

**GEOVISUALIZATION OF MOBILITY PATTERNS
USING MULTISOURCE DATA: A CASE STUDY
AT ENVELOPA CAMPUS, OLOMOUC, CZECHIA**

MASTER'S THESIS

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of

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(PLUS)**

Faculty of Digital and Analytical Sciences

Department of Geoinformatics

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ANOTATION

This diploma thesis focuses on the processing, analysis, and geovisualization of mobility data within the Envelopa Campus of Palacký University, Olomouc. The aim is to identify spatial and temporal mobility trends using multisource data, including Telraam traffic counts, EnCLOD municipal sensor data, Nextbike journey records, and CHMI weather data covering the period of May 2025 to May 2026.

Approaches to mobility monitoring, types of mobility data, data integration, and mobility visualization are reviewed. The analytical component then examines mobility trends across academic periods, weather and event-related associations, and differences between the Telraam and EnCLOD datasets with the same spatial coverage.

The main output of the diploma thesis is an interactive web map dashboard. Processed datasets and analysis are presented as geovisualizations and non-spatial visualizations to allow users to develop an understanding of the spatial and temporal dynamics of mobility within the Envelopa Campus during the study period.

KEYWORDS

Keywords – Data Integration, Spatiotemporal Analysis, Mobility Sensor Data, Mobility Pattern Analysis, Internet of Things (IoT), Web Dashboard

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This thesis has been composed by Maria Anna Fedyszyn for the Erasmus Mundus Joint Master's Degree Program in Copernicus Master in Digital Earth for the academic years 2024/2025 and 2025/2026 at the Department of Geoinformatics, Faculty of Natural Sciences, Paris Lodron University Salzburg, and the Department of Geoinformatics, Faculty of Science, Palacký University Olomouc.

Hereby, I declare that this piece of work is entirely my own, the references cited have been acknowledged, and the thesis has not been previously submitted for the fulfilment of the higher degree.

Signature of student: 

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ASSIGNMENT OF DIPLOMA THESIS

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Theses guidelines

The student will analyse mobility in the Envelopa campus area in Olomouc using data from various sources, with a particular focus on sensor-based geographic data. Primary datasets will include traffic counts from Telraam sensors and relevant records from the Olomouc municipal sensor network built within the Enclod research project. Additional data sources may include anonymised data from mobile operators, fitness tracking applications (e.g. Strava), and other publicly or privately available mobility datasets.

The student will process, analyse, and interpret data collected over a minimum period of six months. Special attention will be given to the spatial and temporal dynamics of mobility in the study area. The results will be presented through a series of interactive and static geovisualizations embedded in a web map application, allowing for digital exploration and interpretation of the findings.

The thesis will also critically assess the quality, usability, and limitations of the employed data sources and methods, providing recommendations for future work in mobility analysis using heterogeneous datasets

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Recommended resources:

- CHESHIRE, J., UBERTI O. (2014): London: The Information Capital: 100 maps and graphics that will change how you view the city. Penguin Books. 240 s. ISBN: 1846148472
- JANEŽ, Miha; Špela VEROVŠEK; Tadeja ZUPANČIČ and Miha MOŠKON, 2022. Citizen Science for Traffic Monitoring: Investigating the Potentials for Complementing Traffic Counters with Crowdsourced Data. online. Sustainability, vol. 14, no. 2, p. 622. Available from: <https://doi.org/10.3390/su14020622>.
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LIST OF ABBREVIATIONS

Abbreviation	Meaning
AMD	Aggregated Mobility Data
AOI	Area of Interest
API	Application Programming Interface
BSP	Bikeshare Programme
BTS	Basic Transmitter Station
CHMI	Czech Hydrometeorological Institute / Český Hydrometeorologický Ústav (ČHMÚ)
CORINE	Coordination of Information on the Environment
EnCLOD	Enhancing Governance Capacities of Local Authorities using Open Data, a European Commission - Interreg Central Europe Programme
GLM	Generalised Linear Model
GPKG	GeoPackage
GRIB	General Regularly distributed Information in Binary
GSM	Global System for Mobile Communications
I-cities	Intelligent Cities
ILC	Inductive Loop Counter
IoT	Internet of Things
KPI	Key Performance Indicator
MPD	Mobile Positioning Data
OSM	OpenStreetMap
SDG	Sustainable Development Goal
STC	Space-Time Cube
UN	United Nations
UPOL	Palacký University, Olomouc / Univerzita Palackého v Olomouci
VGI	Volunteer Geographic Information
YAML	Yet Another Markup Language

