



A Quality Framework for Floating Car Data

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Abstract

This document presents a comprehensive quality framework for Floating Car Data (FCD), developed under the NAPCORE project as part of WG3 Task 3.2. The proposed framework evaluates FCD across four key dimensions: correctness, completeness, timeliness, and hybrid characteristics. Correctness assesses the accuracy and reliability of traffic metrics derived from FCD compared to ground truth data. Completeness examines spatial and network coverage, including missing data. Timeliness focuses on update frequency and data latency, while the hybrid dimension considers penetration rate, sampling rate, granularity, and map-matching accuracy. The framework’s applicability is demonstrated through a case study in Thessaloniki, Greece, involving traffic data collected from a fleet of approximately 1,200 taxis. Results indicate that while the evaluated FCD service provides reasonable accuracy and reliability for most routes, challenges remain regarding data completeness and coverage, especially during off-peak periods and on less frequently travelled roads. The findings underscore the need for targeted improvements in FCD collection and processing methods to enhance its effectiveness for real-time traffic management and ITS applications. This framework serves as a valuable tool for both data providers and National Access Point (NAP) operators to systematically assess and improve FCD quality.

Abbreviations

Abbreviation	Meaning
EC	European Commission
AID	Automated Incident Detection
NAP	National Access Point

RTTI	Real Time Traffic Information
AUF	Average Update Frequency
ITS	Intelligent Transport Systems
ATD	Average Time Delay
PMV	Percentage of Missing Values
WPMV	Weighted Percentage of Missing Values
FCD	Floating Car Data
QF	Quality Framework
C-ITS	Cooperative Intelligent Transport System
SEM	Standard Error of the Mean
SEB	Speed Error Bias
AASE	Average Absolute Speed Error
MAPE	Mean Absolute Percentage Error
PMATE	Per Mile Absolute Time Error
CCEC	Congestion Classification Error in Congestion
ANPR	Automated Number Plate Recognition
TISA	Traveler Information Services Association
PCI	Pearson Correlation Index
MAPE	Mean Absolute Percentage Error
RMSE	PCI Root Mean Squared Error
PMAE	Per Mile Absolute Error
SD	Segmentation Density
TDI	Topological Discrepancy Index
ASR	Average Sampling Rate
APR	Average Penetration Rate

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1. Introduction

In an era where urban mobility is increasingly central to the development of sustainable cities, the need for effective management of transport systems grows even more critical. Such a need calls for the increased exploitation and deployment of Intelligent Transport Systems (ITS), which, throughout their cooperative Day-X variants (Degrande et al., 2019), employ advanced sensing and communication technologies (including vehicle-to-vehicle and vehicle-to-infrastructure) for optimizing traffic flows, enhancing safety, and improving the overall efficiency of transport systems. However, the wide-scale adoption of ITS services heavily depends on meeting the minimum expectations of their end-users, i.e., travellers and road users. In this context, three aspects are increasingly essential for the smooth operation of transport systems (Jelušić et al., 2010; Tomás et al., 2013): i) digitisation, harmonious integration, and high-value processing of multiple information and data sources, ii) availability of the appropriate tools and methodological approaches for assessing the extent to which utilized data sources are timely, complete, error-free, and, in turn, trustworthy, and iii) targeted information diffusion, including the unambiguous determination of information recipients, information content, and diffusion means [i.e., who, what, and how to (optimally) inform].

services. It leverages advanced onboard vehicular technologies—such as GPS receivers and GSM/GPRS transmitters—to support navigation systems and smartphone applications (Pugliese et al., 2009). Concurrently, these technologies facilitate the collection of timestamped geolocations from connected (probe) vehicles that are map-matched to a road network of interest to derive link speeds, travel times, and trajectories. Unlike traditional fixed-location sensors, FCD enables the provision of insights into prevailing traffic conditions across large geographical extents, including roads situated at the lower levels of the road network hierarchy. The collection of FCD is predominantly carried out by private companies on the premise that road users have consented to data collection via license agreements, and with the assurance that transmitted information is anonymized to protect individuals' privacy (Horijon, 2017). Besides, public sector initiatives are also in place to collect FCD and to establish national FCD exchange platforms (Rehrl et al., 2018), indicating a growing interest and involvement from the side of governmental bodies in leveraging this technology. Overall, FCD offers a cost-effective way to monitor road networks, covering traffic flow, travel patterns, congestion, and/or vehicle emissions.

This work aims to contribute on one of the three key aspects of ITS, as identified above, by proposing a quality framework for FCD. It does so by reviewing prior work on this topic, specific needs, use cases, and challenges related to FCD, and testing the developed framework in a case study revolving around the road network of the Metropolitan Area of Thessaloniki, Greece. The suggested quality framework is structured around several key quality dimensions, including correctness, completeness, and timeliness, and focuses on the use of FCD to provide real-time traffic information (RTTI) in line with the ITS Directive (2010/40/EC) and its relevant supplementing Delegated Regulations (No. 2015/962 and 2022/670). It is noted that FCD is not mentioned explicitly as a data category in the EC Delegated Regulations. However, many data categories are derived from FCD which fall under the EC Regulations, notably traffic-status related data, such as “traffic speeds”, “travel times” and “traffic queues”. In this respect, the current document primarily focuses on the quality of the provided traffic-related information by considering critical aspects related to raw FCD and intermediate processing steps as contextual factors.

This document is organized as follows: Section 2 provides a concise review of the available literature in relation to four topics: a) what use cases are supported by FCD, b) how does FCD perform in comparison to alternative data sources, c) what challenges have been identified, and d) what has been already done as regards the evaluation of FCD and ITS data quality. Section 3 presents the methodological approach for assessing the quality of FCD that considers and builds upon the current state of the art. This framework is then tested in a

case study in Thessaloniki, whose design and results are presented in Section 4. Finally, Section 5 sums up, concludes, and indicates the main implications of the proposed framework.

2. Prior work

2.1. Use cases enabled by FCD

FCD contributes to various use cases within the digital transportation landscape. An interesting classification and taxonomy of such use cases is devised by Cerqueira et al. (2018) based on which FCD can be used in the context of the following types of mobility applications:

- **Digital route and map inference:** The inverse problem of map-matching, involving the reconstruction of FCD trajectories with the purpose of inferring the topology (and geometry) of a road network, enabling an appropriate digital (graph-based or more detailed) representation.
- **Traffic sensing and prediction:** Estimation of current or prediction of future traffic statuses, including travel times and speeds along specific road segments and routes. This use case is based on the premise that while FCD do not provide fully accurate information about traffic flow and density (unless penetration rate is quite high), the timestamped geolocation of certain vehicles suffices for inferring prevailing traffic conditions.
- **Trajectory mining:** Inference of realized routes to support the analysis of the route choice behavior of road users, including the identification of routes that are used or not, when, and by whom (e.g., vehicle classes).
- **O-D matrix estimation:** Approximation of origin-destination (O-D) flow matrices, describing the flow counts/mobility demand between specific positions of a given geographical area of interest.

Penetration rate constitutes a key notion in relation to FCD and other ITS technologies, by describing the proportion of vehicles tracked relative to the total number of vehicles within a given area or road network. Considering that this proportion is typically not widespread in most FCD services (Bischoff et al., 2012; Bruwer et al., 2023), the last two use cases distinguished by Cerqueira et al. (2018) are typically simplified to cover, respectively, major routes and pairs of major points of interest. For this and other reasons, FCD is frequently fused with other data sources or enhanced with statistical and machine learning techniques, such as the imputation of missing data and the artificial increase of penetration rate.

A more specific application enabled by the combined use of data obtained from inductive loops and FCD is presented in the work of Klunder et al. (2013), involving an Automatic Incident Detection (AID) system in the Dutch motorway network. This application targets the prevention of accidents at the end of traffic jams by providing queue tail warnings and speed reduction advisory to approaching drivers. The authors underscore that the operation of AID relying solely on inductive loops is rather complex and costly; for this reason, they investigate the potential of combining FCD with loop detectors and assess the effect of different penetration rates. Astarita et al. (2020) present a specific application using FCD to optimize traffic signal timings in real-time. This method quantifies connected vehicles at each intersection and adjusts signal phases by extending green intervals for approaches with higher vehicular loads.

The state-of-the-art overview offered by Jonkers et al. (2017) provides an extensive list of traffic applications in the Netherlands linked with various enabling data sources, including traffic counting devices and FCD. These applications are classified into the following categories: (1) monitoring, (2) provision of info and warnings, (3) advisory, and (4) traffic influence and control. An interesting aspect of this categorization and their respective applications revolves around their similar, yet notably escalating, nature. A typical example constitutes the provision of information about existing alternative routes, the recommendation of alternative routes, and the prescription of alternative routes to be followed by road users or connected vehicles. This example

underscores the necessity of ensuring the high quality of utilized information and data sources, particularly when the interventionism of an ITS service becomes more intense.

2.2. Empirical insights from the use of FCD and identified challenges

Efficient road network management is essential for enhancing traffic safety, travel efficiency, and CO₂ reduction. Achieving this outcome requires a comprehensive understanding of prevailing traffic conditions, leveraging data from multiple sources, including both traditional infrastructure sensors and emerging technologies, including FCD. This section provides an overview of the existing literature on the challenges associated with FCD and empirical findings from its use compared to alternative data sources across various use cases, including those mentioned in the preceding section.

Liu et al. (2012) evaluate the performance of various ITS technologies for travel time estimation along various sections of the Interstate I-287 in New Jersey, USA. The study compares FCD and point-to-point detection systems, by employing data from Co-Pilot devices (treated as the “ground truth”), Bluetooth sensors, electronic toll-collection tags (TRANSMIT readers), and the INRIX database (primarily containing data from trucks and commercial vehicles). Various statistical indices, such as Standard Error of the Mean (SEM), Speed Error Bias (SEB), and Average Absolute Speed Error (AASE), are used to assess performance. Key findings suggest that Bluetooth sensors and TRANSMIT readers align more closely with the ground truth data than INRIX, which consistently reports lower travel speeds, leading to a significantly negative SEB. The study also suggests that the accuracy of speed estimation through TRANSMIT readers remains consistent across different link lengths, while FCD and point-to-point detections show significant variations in reported travel speeds during incidents and traffic disturbances.

Patire et al. (2015) examine how much GPS data is required to ensure accurate speed and travel time information. The study involves a data fusion engine that integrates inductive loops and probe vehicles to improve travel time estimates across various traffic states, including pre-congestion, congestion onset, queue clearance, and post-congestion periods. Performance metrics include Mean Absolute Percentage Error (MAPE), Per Mile Absolute Time Error (PMATE), and Congestion Classification Error in Congestion (CCEC). A key finding is that higher penetration rates are more beneficial than higher sampling rates on freeways. This suggests that collecting less frequent data from a larger pool of unique vehicles is more effective than collecting more frequent data from a smaller number of vehicles. Additionally, even a modest amount of data from probe vehicles is found to enhance travel time estimates more effectively than simply increasing the density of infrastructure loop detectors.

Bruwer et al. (2022) focus on the impact of probe sample bias on the accuracy of travel speeds reported by commercial FCD services. They review existing literature on various assessment indicators and factors influencing FCD speed accuracy, such as speed limits, time of day, penetration rate, speed definition, driving behavior, vehicle types, road geometry, and weather conditions. The study stresses the importance of considering sample bias in FCD accuracy assessments, particularly when FCD is collected from a relatively small and potentially non-representative sample of probes. A case study involving the calculation of AASE and SEB, using FCD speed estimates from two commercial vendors across six South African cities, shows significant discrepancies. The findings indicate that penetration rate and speed bias are not significantly correlated, highlighting a limited capacity of penetration rate to act on its own as a predictor of speed accuracy.

