landmark, A.D., Arnesen, P., Södersten, C.J., Hjelkrem, O.A.: Mobile phone data in transportation research: methods for benchmarking against other data sources. Transportation **48**(5), 2883–2905 (2021)

Mohammadian, A.K., Javanmardi, M., Zhang, Y.: Synthetic household travel survey data simulation. Trans. Res. Part C: Emerg. Technol. **18**(6), 869–878 (2010). Special issue on transportation simulation advances in air transportation research

Molloy, J., Castro, A., Götschi, T., Schoeman, B., Tchervenkov, C., Tomic, U., Hintermann, B., Axhausen, K.W.: The MOBIS dataset: a large GPS dataset of mobility behaviour in Switzerland. Transportation **50**(5), 1983–2007 (2023)

Phithakkitnukoon, S., Hankaew, S., Demissie, M.G., Smoreda, Z., Ratti, C.: Temporary migration flow inference and analysis from perspective of mobile phone network data. IEEE Access **10**, 23248–23258 (2022)

Richard, O., Rabaud, M.: French household travel survey: the next generation. Transp. Res. Procedia **32**, 383–393 (2018)

Saadi, I., Farooq, B., Mustafa, A., Teller, J., Cools, M.: An efficient hierarchical model for multi-source information fusion. Expert Syst. Appl. **110**, 352–362 (2018)

Stopher, P.R., Greaves, S.P.: Household travel surveys: where are we going? Transportation research part A: policy and practice, 41(5), 367–381. Bridging research and practice: a synthesis of best practices in travel demand modeling (2007)

Wang, Z., He, S.Y., Leung, Y.: Applying mobile phone data to travel behaviour research: a literature review. Travel Behav. Soc. **11**, 141–155 (2018)

Zhao, F., Ghorpade, A., Pereira, F.C., Zegras, C., Ben-Akiva, M.: Stop detection in smartphone-based travel surveys. Transp. Res. Procedia **11**(2010), 218–226 (2015)

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