INTRODUCTION

Mobility within the Palacký University, Olomouc (UPOL) Envelopa Campus (referred to within this diploma thesis as the Area of Interest - AOI) is shaped by a combination of university-related activity and wider urban movement. Although several sources of relatively high-resolution mobility data are available which cover this area, there is no comprehensive and integrated understanding of how mobility patterns differ temporally, spatially, and between transport modes.

Standalone traffic counts provide useful information regarding movement intensity at specific locations; however, they are limited in their ability to explain broader spatial and temporal mobility trends. By combining and comparing heterogeneous datasets, it becomes possible to develop a more detailed understanding of how mobility differs within the AOI, variations across academic periods, and how mobility may be influenced by external factors such as weather conditions or events. Such insights can support future decision-making by the university, local authorities, and other stakeholders responsible for transport planning and infrastructure management.

Generally, approaches to collating and analysing heterogeneous mobility datasets with variable resolutions remain fragmented and context-dependent, resulting in datasets that are often underutilised, inconsistently combined, or misinterpreted, leading to inaccurate or even false analytical findings.

The main question addressed in this diploma thesis is: “How can heterogeneous mobility data sources be utilised to assess movement patterns within a specified AOI effectively?” To answer this, the diploma thesis examines how mobility data with varying spatial and temporal resolutions can be acquired, processed, harmonised, analysed and visualised. Data is utilised from Telraam, the EnCLOD municipal sensor network, Nextbike and CHMI weather records. Movement patterns are assessed using metrics such as traffic volume, modal split, peak-hour intensity and changes in mobility over time. Relationships between mobility and weather conditions and events are defined using statistical measures of association, whilst datasets with overlapping spatial coverage are compared using metrics describing agreement, deviation, and relative differences in values. Special attention is therefore given to spatial and temporal mobility patterns, mobility trends under different weather conditions, and the consistency and differences between Telraam and EnCLOD datasets.

Results are presented within this written thesis and through an interactive web map dashboard. The dashboard provides spatial and non-spatial visualizations to communicate analytical findings to the user, as well as exploration of the processed datasets. The diploma thesis also critically evaluates the quality, usability and limitations of the employed data sources and methods. In this way, the diploma thesis provides a better understanding of mobility trends within the AOI but also contributes to a broader question of how heterogeneous mobility datasets can be meaningfully utilised for campus-scale mobility analysis.

1 OBJECTIVES

This diploma thesis aims to analyse mobility within the Palacký University, Olomouc (UPOL) Envelopa Campus (hereby referred to as the Area of Interest - AOI), using data from multiple sources, with a specific focus on sensor-based geographic data. Datasets include traffic counts from Telraam, the Olomouc municipal sensor network built as part of the EnCLOD research project, anonymised origin-destination (OD) data from Nextbike, and weather records from CHMI.

Within this diploma thesis, data is processed, analysed, and interpreted over a period of one year, with special attention to the spatial and temporal dynamics of mobility in the AOI. The results are presented through a series of interactive and static geovisualizations embedded in an interactive web map application, allowing for digital exploration and interpretation of the findings. Overall, the diploma thesis critically assesses the quality, usability, and limitations of the employed data sources and methods, providing recommendations for future work in mobility analysis using heterogeneous datasets.