Houbraken et al. (2018) investigate the potential of FCD for dynamic traffic management, focusing on real-time automated traffic control systems and end-of-queue collision prevention. They propose a speed advice procedure for an Automated Incident Detection (AID) system on Dutch motorways, comparing its performance when fuelled by FCD and loop detector data. The AID system aims to improve traffic conditions and safety by detecting congestion and other incidents and alerting upstream traffic through dynamic overhead signs. The

study makes use of high-frequency FCD (samples generated every second) and compares it with loop detectors with a nominal spacing of 500 meters. The research indicates that the FCD-enabled AID system demonstrates an acceptable time delay, but the use of less granular FCD could significantly affect the system's performance.

Similarly, Klunder et al. (2013) explore a queue tail warning system designed to prevent second-order accidents at the end of traffic congestion. The system, fused with current and smoothed speed measurements to minimize variations and reporting delays, is activated, when average speed drops below 35 km/h, and deactivated, when average speed reaches 50 km/h. The proposed system is tested on M42 motorway in Birmingham, UK, using data from loop detectors and interpolated FCD. In these settings, the study assesses the impact of different FCD penetration rates and detector distances. Results suggest that detector distances of up to 300 meters produce reasonable outcomes, with detection delays and location errors under 25 seconds and 200 meters, respectively. Larger distances increase these delays and errors. Moreover, the study reveals that a 1% FCD penetration rate provides comparable performance to loop detectors spaced 300 meters apart, whereas combining this with detectors spaced 500 meters apart reduces detection times and location errors by approximately 20%.

Rahmani et al. (2013) present a non-parametric method for route travel time estimation, using low-frequency FCD through link-based and route-based approaches. They address sources of bias and challenges and propose correction methods that are summarized in **Table 1**. Tested in a case study in Stockholm, Sweden, both approaches provided accurate route travel time estimates when compared to Automated Number Plate Recognition (ANPR) data. The study also introduces an indicator for comparing different data sources, involving the 25th and 75th percentiles of travel time distributions, representing off-peak periods and rush hours, respectively.

Table 1: Summary of challenges associated with FCD-enabled travel time estimations and associated correction methods (Rahmani et al., 2013).

Challenge/bias source	Description	Correction method
Incomplete route coverage	FCD observations may only capture part of the route, requiring travel times on the remaining sections to be inferred, increasing the risk of bias.	Scale link travel times based on the ratio of average speeds on the overlapping segment and the entire route. FCD concatenation ¹
Time-based sampling	Vehicle trajectory sampling is typically time-based, resulting in closer probe distances at lower speeds and greater distances at higher ones. Congested areas thus accumulate more FCD observations.	FCD concatenation ¹
Influence of adjacent network	FCD observations may partially cover the intended route and include adjacent links, leading to biased travel time distribution between the route and neighbouring links.	Allocate travel time to individual links based on prior estimates or free-flow-based travel times. Exclude FCD observations that exceed a predefined threshold, focusing on the ratio of route travel time to the total travel time of each observation.
Non-uniform route coverage	The coverage of FCD observations along a route can vary as vehicles join or exit through side streets. When travel speeds vary, giving equal weight to all observations may bias route travel time estimation.	Weight observations using a factor reflecting the inverse average vehicle counts along the covered links.
Unknown route entry time	Route travel times are calculated for specific intervals (e.g., 15 minutes) based on when a vehicle crosses the route's starting point. For FCD observations including the start point, the precise entry time is unknown. For those not covering the start point, the entry time needs to be assumed.	FCD concatenation ¹ Extrapolate the first timestamp of each observation based on the estimated travel time between the first probe and the route join point, as well as the hypothetical travel time between the route entry and join points.

¹FCD concatenation involves the following steps: (i) grouping of same vehicle trips into trajectories, (ii) matching trajectories to the analysed route and selecting the overlapping subset, (iii) merging observations in the subset so that: the first and last timestamps of the subset become the first and second timestamps of the observation, the first and last offsets of the subset become the first and second offset of the observation, and the link set of the updated observation includes the union of the subset's links.

Ranacher et al. (2016) focus on the positional accuracy and errors of raw FCD by distinguishing between measurement and interpolation errors. Measurement error is defined as the difference between the actual

position of a probe vehicle at a specific time and the position reported by the GPS at that same moment. Interpolation error arises from the difference between the continuum of a probe vehicle's movement and the discrete snapshots captured in its trajectory. The authors suggest that sampling rate should consider a series of parameters, including measurement error and the primary aim of FCD usage (use case). Through an experiment conducted in Salzburg, Austria, they arrive at several key findings. First, they note that interpolation error has a significant impact on trajectory mining use cases, which can be mitigated by applying temporal re-discretization, involving the artificial reduction of sampling rate (data downsizing). Second, the study finds that interpolation error may lead to a systematic underestimation of distance travelled when sampling is less frequent, whereas measurement error may cause systematic overestimation when sampling is very frequent. Lastly, due to the autocorrelation of measurement error, its influence on travel speed and travel direction calculations diminishes as sampling frequency increases. On that basis, specific sampling rates are proposed depending on the recorded parameter (i.e., paths, distance, speed, driving direction).

Finally, in a related study, Arregui et al. (2018) investigate the influence of the topological and operational aspects of road networks on map-matching accuracy. They categorize map-matching algorithms into four classes of increasing sophistication: (a) geometry-based (point-to-point and curve-to-curve, considering the shape of road links), (b) topology-based (leveraging network connectivity and path continuity constraints), (c) statistical or probabilistic (utilizing confidence regions around observations), and (d) advanced (employing refined statistical, data filtering, and mathematical theories and models). The authors conduct an experiment using a synthetic dataset generated by the Eclipse SUMO traffic simulator, i.e., a digital road network representation from Open Street Maps (OSM), and a grid-based approach to provide spatial aggregations of the topological and functional attributes of the overlaid road network (e.g., edge counts, average edge length, average speed limit, road density). In this context, they introduce a gaussian random error ($\sigma = 20$) to the coordinates of each observation and test the performance of two different map matching algorithms (point-to-curve and spatiotemporal) by comparing the map-matched trajectories with the ground truth edge sequences of each vehicle trip. The results suggest that both algorithms perform worst in urban areas with high road density; however, the spatiotemporal matching typically outperforms the point-to-curve algorithm, despite its dependence on sampling frequency. The findings also indicate that long road segments and increased speed limits positively affect map-matching accuracy, regardless of road density.

2.3. Quality evaluation

This subsection explores prior research on the topic of ITS data quality, including efforts to evaluate the quality of FCD. The European ITS Platform (EU-EIP) has emphasized ITS data quality as a crucial aspect for the harmonized deployment of ITS services and infrastructures across European road networks, including National Access Points, acting as national digital points of access to properly formatted ITS data resources associated with appropriate metadata (Mylonas et al., 2020). In this context, four quality packages have been developed, focusing on (a) safety-related and real-time information services, (b) multimodal travel information services, (c) intelligent truck parking services, and (d) Cooperative Intelligent Transport System (C-ITS) services. An extensive collection of relevant documents and guidelines is available through the EU-EIP repository (EU-EIP, 2020). These packages serve as quality assessment guidelines, outlining definitions, criteria, and methods for assessing data quality. Within this framework, “quality criteria” describe measurable aspects used to assess ITS data quality, which may be linked to various quality metrics, such as those mentioned in Section 2.2. “Quality requirements” encompass specific criteria and expectations for data quality established by stakeholders, tailored to specific use case needs. “Quality assessment methods” refer to the techniques and procedures used to assess and measure data quality, essentially quantifying each metric and, therefore, each criterion.

Table 2 demonstrates 11 quality criteria from the EU-EIP quality package related to safety-related and real-time traffic information services (Kulmala et al., 2019). These criteria focus on evaluating the quality of information derived from conventional traffic counting or monitoring devices (e.g., inductive loops, CCTV cameras), following the specifications of the relevant Delegated Regulations supplementing the ITS Directive (see Section 1). The criteria apply to event information (e.g., incidents on the road network), traffic status-related information (e.g., travel times), or both, covering spatial and temporal dimensions and accuracy.

Table 2: Summary of quality evaluation criteria utilized in the SRTI/RTTI quality package of EU-EIP [adapted from Kulmala et al. (2019)].

Criterion	Description	Applies to	
		event information	traffic status-related information
Geographical coverage	Percentage of road network covered by the information service	✓	✓
		✓	✓
Availability	Percentage of time the information service is available	✓	
Timeliness (start)	Time difference between the occurrence and acceptance of an event		✓
Reporting period	Time interval for refreshing traffic state reports	✓	
Timeliness (update)	Time interval between the occurrence of an event and its acceptance by the information service	✓	
	Average age of data included in the latest reporting period		✓
Latency (content side)	Time interval between the acceptance of an event and its publication	✓	
	Time interval between the determination/calculation of the information content and its publication		✓
Location accuracy	Difference between the referenced location of the published event and its actual location	✓	
Classification correctness	Extent to which published events are classified correctly.	✓	
Error rate	Extent to which published information displays deviations from actual traffic status		✓
Event coverage	Types of events covered by the information service	✓	
Report coverage	Locations for which traffic status information is provided at any reporting period		✓

A much relevant set of criteria are also proposed in the white paper published by the Federal Highway Administration [FHWA (Ahn et al., 2008)]. These include: (a) accuracy (correlation of reported with actual values), (b) completeness (from a temporal point of view), (c) timeliness (proximity to real-time), (d) typical coverage (from a spatial perspective), and (e) accessibility (latency). On the other hand, Rehrl et al. (2018) introduce the concept of quality dimensions for evaluating the quality of FCD exchanged through a relevant national platform, including: (i) completeness, (ii) spatial accuracy, and (iii) timeliness. Completeness includes sub-criteria that measure: the share of successfully processed timestamped geolocations, the coverage of the predefined road network, and penetration rate. Spatial accuracy measures the mean sampling interval between successive timestamped geolocations and their mean matching distance to the road network. Timeliness is associated with both processing and publication delays. Notably, Rehrl et al. (2018) also introduce the concept of evaluation period, suggesting that most proposed measures should be evaluated continuously, except for penetration rate, which can be assessed annually in conjunction with inductive loop detections. Their evaluation framework is more heavily focused on raw FCD, in contrast to the approaches of EU-EIP and FHWA.

Cerqueira et al. (2018) adopt a similar approach, identifying the following FCD quality dimensions: (i) granularity, (ii) micro-temporal coverage, (iii) macro-temporal coverage, (iv) spatial coverage, (v) missing data, (vi) reliability, and (vii) accuracy. The first four dimensions are related to data value (i.e., their usefulness and relevance in supporting end-user applications). Granularity, for example, is evaluated through sampling rate, with an average value of 15 seconds or less considered optimal. Macro-temporal coverage focuses on measuring the time span, including the spread and uniqueness of weekdays covered, while micro-temporal

coverage is evaluated on a finer temporal scale, considering within-day coverage and diversity. Spatial coverage evaluates the spatial information present in the data using a grid decomposition technique, with each cell weighted based on the density of the road network, proximity to landmarks, and neighborhood with other key cells. The last four FCD quality dimensions relate to data veracity (i.e., data integrity and completeness). Missing data refers to gaps between successive FCD traces, which can escalate to “black holes” when the duration since the last transmission exceeds twice the median sampling rate. Reliability is associated with logical precision; for instance, whether a vehicle’s recorded positions indicate implausible travel distances within a limited time frame. Finally, accuracy is determined by measuring the difference between the GPS-reported positions and the vehicle’s actual location.