In accordance with this, the following objectives have been derived:

Objective 1: Review existing methods for combining multisource mobility data with heterogeneous spatial and temporal resolutions

Existing approaches to the integration, harmonisation and visualization of multisource mobility data are reviewed to provide a methodological basis for the diploma thesis. This is important because mobility datasets often differ in their spatial coverage, temporal resolution, sensor specifications and the recorded mobility mode, meaning that they cannot be simply or directly combined without careful considerations. The review identifies methods which are transferable to the AOI and provides the methodological basis for the comparison of datasets and for the design of the interactive web map dashboard.

Objective 2: Collect, process, and harmonise heterogeneous mobility datasets for the Envelopa Campus

Mobility datasets for the AOI are collected, cleaned, and prepared for comparison and visualization regardless of variation in the data source, structure, and spatio-temporal coverage. This is necessary because the available datasets originate from different sources and, therefore, vary in detail and structure. Harmonisation of the data enables spatial, temporal, and mode-based analysis.

Objective 3: Analyse mobility patterns, including an evaluation of data/method limitations

Mobility patterns within the AOI are analysed, with attention to spatial concentrations of movement, temporal variation, weather-related associations and differences between data sources. This is important for developing an understanding of how movement varies throughout the AOI. It also evaluates the limitations of the datasets and methods used, including where it is possible to meaningfully combine heterogeneous mobility datasets, and contrastingly, where this comparison may be limited or misleading.

The identification of what the available datasets can and cannot reliably show, and general data limitations, is necessary to avoid misinterpretation of analysis and instead clarify how multisource mobility datasets can be meaningfully combined.

Objective 4: Develop and implement an interactive web map dashboard for communicating mobility patterns

An interactive web map dashboard is developed, which presents the processed mobility datasets, analytical outputs and key findings in an accessible visual form. The dashboard is valuable in providing a tool for the presentation of heterogeneous mobility data, as this information can be difficult to interpret through static figures and tables alone.

The dashboard supports exploration of spatial and temporal mobility patterns, comparison between datasets, and interpretation of the limitations within the data. The overall purpose of the dashboard is to communicate the results of the analysis whilst providing a clear example of how heterogeneous mobility data can be presented to users.

Overall, the results of the diploma thesis provide a valuable contribution to mobility analysis within the UPOL Envelopa Campus by demonstrating how heterogeneous mobility datasets can be combined, compared and communicated in a meaningful way. By utilising sensor-based traffic counts, municipal sensor data, bike-share records, and weather information, the diploma thesis provides a more comprehensive understanding of spatial and temporal mobility patterns in the AOI than what was previously known, and more than any single dataset alone could provide.

The resulting analysis identifies mobility trends, data gaps, and data limitations, which support better interpretation of mobility in the AOI. Additionally, the interactive web map dashboard makes the results accessible and understandable to users, thus increasing the practical value of the project. In this way, the diploma thesis sets a foundation for future mobility research at UPOL, whilst providing a transferable example of how multisource mobility data can be utilised for mobility analysis.

2 STATE OF THE ART

2.1 Mobility and Mobility Patterns

Mobility refers to the movement of people, vehicles or goods through space and time, whilst mobility data broadly refers to recorded observations of movement. This includes data from mobile phones, GPS devices, radio-frequency identification (RFID) systems, mobility-related devices (Turnnidge, et al., 2025), and other sensing systems; however, the common theme is data with a location element (Pelekis & Theodoridis, 2014).

Mobility patterns can be understood as how and when people, vehicles, or goods move through space, shaping how spaces are used and experienced. Analysing mobility flows is key to understanding movement patterns of people, including flow direction, intensity, and distribution. This aligns with computational movement analysis, which treats movement data as a spatio-temporal phenomenon requiring attention to movement traces, scale, uncertainty, and semantic interpretations (Laube, 2014). Monitoring urban mobility increasingly relies on the collection of movement data to support infrastructure provision and gain a better overall understanding of the movement choices individuals make.

Developing an understanding of mobility flow patterns is crucial for supporting stakeholders in making better-informed decisions. Higher spatial and temporal resolution of data can support more detailed analysis, yet the utilisation of this data is dependent upon data quality, representativeness, privacy constraints, and relevance for the analytical application.

GIS supports the storage, integration, analysis and visualization of mobility data, making it a key tool for transport-related analysis. The role of GIS in supporting transport planning has been well documented over the past 30 years (Zaroujtaghi, et al., 2025). In particular, GIS has been identified as important for geospatial transport data, disaggregated transport models and the geovisualization of transport-model results (Loidl, et al., 2016). In the current data-rich context, GIS is increasingly connected to the development of ‘smart cities’ to support more sustainable and responsive systems (Albino, Berardi, & Dangelico, 2015) (Eremia, Toma, & Sanduleac, 2017). This relies upon the expansion of the Internet of Things (IoT) (Xia, Yang, Wang, & Vinel, 2021) and an associated data-driven approach. The value of this approach is dependent on not only the availability of mobility data but also the ability to access, process, analyse and communicate findings effectively.

The analysis of mobility trends is useful to better understand how space is utilised by people; however, these patterns cannot be fully observed or quantified directly, and therefore, must be inferred from mobility data, which can be collected through different monitoring methods.

2.2 Mobility Monitoring Methods and Sources

Mobility monitoring can be done through a range of methods, each recording a different aspect of movement. These methods produce different formats of mobility data, including point-based counts, continuous trajectories, aggregated network flows, volunteered records and qualitative information. The suitability of each method depends

upon the spatial scale of the study, the required temporal resolution, the mode of mobility being analysed, and the desired level of detail to interpret mobility patterns.

Fixed-Location Monitoring

Data is recorded at a specific point, including traffic counters, inductive loop counters (ILCs) and camera-based systems, amongst other stationary sensors, to record details such as the number, direction or type of moving objects passing a given location. Typical outputs include timestamped counts, directional flows, modal classifications and, in some systems, speed or occupancy information. These methods are useful for the identification of temporal variation in movement, such as peak periods, directional flows and changes in intensity over time. They are limited to a predefined location and, typically, do not include information regarding the origin or destination of the journey, the route, or the purpose of the journey. The resulting data is, therefore, primarily point-based, making it suitable for comparing monitored locations but less suitable for reconstructing movement paths.

Mobile and Trajectory-Based Monitoring

Data is collected from devices which move with the user, vehicle or object which is being monitored. This includes GPS devices, smartphone-based trackers, bike-sharing platforms (BSPs), mobility applications, or sensors installed within a vehicle. The resulting data from these devices commonly consists of sequences of coordinates with timestamps, which may be stored as coordinate sequences, GPS tracks or GPX files. These records can be understood as spatial trajectories which require specific preprocessing, indexing, uncertainty handling and pattern-mining techniques before they can be properly interpreted (Zheng & Xiaofang, 2011). These records can be used to derive routes, speeds, stopping behaviours, and identification of frequently used segments.

Fitness and mobility applications, such as Strava, provide GPS-based records of walking, running, or cycling activity. Platform-based sources, such as Nextbike, provide different forms of mobility data depending on the system, including station locations, bike availability, trip start and end times, trip duration, and origin-destination (OD) pairs. These datasets can therefore support the analysis of route choice, travel behaviour, demand, and the identification of frequently used corridors.

These methods can provide detailed information regarding the route taken and velocity; however, they rely upon user participation and the availability of devices and are more affected by the positional accuracy of measurements. Trajectory-based data is particularly relevant for route-choice analysis and the identification of frequently used segments.

Network-Based Monitoring

Movement is inferred through the interaction between mobile devices and communications infrastructure. Network data can be used to estimate coarser mobility flows based on communication between devices and base transceiver stations.

An example of this is mobile positioning data (MPD), also known as Global System for Mobile Communications (GSM), which is available directly from mobile operators; every phone SIM connects to the nearest transmitter within a basic transmitter station (BTS) network, as the user moves across areas, providing movement records for each phone. This system does not utilise GPS in any form; the records are purely based upon the provider's network infrastructure. Data may include call detail records, signalling data, or other network-based records, each with varying levels of spatial accuracy,

temporal frequency and general statistical suitability (United Nations Economic Commission for Europe (UNECE), 2024). Previous studies have used such data to visualise intermunicipal commuting in Czechia (Burian, Žejdlík, & Rypl, 2025).