The QBENCH method proposed by the Traveler Information Services Association (TISA, 2022) introduces an additional dimension for evaluating the quality of travel time estimates. This dimension focuses on error tolerances and deviation-dependent information accuracy, using four quality thresholds to identify minor and major overestimations or underestimations:

$$\begin{aligned} QT_{\text{minor}}^{\text{over/under}} &= (-)84 \pm 0.06 \times ATT [\text{sec}] \\ QT_{\text{major}}^{\text{over/under}} &= (-)168 \pm 0.12 \times ATT [\text{sec}] \end{aligned} \quad (1)$$

where ATT denotes the actual trip-based travel time as measured by the “ground truth” information source. The minus signs apply in cases of travel time underestimation. Based on this approach, three quality levels are distinguished depending on the extent to which the reported travel time deviates from the actual travel time. For example, an overestimation of 240 seconds is categorized as: (a) major (low quality), when ATT is less than 600 seconds, (b) minor (moderate quality), when ATT is less than 2600 seconds, and (c) negligible (high quality), when ATT is greater than 2600 seconds. In a similar but slightly different context Brouwer (2014) identifies three quality levels by jointly considering error and coverage rates. Error rates are defined as the percentage of inaccurately reported delays, while coverage rates are the percentage of correctly identified traffic jams. From this perspective, an error rate of 20% is associated with: (a) poor quality, when accompanied by a coverage rate of less than 25%, (b) good quality, when accompanied by a coverage rate of less than 60%, and (c) very high (premium) quality, when the coverage rate exceeds 60%.

Finally, Huber and Bogenberger (2013) offer an interesting framework that differentiates between travel time information provided by a real-time traffic information (RTTI) service, such as an in-car navigation system, and the actual travel time inferred through an ex-post reconstruction process. The RTTI can be calculated using either complex or simple methods, such as net aggregation of real-time travel times for each segment of a traffic path. The actual travel time is reconstructed by adopting a spatiotemporal perspective, focusing on the analyzed traffic path and the dynamic fluctuations in travel times for each segment, as derived during each information update period. In this approach, travel time is reconstructed using a speed-based trajectory method with a finite or smoothed (continuous) speed function. While this offline process adds complexity to quality evaluation and may not be directly implementable in real-time conditions, it serves as a valuable framework for comparing information sources that provide real-time estimates with those that directly measure a variable of interest, such as travel time captured by point-to-point systems like Bluetooth detectors and e-tag systems.

3. FCD quality evaluation framework

The summary of the state of the art offered in the previous subsection provides valuable insights into the use and effectiveness of FCD and the processes for evaluating the quality of various traffic information data sources. In this subsection, we aim to develop a comprehensive Quality Framework tailored to the provision of traffic information derived from FCD. To this end, **Table 3** introduces some elementary notation, with critical elements discussed further in text.

Table 3: Mathematical notation.

Sets			
V	Set of network nodes	A	Set of grid cells overlaying the entire road network.
L	Set of network links	A*	Set of grid cells overlaying FCD segments
T	Set of FCD time aggregation intervals included in the FCD evaluation period	L*	Set of network links intersecting completely or partially with FCD segments
S	Set of FCD segments	L*(i)	Set of network links that completely intersect with or their centroid is closest to the <i>i</i> th FCD segment
P	Set of traffic paths tracked by the evaluated FCD service	S _c	Set of FCD control segments
S(i)	Set of FCD segments falling along the <i>i</i> th traffic path		
Parameters			
x _{FCD} (k, i)	Traffic information derived from FCD for the <i>k</i> th traffic path (or FCD segment) at the <i>i</i> th time aggregation interval	tt _f (k)	Travel time on the <i>k</i> th traffic path assuming free-flow conditions
x _{GT} (k, i)	Traffic information derived from the ground truth data source for the <i>k</i> th traffic path (or FCD segment) at the <i>i</i> th time aggregation interval	l(i)	Length of the <i>i</i> th linear element
N _{UProbes} (i, j)	Number of unique probe vehicles tracked on the <i>j</i> th segment during the <i>i</i> th time aggregation interval	t(i)	Timestamp reflecting the <i>i</i> th time aggregation interval
N _{ProbeT} (i, j)	Number of non-unique probe vehicles tracked on the <i>j</i> th segment during the <i>i</i> th time aggregation interval (data points)	t'(i)	Timestamp reflecting the time when the information corresponding to the <i>i</i> th time aggregation interval is made available for use by data consumers
V(i, j)	Traffic volume on the <i>j</i> th FCD control segment during the <i>i</i> th time aggregation interval	VF(i, j)	Number of vehicle fleets tracked on the <i>j</i> th FCD segment during the <i>i</i> th time aggregation interval

It is assumed that the road network is represented by a weighted directed graph $G(V, L)$, where V denotes the set of network nodes and L the set of network links, weighted by their free-flow travel cost. This graph, G , is referred to as the “reference road network” encompassing the entire road infrastructure within the spatial extent of the evaluated FCD traffic information service. Additionally, a distinction is made between FCD segments (denoted by S) and road network links, as they may not coincide depending on the evaluated data source, as schematically illustrated in **Figure 1**. In this context, let $L^* \subseteq S$ denote the set of network links that intersect completely or partially with all FCD segments, and $L^*(i), i \in S$ the set of network links that completely intersect with or have their centroid closest to the i^{th} FCD segment. The former is used to evaluate network coverage, while the latter helps in understanding the granularity of the provided traffic information. $S_c \subseteq S$ represents the set of FCD control segments, which are assumed to be equipped with infrastructure loop detectors (or any similar devices) that facilitate traffic volume counting. Finally, let P denote the set of traffic paths tracked by the evaluated FCD service and $S(i)$ the (sub)set of FCD segments falling along the i^{th} traffic path.

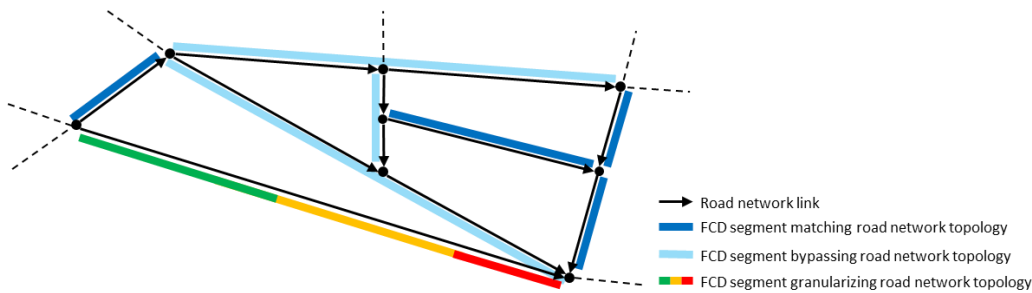


Figure 1: Schematic illustration of FCD segments in relation to road network topology.

As for the parameters included in **Table 3**, $x_{FCD}(k, i)$ and $x_{GT}(k, i)$ represent the provided traffic information for the k^{th} path at the i^{th} time aggregation interval, as derived from the evaluated FCD and the assumed “ground truth” traffic information service, respectively. These parameters introduce two fundamental assumptions of the proposed framework. The first assumption concerns the aggregation of traffic information at the level of traffic paths. This approach is adopted since it is generally more practical to compare path-based

traffic information between different data sources, given their varying geo-referencing bases. As a result, major traffic paths often serve as a common denominator for comparisons between the evaluated FCD service and the ground truth. The second assumption involves the existence of a “ground truth” traffic information service, which typically presents several challenges. Defining the criteria for a data source to qualify as “ground truth” falls outside the scope of this research. However, it is assumed to be influenced by factors such as penetration rate, sampling rate, and other aspects, such as the degree to which it provides a direct measurement of the variable of interest. $tt_f(k)$ is defined as time needed for a conventional vehicle to traverse the k^{th} traffic path under free-flow conditions. It can, thus, be determined by aggregating the free-flow travel times of all links along the k^{th} path. This aggregation can be derived by analyzing a representative sample of historical speed data and applying, for simplicity, the 85th percentile rule (Dixon et al., 1999). $N_{probes}(i)$ and $N_{probes}(i, j)$ refer to the unique vehicles tracked along a specific FCD segment. The term “unique” is used herein to distinguish these vehicles from the multiple tracking of the same vehicles along an FCD segment. Finally, the evaluation period refers to the period (i.e., set of time aggregation intervals) over which the FCD quality evaluation is conducted.

Table 4 presents the building blocks of the proposed FCD quality framework, encompassing its quality dimensions and their associated quality criteria and metrics. It is noted that evaluation criteria are discerned into direct, contextual, and informative. Direct criteria relate directly to the provided traffic information and can be used for evaluating its quality. A typical example constitutes the extent to which the provided information is correct as well as the extent of covering the road network of interest. Contextual criteria, on the other hand, are not directly associated with the provided traffic information, but consider key factors affecting its accuracy and representativeness (e.g., penetration rate). Finally, informative criteria provide useful information for assessing and understanding the suitability of an FCD source; however, they cannot be used in a formalistic manner to judge or rank the quality of the provided information. For example, while segmentation density is beneficial for certain use cases, such as the provision of queue tail warnings, an exceptionally detailed segmentation may result in challenges associated, for example, with the need of processing large amounts of data, data sparsity, over-interpretation of localized variations, and others. The subsequent subsections offer a systematic discussion of the various quality dimensions of the proposed framework, including their associated criteria and metrics.

3.1. Correctness dimension

The first quality dimension, correctness, encompasses the following quality criteria: accuracy – error rate, bias rate, classification correctness, and reliability. Accuracy reflects how precisely FCD represents real-world conditions without inaccuracies or discrepancies. It is quantified using four different metrics: Pearson Correlation Index (PCI), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Per Mile Absolute Error (PMAE). PCI evaluates whether FCD has a linear relationship with the ground truth by assessing how closely their data points cluster around a straight line, indicating the degree and direction of their association. MAPE measures the average percentage difference between FCD estimates and the ground truth, providing an average error rate. RMSE is similar to MAPE but penalizes substantial errors more intensively. PMAE provides insight into the error amount relative to the spatial extent of the monitored routes.

Bias rate is similar to the error rate but considers errors from a systematic perspective, including the direction of the error—whether FCD consistently overestimates or underestimates prevailing traffic conditions. It is measured using the Mean Bias Percentage Error (MBPE), which, unlike MAPE, does not use absolute values, thereby capturing error directions.

Classification correctness refers to the ability of FCD to correctly classify prevailing traffic conditions. It is measured using a single metric: Congestion Classification Error in Congestion (CCEC), as suggested by Patire et al. (2015). CCEC assesses how often the FCD and the ground truth agree on whether congestion is occurring. It calculates the differences between FCD’s congestion classification and the ground truth for each time interval, when (and only when) the ground truth indicates congestion. This discrepancy is then normalized by

the number of intervals with observed congestion, resulting in an average error rate. A lower CCEC value indicates better FCD performance in accurately classifying congested conditions. The value of parameter a included in the mathematical formulation of CCEC can be set to 3, unless otherwise specified, following the empirical threshold adopted by Ji et al. (2014). This threshold is based on the premise that when average vehicle speeds along a given linear element drop below the $1/3$ of free-flow speed, then is linear element is classified as congested.

In a similar context, reliability assesses the ability of FCD to avoid minor and major estimation errors. It is evaluated using three quality metrics. The first metric, Minor Threshold Reliability, measures the proportion of time intervals where the FCD inaccuracies remain lower than predefined minor threshold values, thus reflecting how often the FCD stays within acceptable bounds for minor errors. The second metric, Major Threshold Reliability, does the same by considering major threshold values, thus reflecting how often the FCD avoids significant deviations from the actual traffic conditions. The threshold values suggested by TISA (2022) can be applied to both metrics, particularly for the provision of travel time information. Finally, Overall Reliability (OR) is the average of Minor and Major Threshold Reliability, providing an overall measure of the FCD's performance in maintaining accuracy within both minor and major error thresholds. OR can be weighted to place different importance on minor and major errors, depending on the specific use case requirements.