The method is useful for the analysis of mobility trends at larger spatial scales and can provide insight into general flow patterns across regional areas, as this data is usually aggregated for privacy reasons and does not provide information on transport modes. Generally, they are less suitable for fine-scale analysis at a local scale because the spatial resolution of the data is dependent upon the density and configuration of the communication network infrastructure.

Crowdsourced and Citizen-Science Monitoring

Mobility data is contributed by members of the public, and may include volunteered traffic counts, user-generated GPS tracks, participatory mapping or sensor systems installed and maintained by citizens. Data crowdsourcing can be defined as data that is collected by several contributors (Estellés-Arolas & González-Ladrón-de-Guevara, 2012), whilst citizen-science monitoring places more of an emphasis on public participation in the data collection process.

Previous studies have shown the successful complementing of data from Telraam, a citizen-operated traffic counting sensor, with inductive loop counter (ILC) data, demonstrating how citizen-generated counts can support mobility analysis (Janež, Verovšek, Zupančič, & Moškon, 2022).

Public participation has the potential to increase spatial coverage whilst strengthening community engagement in decisions being made in a local mobility setting. This is valuable where monitoring would otherwise be dependent solely on official infrastructure, governmental resources or dedicated transport surveys, which may be costly or infeasible in some contexts.

Citizen-science approaches are not only limited to the analysis of mobility trends but form part of a wider movement towards participatory data collection across disciplines (Becken, Connolly, Chen, & Stantic, 2019). Within the setting of smart cities, crowdsourced contributions can increase data availability and enable more citizen-centred approaches to be incorporated into urban planning decisions (Caceres, Sierra-Alonson, Cuesta, Vela, & Caverio Barca, 2020).

Open data is that which is freely accessible and usable by the public; the key motivators to the provision of open data are transparency, releasing social and commercial value, and participatory governance (Attard, Orlandi, Scerri, & Auer, 2015). Unlike sensor or trajectory data, open data may not directly record movement but instead provides contextual information to assist in the interpretation of mobility patterns. OpenStreetMap (OSM) is a common example of volunteered geographic information, providing data on road networks, cycle infrastructure, and points of interest. This is in contrast to datasets which have licensing and accessibility conditions that influence their suitability or even availability for mobility analysis (Mahajan, et al., 2022).

The combination of the IoT, open data, and citizen-centred research data enhances the development of smart cities in terms of increased data availability and giving communities a sense of involvement (Shahrour & Xie, 2021). Within mobility studies, open data provides contextual layers such as transport networks, details of infrastructure characteristics, land use information or administrative boundaries which may directly or indirectly influence mobility trends.

Survey-Based Monitoring

These methods include questionnaires, interviews, and travel diaries and often incorporate a perception-based approach, including the consideration of perceived safety or emotional responses to space, providing detail which cannot usually be captured by sensors. Participatory mapping can also be used to spatially locate perceived barriers, unsafe locations, preferred routes or emotionally significant places.

These methods complement sensor-based approaches by giving context to explain why trends occur. They can record details on trip purpose, perceived safety, comfort, travel preferences, and the regularity of routines. Results are more sensitive to response bias and limited sample sizes; nevertheless, they remain valuable for the interpretation and, where appropriate, quantification of social and experiential aspects of mobility.

Mixed Method Approaches

The relationship between individuals, especially cyclists, and mobility spaces is complex and cannot be accurately captured using a single method (Loidl, Werner, Füssl, Kratochwil, & Resch, 2025). Sensor-based approaches can provide information related to movement volumes, locations, or trajectories, but they are unable to fully explain the purpose of journeys, the logic behind route choices, or how typical a journey is for an individual's routine. For example, sensors alone are incapable of identifying whether a trip is intermodal in nature (Gebhardt, et al., 2016), the purpose of the journey, or the exact origin and destination.