3.2. Completeness dimension

The second quality dimension, completeness, evaluates how extensively the FCD covers both the spatial and infrastructural aspects of the area of interest, as well as the presence of missing data. It encompasses three main criteria: spatial coverage, network coverage, and missing values. Spatial Coverage focuses on the spatial characteristics of the evaluated FCD source by assessing the uniformity of coverage across the area of interest. This involves dividing the reference road network into a grid of appropriately shaped and sized cells that overlay the entire network in an end-to-end manner. Spatial coverage is then quantified using two quality metrics. The first one, Grid Coverage (GC), measures the proportion of grid cells where the FCD provides data, indicating how comprehensively the data spans the entire area of interest. A grid cell is considered “covered” by the FCD service if it overlays at least one FCD segment. The second one, Weighted Grid Coverage (WGC), is similar to GC, but applies weighting factors to grid cells, accounting for their significance across the spatial extent. Weights can be determined based on the number of Points of Interest (POIs) enclosed in each cell, placing greater importance on areas likely to generate and attract a higher number of vehicle trips. The weighting factor for each cell ($w_{1,j}$) is, thus, determined as follows:

$$w_{(1,j)} = N_{POI,j} \quad (2)$$

where $N_{POI,j}$ denotes the total number of POIs enclosed in grid cell j . It is important to note that not all POI types have the same impact on traffic patterns. Therefore, weighting factors can be applied depending on the characteristics of the study area, the resolution of POIs, and analyst perception. For instance, major transit hubs or shopping centers are likely to generate more traffic than smaller retail stores or parks. This can be achieved by classifying POIs into various categories and assigning a different weighting coefficient to each category. Furthermore, the size of the grid cells should be location-dependent. In dense urban areas, smaller grid cells provide finer spatial resolution to accurately capture variations in trip origins and destinations. Conversely, peri-urban and inter-urban areas can be overlaid with larger grid cells due to fewer variations in trip patterns. Since 0.5 kilometers is considered a generally acceptable walking distance (Yang & Diez-Roux, 2012), urban areas can be overlaid with 0.5×0.5 km grid cells. For peri-urban and inter-urban areas, this size can be progressively increased to reflect their broader spatial characteristics.

Network coverage complements spatial coverage by assessing how thoroughly the FCD covers the road infrastructure itself. While spatial coverage evaluates the presence of FCD data within the broader geographical area (using grid cells), it does not guarantee that all roads within those cells are adequately

covered. A grid cell might appear covered if it overlays an FCD segment; however, this convention does not consider all streets or critical road segments within that cell. Therefore, network coverage extends spatial coverage by accounting for network topology. It is quantified via two metrics. Link Coverage (LC) provides a straightforward measure of the proportion of road network links covered by the FCD. This metric offers a basic indication of how much of the road network is represented in the FCD data. Weighted Link Coverage (WLC) considers the hierarchical importance of each link within the road network. This importance can be assessed by applying weights to each road link based on parameters such as traffic volume. An alternative weighting parameter constitutes betweenness centrality (White & Borgatti, 1994; Kazerani & Winter, 2009), which indicates how frequently a road link is used as part of the shortest paths between all nodes in the network. This method highlights links that are crucial for network operations and requires significantly fewer data inputs than traffic flow measurements. Thus, the weighting factor for each road link ($w_{2,j}$) is determined as follows:

$$w_{(2,j)} = BC_j \quad (3)$$

where BC_j denotes the betweenness centrality of road link j . Alternatively, betweenness centrality can be multiplied by the length of the road links, ensuring that longer links are prioritized:

$$w_{(2,j)} = BC_j \times L_j \quad (4)$$

Finally, missing values evaluate the presence of gaps in the FCD, which can significantly impact the overall quality and usability of the provided traffic information. This is assessed using two metrics. Percentage of Missing Values (PMV) measures the proportion of missing values by counting the number of missing observations and dividing by the total number of observations. An observation is considered “missing” when $x_{FCD}(i, j) \neq \emptyset$ for the i^{th} traffic path (or FCD segment) at the j^{th} time aggregation interval. Similar to PMV, Weighted Percentage of Missing Values (WPMV), measures the proportion of missing values by accounting for the importance of each observation. Since both PMV and WPMV have a temporal orientation—missing values can vary across different time aggregation intervals—observations can be weighted by considering the typical traffic intensity of the associated temporal periods (e.g., peak and off-peak hours). This approach allows the penalization of missing data during periods of higher traffic intensity (e.g., AM and PM peak periods), which are perceived as more crucial for traffic management and analysis. Hence, the weighting factor associated can be formulated as follows:

$$w_{(3,i)} = \begin{cases} w_{(3,0)}, & \text{for periods of low traffic intensity} \\ w_{(3,1)} = w_{(3,0)} + \Delta_1, & \text{for periods of greater traffic intensity} \\ \dots & \\ w_{(3,n)} = w_{(3,0)} + \Delta_n, & \text{for periods of very high traffic intensity} \end{cases}$$

where $w_{3,0}$ represents the base weight under low traffic intensity and Δ_i an adjustment factor to account for the increased importance of time periods corresponding to escalated traffic intensities.

3.3. Timeliness dimension

The third quality dimension, timeliness, is purely related to temporal aspects of FCD. It is associated with two quality criteria, i.e., freshness and latency. Freshness assesses how frequently information derived from FCD is updated, while latency refers to the time delay or lag between the update of an FCD record and the moment this record is made available for use by data consumers or service providers through a data exchange system or platform. Freshness is measured via the Average Update Frequency (AUF), reflecting the average time difference between consecutive FCD time aggregation intervals. On the other hand, Average Time Delay (ATD) is used to evaluate latency, indicating the average time difference between all FCD time aggregation intervals and the moment at which the respective information is accessible to FCD users.

3.4. Hybrid dimension

The last dimension encompasses a range of criteria that integrate both intrinsic characteristics of the FCD and contextual factors related to its collection, processing, and composition. This dimension is crucial for assessing

the depth, accuracy, and representativeness of the FCD in real-world traffic scenarios. It consolidates the following criteria: granularity, penetration rate, sampling rate, map-matching, and fleet composition. Granularity refers to the level of detail provided by the FCD in terms of spatial resolution. It is quantified through different quality metrics. Segmentation Density (SD) measures the density of FCD segments within the reference paths. A higher SD value indicates a finer per mile (or kilometer) granularity, and vice versa. On the other hand, Topological Discrepancy Index (TDI) assesses from a systematic perspective the difference between the lengths of road network links and the corresponding FCD segments, thus offering insights into the extent to which FCD segmentation complies (or not) to the topology of the reference road network. A positive TDI value indicates that, on average, the lengths of the FCD segments are shorter than those of the corresponding road network links, and vice versa. A TDI value close to zero indicates a good match between FCD segments and road network links. Furthermore, it is important to note that granularity constitutes an informative criterion, considering, as mentioned in the introduction of the current section, that a finer granularity may be beneficial for certain use cases (e.g., safety-related ones) and simultaneously create challenges or additional computational burden for others.

Penetration rate indicates the proportion of the total vehicle population contributing to the FCD. A higher penetration rate suggests more representative traffic data, and vice versa. It is measured through Average Penetration Rate (APR) metric that calculates ratio of FCD-equipped vehicles to the total number of vehicles across the FCD control segments.

Sampling rate refers to the frequency at which data points are collected from probe vehicles. It affects the continuity of the derived metrics, such as travel times and speeds. It is quantified through the Average Sampling Rate (ASR) metric.

Map matching involves the process of aligning raw FCD traces (data points) with the underlying road network. This metric categorizes, from a qualitative point of view, existing techniques based on their complexity and accuracy (i.e., geometric, topologically enhanced, statistically enhanced).

Finally, fleet composition refers to the diversity of vehicle types contributing to the FCD, as a means of investigating the plurality of captured traffic behaviours.

Table 4: Overview of proposed quality dimensions, criteria, and metrics.

Quality criterion	Type	Quality metric	Formulation	Value range
Dimension: Correctness				
Accuracy – error rate	Direct	Pearson Correlation Index (CI)	$CI(k) = \frac{\sum_{i \in T} (x_{FCD}(k,i) - \bar{x}_{FCD}(k))(x_{GT}(k,i) - \bar{x}_{GT}(k))}{\sqrt{\sum_{i \in T} (x_{FCD}(k,i) - \bar{x}_{FCD}(k))^2 \sum_{i \in T} (x_{GT}(k,i) - \bar{x}_{GT}(k))^2}}$, where $\bar{x}_{FCD}(k) = \sum_{i \in T} x_{FCD}(k,i) / \sum_{i \in T} 1$, $\bar{x}_{GT}(k) = \sum_{i \in T} x_{GT}(k,i) / \sum_{i \in T} 1$, and $k \in P$.	-1 to 1
		Mean Absolute Percentage Error (MAPE)	$MAPE(k) = \sum_{i \in T} \left \frac{x_{FCD}(k,i) - x_{GT}(k,i)}{x_{GT}(k,i)} \right / \sum_{i \in T} 1$, where $k \in P$.	0 to 1
		Root Mean Squared Percentage Error (RMSPE)	$RMSPE(k) = \sqrt{\sum_{i \in T} \left(\frac{x_{FCD}(k,i) - x_{GT}(k,i)}{x_{GT}(k,i)} \right)^2 / \sum_{i \in T} 1}$, where $k \in P$.	0 to 1
		Per Mile Absolute Error (PMAE)	$PMAE(k) = \sum_{i \in T} x_{FCD}(k,i) - x_{GT}(k,i) / \sum_{i \in T} 1(k)$, where $k \in P$.	0 to 1
Bias rate	Direct	Mean Bias Percentage Error (MBPE)	$MBPE(k) = \sum_{i \in T} \left(\frac{x_{FCD}(k,i) - x_{GT}(k,i)}{x_{GT}(k,i)} \right) / \sum_{i \in T} 1$, where $k \in P$.	-1 to 1
Classification correctness	Direct	Congestion Classification Error in Congestion (CCEC)	$CCEC(k) = \frac{1}{\sum_{i \in T} \delta_{x_{GT}(k,i) > a \times tt_f(k)} - \delta_{x_{GT}(k,i) > a \times tt_f(k)}} \sum_{i \in T} \delta_{x_{FCD}(k,i) > a \times tt_f(k)} - \delta_{x_{GT}(k,i) > a \times tt_f(k)} $, where $\delta_{x_{GT}(k,i) > a \times tt_f(k)}$ and $\delta_{x_{FCD}(k,i) > a \times tt_f(k)}$ equal to 1 if the encompassed conditions are satisfied and 0 otherwise and $k \in P$.	0 to 1
Reliability	Direct	Minor Threshold Reliability	$R_{minor}(k) = 1 - (P_{minor\ under}(k) + P_{minor\ over}(k))$, where $P_{minor\ under}(k) = P_{i \in T}(x_{FCD}(k,i) - x_{GT}(k,i) < QT_{under}^{minor}(k,i))$, $P_{minor\ over}(k) = P_{i \in T}(x_{FCD}(k,i) - x_{GT}(k,i) < QT_{over}^{minor}(k,i))$ and $k \in P$.	0 to 1
		Major Threshold Reliability	$R_{major}(k) = 1 - (P_{major\ under}(k) + P_{major\ over}(k))$, where $P_{major\ under}(k) = P_{i \in T}(x_{FCD}(k,i) - x_{GT}(k,i) > QT_{under}^{major}(k,i))$, $P_{major\ over}(k) = P_{i \in T}(x_{FCD}(k,i) - x_{GT}(k,i) > QT_{over}^{major}(k,i))$ and $k \in P$.	0 to 1
		Overall Reliability	$R(k) = (R_{minor}(k) + R_{major}(k)) / 2$, where $k \in P$.	0 to 1
Dimension: Completeness				
Spatial coverage	Direct	Grid Coverage (GC)	$GC = \frac{\sum_{j \in A^*} 1}{\sum_{j \in A} 1}$	0 to 1
		Weighted Grid Coverage (WGC)	$WGC = \frac{\sum_{j \in A^*} w_{(1,j)}}{\sum_{j \in A} w_{(1,j)}}$	0 to 1
Network coverage	Direct	Link Coverage (LC)	$LC = \frac{\sum_{j \in L^*} 1}{\sum_{j \in L} 1}$	0 to 1
		Weighted Link Coverage (WLC)	$WLC = \frac{\sum_{j \in L^*} w_{(2,j)}}{\sum_{j \in L} w_{(2,j)}}$	0 to 1
Missing values	Direct	Percentage of Missing Values (PMV)	$PMV = \frac{\sum_{i \in T} \sum_{j \in S} \delta_{i,j}}{\sum_{i \in T} \sum_{j \in S} 1}$, where $\delta_{i,j}$ is an indicator variable with $\delta_{i,j} = 1$ if $x_{FCD}(i,j) \neq \emptyset$ and $\delta_{i,j} = 0$ otherwise	0 to 1
		Weighted Percentage of Missing Values (WPMV)	$WPMV = \frac{\sum_{i \in T} \sum_{j \in S} \delta_{i,j} w_{(3,i)}}{\sum_{i \in T} \sum_{j \in S} w_{(3,i)}}$, where $\delta_{i,j}$ is an indicator variable with $\delta_{i,j} = 1$ if $x_{FCD}(i,j) \neq \emptyset$ and $\delta_{i,j} = 0$ otherwise	0 to 1
Dimension: Timeliness				
Freshness	Direct	Average Update Frequency (AUF)	$AUF = \sum_{i \in T[0:T]-1} t(i+1) - t(i) / \sum_{i \in T[0:T]-1} 1$	≥ 0
Latency	Direct	Average Time Delay (ATD)	$ATD = \sum_{i \in T} t'(i) - t(i) / \sum_{i \in T} 1$	≥ 0
Dimension: Hybrid				
Granularity	Informative	Segmentation Density (SD)	$SD = \sum_{k \in P} \frac{\sum_{l(k)} 1}{l(k)} / \sum_{k \in P} 1$	≥ 0
		Topological Discrepancy Index (TDI)	$TDI = \sum_{i \in S} \frac{l(i) - l(i)}{\sum_{j \in L^*(i)} l(i)} / \sum_{i \in S} 1$	$(-\infty, +\infty)$
Penetration	Contextual	Average Penetration Rate (APR)	$APR = \sum_{i \in T} \frac{N_{UProbes(i,j)}}{\sum_{j \in S_c} V(i,j)} / \sum_{i \in T} 1$	0 to 1
Sampling	Contextual	Average Sampling Rate (ASR)	$ASR = \sum_{i \in T} \sum_{j \in S} \frac{N_{UProbes(i,j)}}{N_{ProbeT(i,j)}} / \sum_{i \in T} \sum_{j \in S} 1$	≥ 0
Map matching	Contextual	Map-Matching Method (MMM)	Possible options: (1) Geometrical, (2) Topological, (3) Statistically enhanced	-
Fleet composition	Contextual	Fleet Composition Score (FCS)	$FCS = \sum_{i \in T} \sum_{j \in S} VF(i,j) / \sum_{i \in T} \sum_{j \in S} 1$	≥ 0

4. Case study

4.1. Setup

Thessaloniki, Greece's second-largest city with a population exceeding 1 million, serves as a crucial multimodal hub with vital social, financial, and commercial functions. The city frequently experiences traffic disruptions in key areas due to bottlenecks, illegal parking, and both planned and unplanned events, putting a significant strain on its existing infrastructure. In that sense, there is a great need for trusted and reliable traffic information services, as a means of supporting travellers and road users to plan in a more effective manner their trips and itineraries.

The current case study aims to assess the quality of a publicly accessible traffic information service, namely TrafficThess. This service utilizes FCD obtained from a taxi fleet of considerable size (approximately 1,200 vehicles) to provide travel speed information for specific road segments within the metropolitan area of Thessaloniki. This information is updated at 15-minute intervals. Additionally, the study employs a route monitoring service provided by a commercial vendor, which is regarded, for the purposes of this study, as the "ground truth" traffic information source. Hence, the current evaluation seeks to determine the extent to which TrafficThess, with its reliance on FCD from a more limited fleet, can effectively support ITS and traffic management services in a manner comparable to a commercial service that draws on a substantially larger pool of connected vehicles, offering, among others, greater granularity and more frequent updates.

The scope of the study encompasses 16 selected directional traffic paths (routes) that cover in a representative manner the majority of the city and its most significant street corridors (**Figure 2**). Due to the limited availability of the ground truth traffic information source, the evaluation period spans 10 days, from September 5 to 14, 2023. Furthermore, for the purposes of the study, particularly for the quantification of the APR metric, an additional data source is utilized involving loop detectors installed in the vicinity of various intersections across the city, falling along and beyond the evaluated traffic routes.

According to existing traffic analyses, each corridor in Thessaloniki exhibits distinct patterns for peak and off-peak periods, influenced by various factors such as location, road infrastructure, and traffic demand. These variations are often linked to the city's diverse activities, including business operations, educational institutions, and commercial centres, all of which contribute to fluctuating traffic volumes throughout the day. However, for the purposes of the study, particularly for the quantification of the WPMV metric, a standardized timeframe has been adopted for both morning (AM) and afternoon (PM) peak periods. On weekdays, Morning Peak is defined as occurring between 08:00 and 11:00, capturing the morning rush hour as people commute to work, school, and other activities. The Afternoon Peak on weekdays is defined from 15:00 to 20:00, covering a broad time frame that accounts for the varied end times of work, school, and after-work activities. For Saturdays, the Weekend Peak includes two distinct time slots: from 12:00 to 17:00 and again from 20:00 to 22:00, reflecting shopping, leisure activities, and evening social events. On Sundays, the Weekend Peak is defined between 12:00 and 18:00, a period typically associated with recreational and social activities. Outside of these periods, traffic is classified as Off-Peak, indicating lower traffic volumes and generally smoother travel conditions.

4.2. Results

Figure 3 summarizes case study results regarding the correctness quality dimension. The provided scatter plots compare the estimated travel times across the 16 selected traffic routes, as derived from the evaluated FCD service (y-axis) and the ground truth information source (x-axis). In both cases, travel times are calculated as the net aggregation of the travel times of each segment along the evaluated route. It is noted that according to the suggestions of Huber and Bogenberger (2013) travel time induced from FCD should be reconstructed to reflect their actual values. However, given that travel times are estimated in both cases by utilizing FCD processed in the same manner, no bias is introduced in the analysis. Furthermore, the number of data points included in **Figure 3** varies, as some time aggregation intervals were excluded when travel times were

unavailable for all links of a given route. However, in order to provide some flexibility in the analysis and avoid the unnecessary reduction of the sample size, the travel times of extremely short links (e.g., shorter than 50 meters) are programmatically replaced with typical time-dependent values (obtained from the analysis of a sample of 1 year), when these are found to be missing.

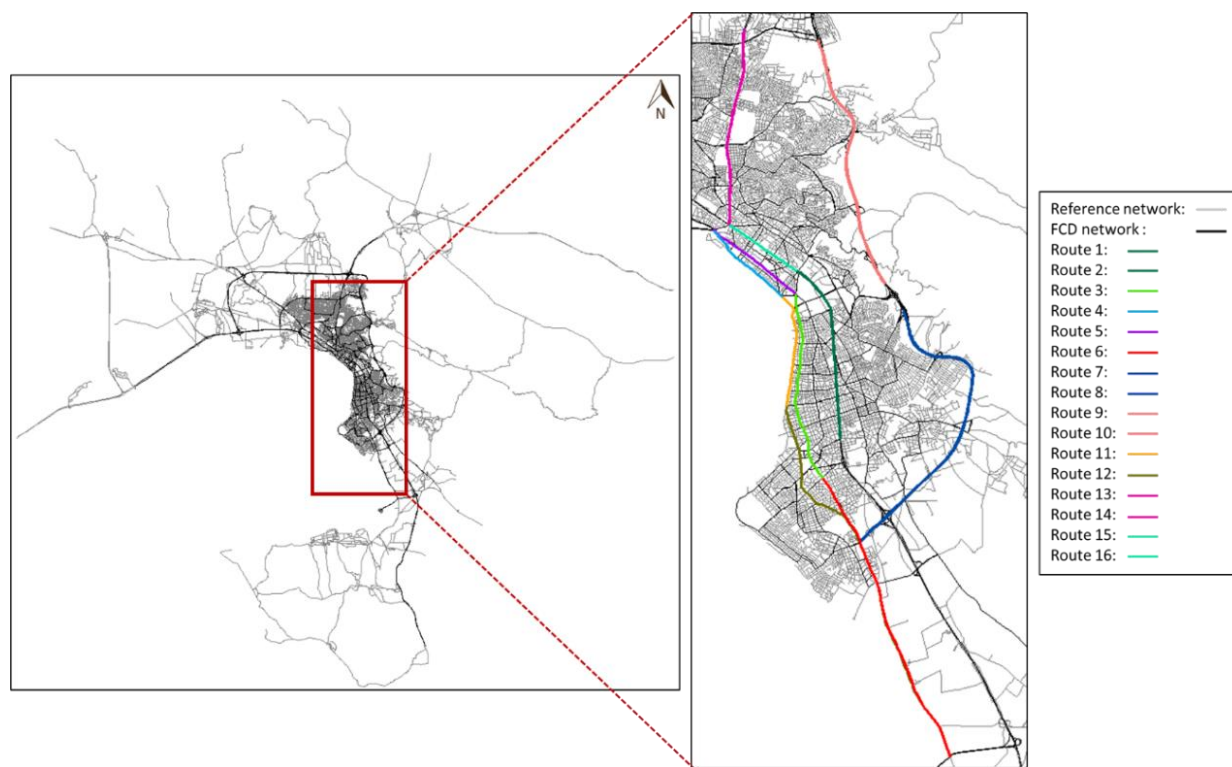


Figure 2: Overview of the study area and evaluated traffic routes.

The evaluated FCD service performs quite well along Routes 1, 2, 3, 4, 6, 12, and 16. The FCD estimates for these routes show strong positive correlation with the ground truth data (CI ranges from 0.85 to 0.93), demonstrating consistency in capturing travel time variations (e.g., increases or decreases). The error rate is particularly low along Routes 3, 6, and 12, with MAPE between 6.02% and 7.17% and RMSPE ranging from 7.39% to 9.36%. Conversely, Routes 1, 2, 4, and 16 show slightly higher errors, with MAPE values between 11.98% and 12.75%, indicating that while the estimates follow the overall trend, there are some deviations in precise time predictions. Nonetheless, reliability remains high across all these routes (ranging from 0.81 to 0.98), indicating that the FCD travel time estimates rarely exceed minor or major accuracy thresholds. Route 4 presents some challenges with congestion classification (CCEC = 0.52), likely due to the effect of the adjacent road network that is not included in the FCD segmentation and some local detours made by taxi drivers to avoid congestion.