For this reason, mixed-method approaches are often utilised when a more holistic understanding of mobility is desired. Employing a combination of fixed sensors, trajectory data, crowdsourced contributions, and survey-based methods helps to balance the weaknesses of individual data sources and can provide a more complete understanding of mobility trends. Figure 1 illustrates how different sensor and non-sensor methods can be combined to produce a more comprehensive dataset for the analysis of interactions between cyclists and mobility spaces. This is particularly relevant to studies of active mobility where movement patterns are influenced by a wider range of variables, not just infrastructure and distance, but also perception, comfort, safety and overall experience.

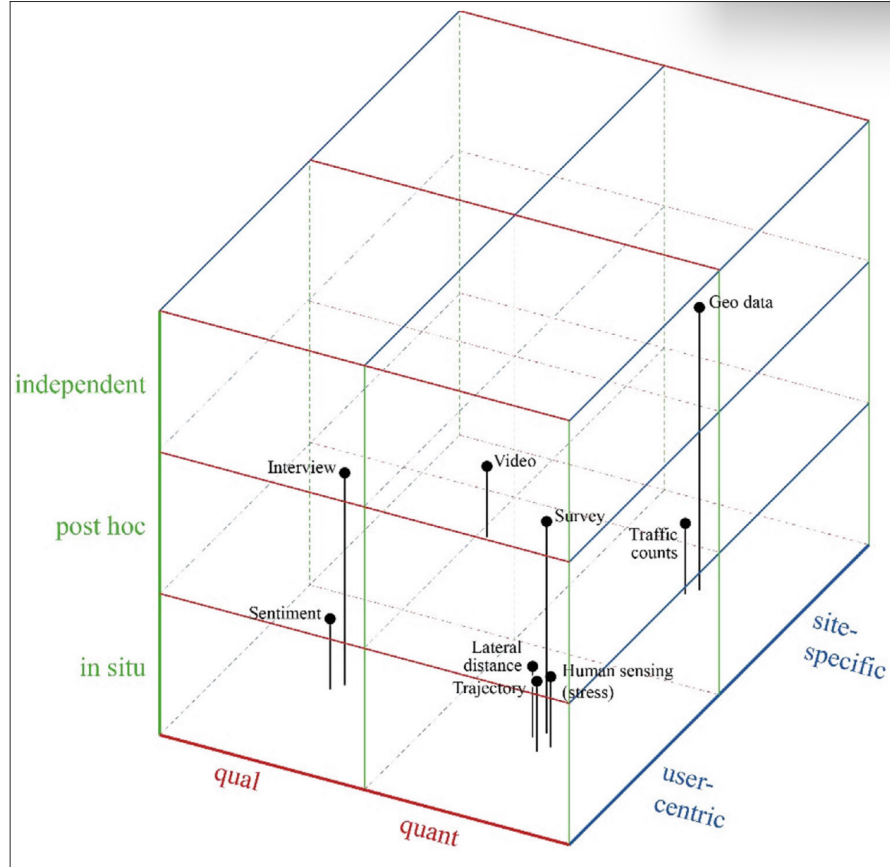


Figure 1: Different types of sensors, which are used to generate a comprehensive data set for analysing the interaction of cyclists with mobility space in a mixed methods approach, from (Loidl, Werner, Füssl, Kratochwil, & Resch, 2025)

2.3 Limitations of Mobility Data

Despite the increasing availability of mobility data, several limitations need to be considered when utilising the data for analysis. Improving the utilisation of data provided by IoT is key to creating more “interconnected and intelligent urban spaces”, but this relies on addressing challenges related to data heterogeneity, data quality control, privacy considerations and scalability (Fadhel, et al., 2024). These limitations are especially relevant in mobility studies where datasets are often collected using different methods, at different spatial and temporal resolutions, and with varying levels of accuracy and representativeness.