The evaluated service exhibits variable performance across Routes 5, 9, 10, 13, 14, and 15. On Route 5, it demonstrates a strong correlation with the ground truth (CI = 0.81) but incurs moderate error rates (MAPE = 21.27%) and some underestimation of travel time (MBPE = -20.24%), with an overall reliability of 0.73. Route 9 and 10 both show high correlation with the ground truth (CI = 0.85 and 0.98, respectively); however, they experience significant errors (MAPE = 39.86% for Route 9 and 48.49% for Route 10) and overestimation of travel times (MBPE = 39.01% and 48.36%). These high error rates and travel time overestimation can be attributed to the fact that Routes 9 and 10 lie along the city's ring road, where professional and non-professional drivers exhibit wide variable driving behaviors. Both routes also struggle with congestion classification (CCEC = 0.00), though they maintain reasonable overall reliability (0.75 for Route 9 and 0.63 for Route 10). Route 13 shows strong overall performance (CI = 0.81, MAPE = 18.17%) with slight underestimation (MBPE = -17.42%) and acceptable reliability (0.71). Despite a lower correlation on Route 14 (CI = 0.55), the evaluated FCD maintains low error rates (MAPE = 11.00%) and very high reliability (0.94). Finally, Route 15

exhibits a good correlation ($CI = 0.75$) with moderate errors ($MAPE = 19.90\%$) and slight underestimation ($MBPE = -11.95\%$), alongside high reliability (0.81).

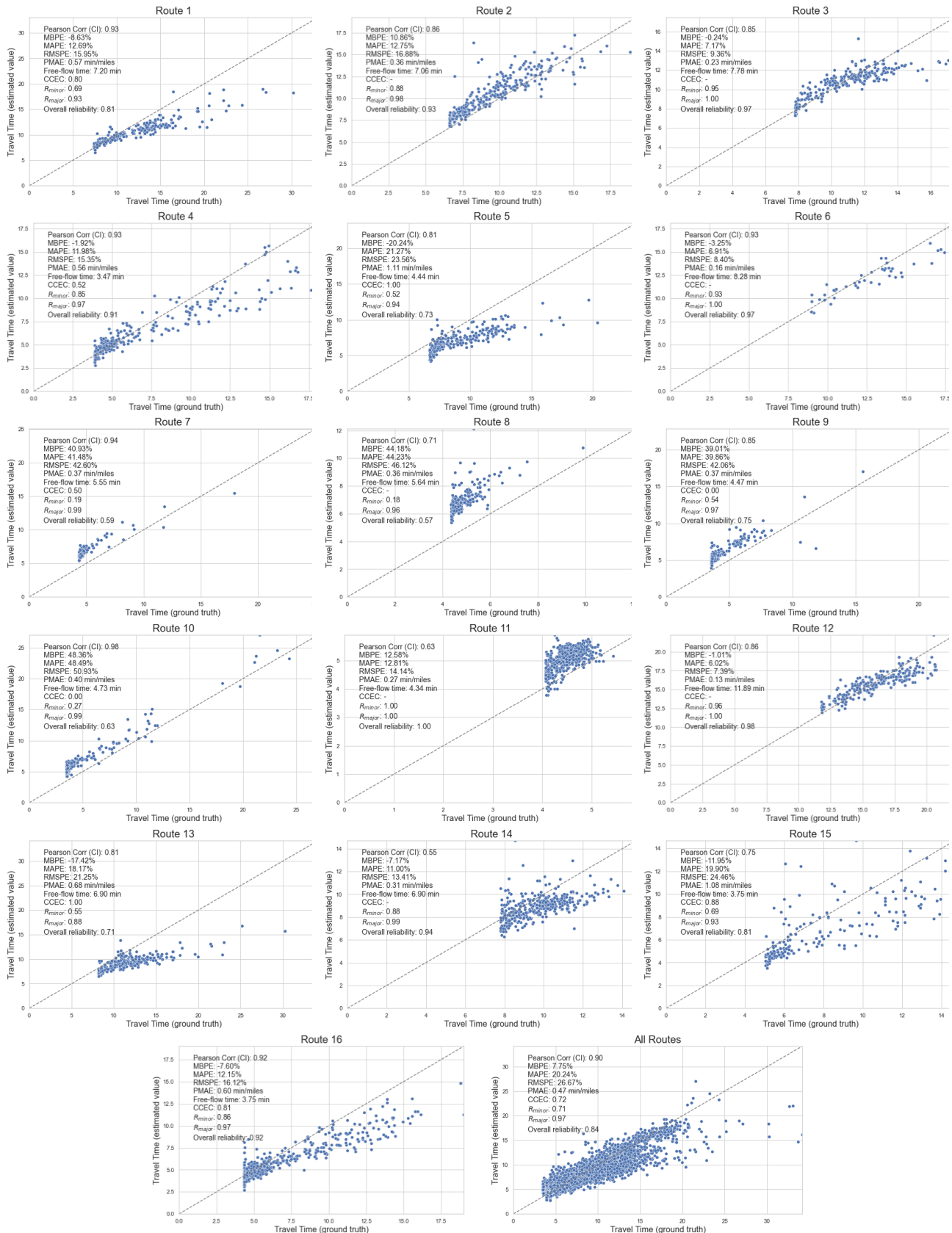


Figure 3: Summary of case study results with respect to correctness quality dimension.

On the other hand, Routes 7 and 8 exhibit high trend detection but notably poor accuracy and reliability. Both routes, located on the ring road, demonstrate significant overestimation of travel times. On Route 7, while the correlation with ground truth is high ($CI = 0.94$), the error margins are considerable ($MAPE = 41.48\%$, $MBPE = 40.93\%$), and the overall reliability remains moderate (0.59). Similarly, Route 8, despite a lower correlation ($CI = 0.71$), suffers from similarly high error rates ($MAPE = 44.23\%$, $MBPE = 44.18\%$) and moderate reliability (0.57). Both routes face significant challenges with minor threshold accuracy ($R_{\text{minor}} = 0.19$ for Route 7 and 0.18 for Route 8), while congestion classification is only partially effective on Route 7 ($CCEC = 0.50$). These issues are likely influenced by the variable driving behavior on the ring road, underscoring the importance of factors, such as FCD fleet composition and penetration rate.

Route 11 shows moderate correlation with the ground truth ($CI = 0.63$) but demonstrates very low error rates ($MAPE = 12.81\%$, $MBPE = 12.58\%$) and perfect reliability (1.00 for both minor and major thresholds). While the low correlation suggests that the evaluated FCD may not perfectly capture every fluctuation in travel time trends, the low error rates indicate that when deviations do occur, they remain minor, resulting in reliable and accurate travel time estimates overall.

When considering all routes together, the evaluated FCD service shows high correlation with the ground truth ($CI = 0.90$) as well as moderate error and bias rates ($MAPE = 20.24\%$, $MBPE = -7.75\%$). The PMAE of 0.47 min/miles suggests that deviations in travel time estimates are moderate relative to the length of the evaluated routes (i.e., approximately 28 seconds per mile). This judgement is based on the fact that the study area encompasses a metropolitan traffic environment, suffering frequently from bottlenecks and congestion. Moreover, while larger deviations are sometimes evident, as shown by the RMSPE of 26.67% , the overall reliability remains high at 0.84 , particularly for major reliability thresholds ($R_{\text{major}} = 0.97$). Finally, congestion classification accuracy seems rather moderate ($CCEC = 0.72$), pointing to difficulties in consistently identifying congested traffic conditions.

As regards the completeness quality dimension, particularly the network coverage criterion, the evaluated FCD service shows relatively low link coverage ($LC = 24.2\%$), as evidenced in **Figure 4**. However, when the network hierarchy is factored in through the betweenness centrality measure, WLC increases substantially to 77.8% . This suggests that the evaluated FCD service captures in a more effective manner the most strategic and frequently utilized road segments of the analyzed road network. Furthermore, the combined use of betweenness centrality and link length as weighting factors further raises WLC to 79.0% , underscoring the focus of the evaluated FCD service on key road segments of greater length.

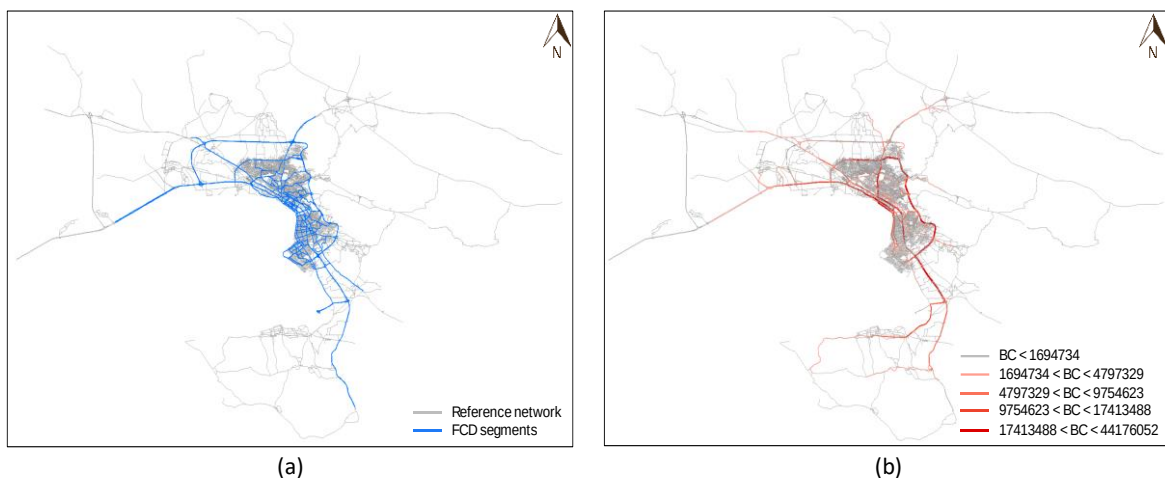


Figure 4: Overview of network coverage analysis. (a) Reference versus FCD network. (b) Road network hierarchy reflected through link betweenness centrality.

Figure 5 presents the outcomes of the spatial coverage analysis, which is based on the discretization of the study area into a grid of rectangular cells. The cell size varies according to the type of the overlaid areas, i.e., urban areas are covered by 0.5 x 0.5 km cells, peri-urban areas by 1 x 1 km cells, and interurban areas by 1.5 x 1.5 km cells. As it appears, the evaluated FCD service exhibits a moderate grid cell coverage (GC = 44,9%). However, when the spatial extent is weighted by the distribution of existing POIs, the grid coverage increases to 63.8% (WGC = 63.8%). This suggests that the FCD service prioritizes areas with higher traffic demand and activity, despite not fully covering the broader geographical area. The utilized POIs are sourced from Open Street Maps (OSM) via the Overpass API, by considering a wide range of categories related directly or indirectly to mobility, such as aeroways, amenities for food, education, public transport facilities, finance, healthcare, entertainment, public services, accommodation, commerce, public buildings, and stadiums.

Figure 6 outlines the results from the missing records analysis. As illustrated in the provided heatmaps, Routes 3, 5, 11, and 16 exhibit minimal travel time information gaps, with less than 15% missing records. In contrast, Routes 1, 2, 4, 10, 13, 14, and 15 show a higher percentage of missing information, ranging between 20% and 60%. Finally, Routes 6, 7, 8, 9, and 12 demonstrate the most significant data gaps, with missing records exceeding 60%. This poor performance can be partially attributed to the specific characteristics of the roads covered by the traffic information service. For instance, Routes 7 and 8, which are part of the city's ring road, experience high data gaps due to their infrequent use by taxi drivers.

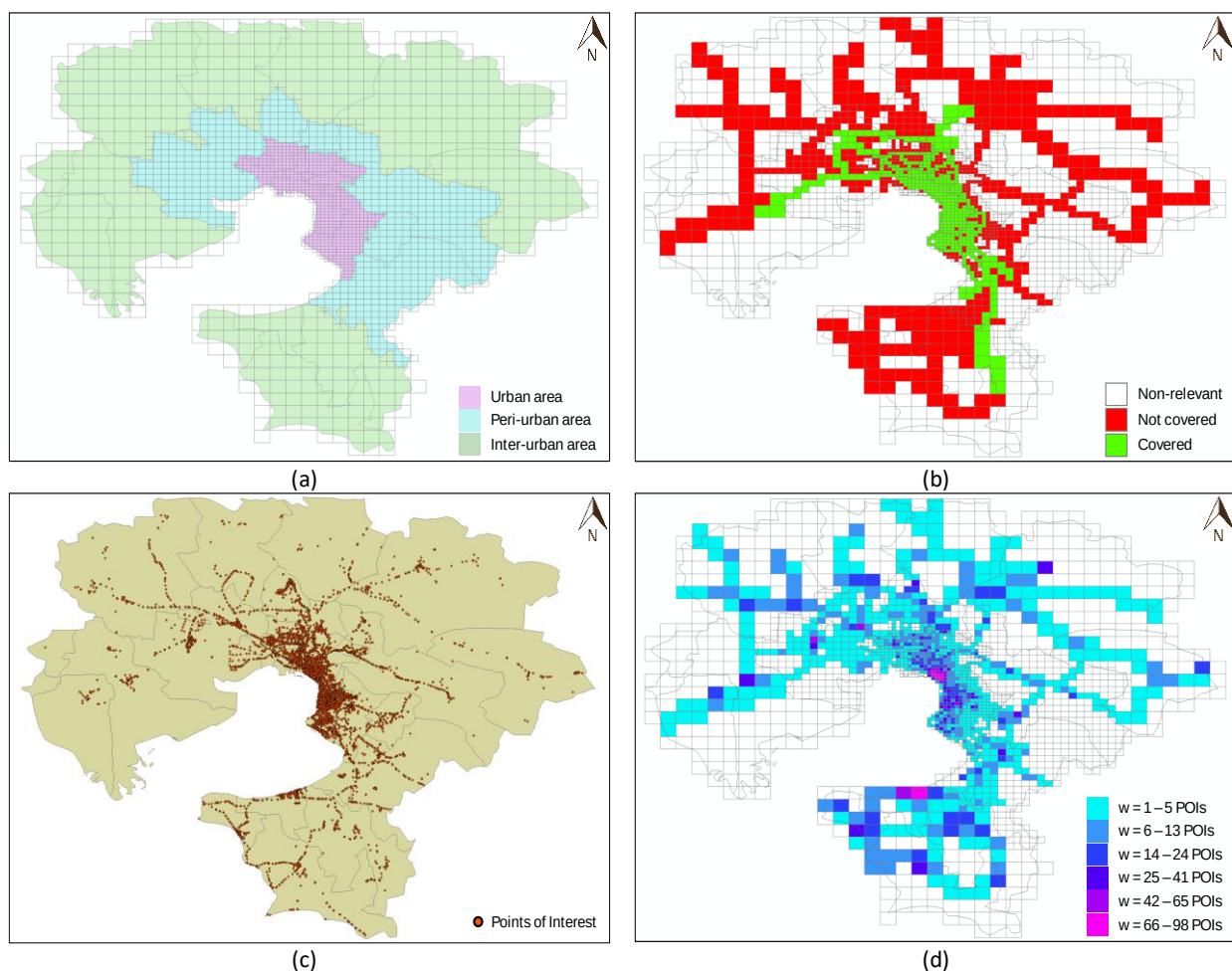


Figure 5: Overview of spatial coverage analysis. (a) Study area discretisation. (b) Grid cells covered and not covered by the evaluated FCD service. (c) Spatial distribution of POIs across the study area. (d) Weighting of covered and non-covered grid cells based on the number of POIs enclosed in each cell.

However, for other routes, the issue stems from additional factors, such as the overly dense segmentation of the covered road network coupled with the fixed time-based sampling of taxi probes. A representative case can be found on the initial sections of Route 6, wherein an FCD segment with a length of approximately 300

meters is characterized by high vehicle speeds, which result in frequent instances where no vehicle—particularly taxi—is matched to this segment. Consequently, this lack of vehicle detection generates a substantial number of missing records, hindering the calculation of travel time across the entire route. The implications of this issue for FCD segmentation are significant, particularly in relation to speed profiles. When segments are too short in areas with high speeds, vehicles may pass through these segments without being detected, leading to incomplete data (unless FCD sampling rate is dynamically adapted to the current vehicle speed). To mitigate this problem, more strategic segmentation is required, especially in high-speed zones, to ensure that segment lengths align more appropriately with typical vehicle flow patterns and minimize the likelihood of missing data.

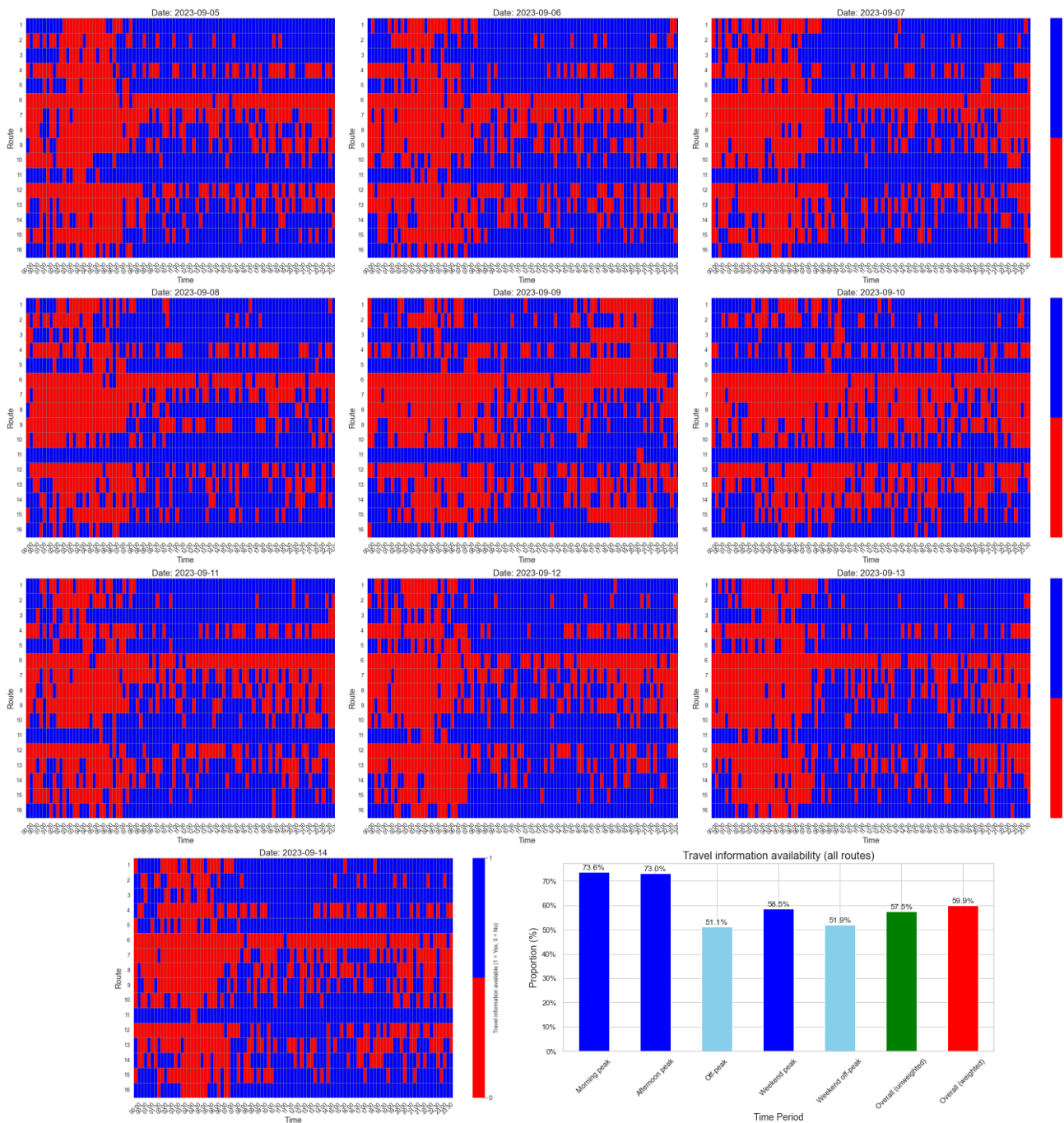


Figure 6: Results of missing records analysis.

In overall terms, the travel time information availability varies significantly across different time periods. The morning peak (72.6%) and afternoon peak (72.0%) show the highest availability, reflecting more

comprehensive data coverage during high-traffic periods. However, during off-peak hours, availability drops considerably to 50.1%. The weekend peak (58.5%) and weekend off-peak (51.5%) also show a decline in availability compared to weekday peaks. As a result, the overall availability of travel time information amounts to 57.5% and 59.9% in unweighted and weighted terms, respectively ($PMV=0.425$ and $WPMV=0.401$). Note that in the current assessment the following weighting factors have been considered: $w_{(3,AMpeak)}=w_{(3,PMpeak)}=3$, $w_{(3,off-peak)}=w_{(3,weekend-peak)}=2$, and $w_{(3,weekend-off-peak)}=1$.

With respect to the timeliness quality dimension, as noted in Section 3.1, the evaluated FCD service is configured to provide fixed information updates every 15 minutes ($AUF=15$ minutes). As regards the ATD metric, 30 samples have been picked up during the data collection period. The average delay between the information update and the time this information becomes usable—through the TrafficThess web interface—is on average 10.8 seconds.

In terms of the hybrid quality dimension, particularly the granularity criterion, the segmentation density across the evaluated traffic routes averages 3.6 segments/km. As shown in **Figure 7(a)**, this value varies by route. Several routes located entirely within the urban extent (e.g., Routes 1, 2, 15, and 16) exhibit a segmentation density exceeding 5 segments/km, while routes situated in the peri-urban environment (e.g., Routes 7-10) display a density of 1 segment/km or less. Additionally, the evaluated service demonstrates a Topological Discrepancy Index (TDI) of -0.31, indicating that FCD segments tend to bypass, in overall terms, the topology of the analysed road network. However, as shown in **Figure 7(b)**, this is not the case for all FCD segments; a significant number of them matches with network topology, while in several other cases, FCD segments tend to oversimplify network topology by excluding intersections of the covered arterials with several secondary and local streets.

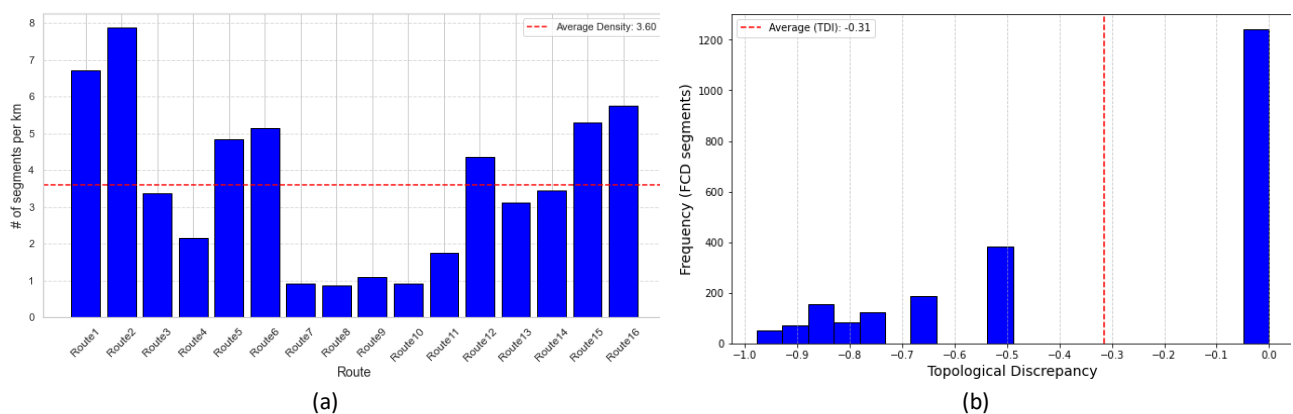


Figure 7: Overview of results pertaining to granularity quality criterion. Average segmentation density (a). Topological Discrepancy Index (b).

Figure 8(a) illustrates the locations of the inductive loop detectors and control segments utilized to assess the penetration rate of the evaluated FCD service. Both elements are positioned along or beyond the 16 traffic routes utilized in the assessment of the accuracy dimension. **Figure 8(b)** shows the penetration rate of the FCD service from September 5 to 14, 2023, calculated as the ratio of unique taxi probes tracked during each time aggregation interval, $N_{probes}(i)$, to the total traffic volume for the same interval. As it appears, the distribution of penetration rates follows a ‘power law’ pattern, with a large number of segments crossed by only a few taxis per interval, and a very small number of segments with frequent taxi crossings. This results in a relatively low average penetration rate, i.e., $APR = 6.4\%$. However, it is acknowledged that this figure provides only indicative value since the evaluation period is rather limited and only specific segments of the city’s road network are included in the set of FCD control segments.

Figure 9(a) shows that the penetration rate of the evaluated FCD service further decreases during peak time periods and increases slightly during the off-peak ones. According to the correlation coefficients reported in **Figure 9(b)** and **Figure 9(c)**, this variation is primarily driven by changes in traffic volumes rather than the number of unique taxi probes tracked. This practically suggests that the higher penetration rates during the

off-peak periods are due to reduced traffic volumes rather than to an increase in taxi probe tracking rate, which remains largely consistent across the various time periods.

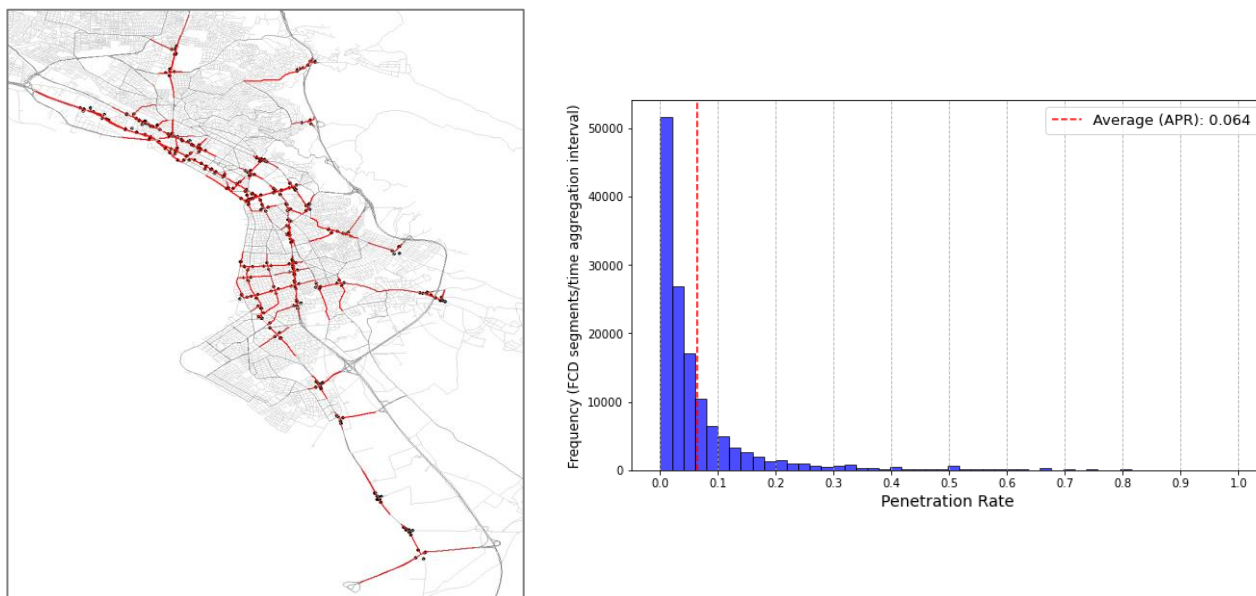


Figure 8: Overview of penetration rate analysis. (a) Location of inductive loops and FCD control segments. (b) Distribution of penetration rate during the FCD evaluation period.

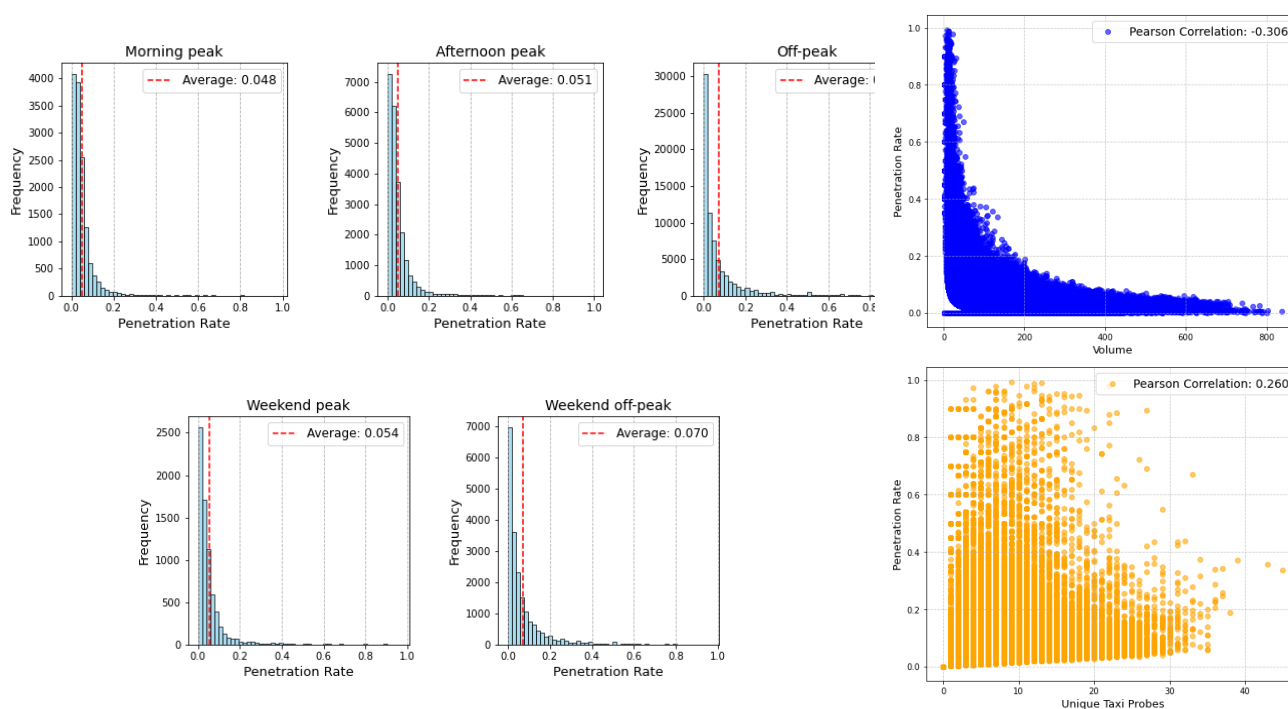


Figure 9: Penetration rate analysis during specific time periods classified based on traffic intensity. (a) penetration rates. (b) penetration rate versus traffic volumes. (c) penetration rate versus unique taxi probes tracked.

Figure 10 presents the results of the sampling rate analysis. For the entire set of FCD segments, the average sampling rate (ASR) is 1.66, meaning that, on average, each vehicle is captured once per approximately 9 minutes. However, it is important to recognize that ASR is influenced not only by the sampling frequency but also by the varying lengths of the FCD segments. As demonstrated in **Figure 10**, the average sampling rate increases when longer segments are included in the analysis. This finding highlights another implication of FCD segmentation: shorter segments inherently provide fewer opportunities for vehicle detection and sampling. Note that the classification used in **Figure 10** is based on the 33rd and 66th quantiles of the FCD segment length distribution.

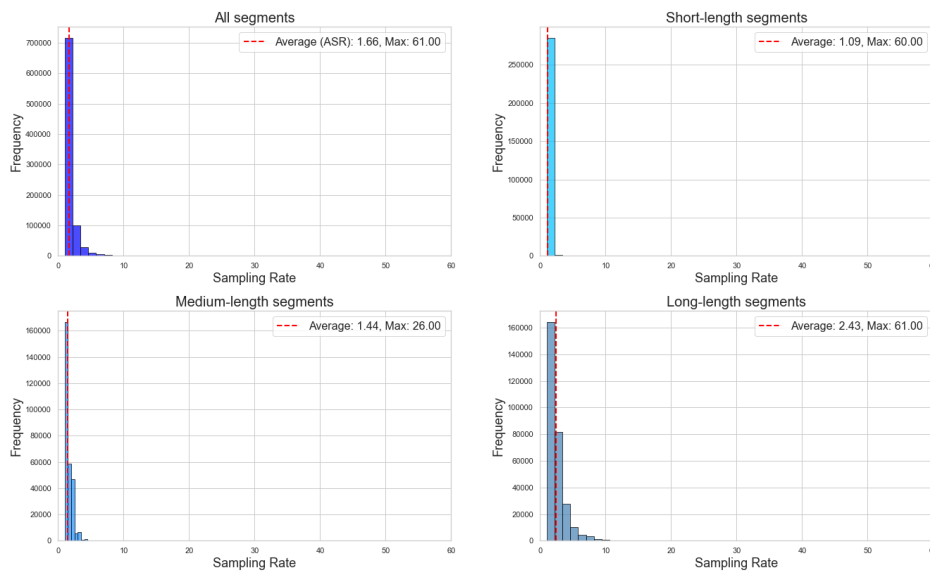


Figure 10: Overview of sampling rate analysis (all FCD segments and segments classified based on their length).

As regards the final two criteria of the hybrid dimension, map matching in the evaluated FCD service is executed through PostGIS spatial and trajectory assembling operators. Therefore, the MMM method is classified as geometrical. Finally, fleet composition is fixed at any information update interval, since the evaluated FCD stems from a single taxi fleet. Therefore, $FCS \leq 1$.

5. Discussion and conclusions

This report presents a comprehensive framework for evaluating FCD quality, addressing a significant need in the ITS domain for accurate and reliable traffic data to support advanced mobility solutions. As FCD becomes a more prominent source in traffic management, its quality directly affects the effectiveness of ITS applications, such as real-time traffic monitoring, route optimization, and congestion management. FCD offers extensive spatial coverage and cost-effective scalability, distinguishing it from traditional infrastructure-based data collection methods and establishing it as a fundamental component of modern traffic analytics. However, its utility depends largely on the accuracy, completeness, timeliness, and representativeness of the data. The proposed framework systematically assesses these dimensions, providing a robust understanding of FCD performance, including its limitations. Furthermore, the framework is applied to a real-world case study in the Thessaloniki metropolitan area to demonstrate its practical applicability and gain additional insights into FCD quality.

The framework is based on established data quality assessment principles, incorporating key dimensions to capture the complex and multidimensional aspects of FCD performance. The correctness dimension assesses the alignment of FCD-derived traffic metrics with ground truth data, focusing on accuracy, error margins, and reliability. Completeness examines the spatial and network coverage of FCD, providing insights into its geographical representation and infrastructural inclusiveness. Timeliness considers the speed at which data is updated and made available. Finally, hybrid metrics, including penetration rate, sampling rate, and granularity, reflect the contextual and compositional characteristics of FCD.

The study has implications for both data providers and NAP operators, providing a systematic framework to assess and improve FCD quality. For NAP operators, the framework offers a structured approach to gain insights into the quality of published or prospective FCD, supporting more informed decisions on data integration into national mobility platforms, such as NAPs. For data providers, it serves as a benchmarking tool to identify strengths and limitations, enabling targeted improvements in data sampling, segmentation, and other step of the FCD processing chain.

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