One of the main challenges concerns spatial and temporal resolution. Mobility datasets vary considerably according to the source and mode of mobility being recorded, which can then pose issues when comparing or combining datasets. For example, mobile positioning data (MPD) is generally available at a coarser resolution because it is derived from interactions between mobile devices and communication network infrastructure rather than from GPS. Spatial resolution is of varying granularity, but generally coarse (ranging from 500 m² in urban locations to kms² + in more rural areas). This makes MPD useful for identifying broader regional flows but less suitable for detailed local-scale analysis. In addition, MPD is usually aggregated to ensure user privacy and does not deliver any data on the users’ mode of transport (Dvorak, 2020), (Ministry of the Interior of the Czech Republic, 2024).

Data quality and positional accuracy are also important limitations, particularly for GPS-based and tracker-based datasets. Accuracy issues may arise due to the inaccuracy of devices and/or low sampling rates, leading to uncertainty of the specific location between two known points (Graser, Stutz, & Loidl, 2021), (Mokbel, et al., 2024). This is especially relevant to trajectory-based sources, such as mobility applications and BSP data, where positional errors can create noise in the data and affect route reconstruction, speed estimation, and the identification of frequently used segments (Hu, et al., 2023).

Another limitation is the bias and representativeness of data. App-based and crowdsourced mobility datasets are often dependent on user participation, voluntary data sharing, or the use of a specific application. Although smartphones are widely used, studies based on mobile devices or app-generated data may rely on relatively small or self-selecting samples, which are not necessarily representative of the wider population's activity (Gjoreski, et al., 2018). Similarly, data from applications such as Strava may be disproportionately generated by individuals with more active lifestyles, meaning that it cannot be deemed to be representative of all users of a transport network. Despite this, such datasets can still provide value when interpreted carefully, and previous studies have found that Strava data can correlate with official counts (Davies, 2019).

Volunteer geographic information (VGI) sources, such as OpenStreetMap (OSM), provide valuable open spatial data for mobility analysis. These datasets can contain uncertainty due to incomplete, outdated, or incorrect observations (Mooney & Minghini, 2017). VGI can provide important contextual information; however, its quality and completeness should be carefully assessed before it is used as a basis for mobility analysis or network interpretation.

Privacy is another key concern within mobility research. As the spatial and temporal resolution of mobility data improves, the risk of revealing sensitive information about individuals also increases. High-resolution movement data has the potential to expose information regarding users' lifestyles, habits, or even identities (Pyrgelis, De Cristofaro, & Ross, 2016). To address this, data is often provided in aggregated form as Aggregated Mobility Data (AMD) from mobile phone operators. This aggregation protects an individual's privacy by showing collective patterns rather than individual movements (Turnnidge, et al., 2025), but it also reduces the spatial and temporal detail, which can weaken the analytical value of the dataset. As such, the use of mobile phone data requires not only the application of aggregation methods but also following clear governance models which balance analytical value with privacy protection (de Montjoye, et al., 2018).

Additional technological and methodological limitations include cybersecurity, data protection, the use of artificial intelligence (AI), visualization design choices, and the risk of introducing bias through selective processing or user-interface decisions (Zaroujtaghi, et al., 2025). Although previous studies have demonstrated methods for reducing privacy risks in mobility data analysis (Pyrgelis, De Cristofaro, & Ross, 2016), these approaches do not completely remove the need for careful consideration of data sensitivity, uncertainty, and ethical usage (Mokbel, et al., 2024), and this risk has been demonstrated by research which has exemplified how the use of a small number of spatio-temporal points can be sufficient to identify individuals within a larger mobility dataset (de Montjoye, Hidalgo, Verleysen, & Blondel, 2013).

Mobility data can provide many opportunities for analysing mobility trends, but it requires careful interpretation. Variation in resolution, accuracy, representativeness, privacy protection and dataset completeness strongly influence findings which can be made from datasets. These limitations are most relevant when multiple mobility datasets are combined, as each source may reflect a different methodological origin, spatial and temporal resolution, population sample and overall level of uncertainty.

2.4 Data Integration and Data Fusion

Mobility studies often rely on multiple datasets, each capturing different aspects of movement; however, as outlined in the previous section, these datasets can differ in spatial and temporal resolution, accuracy, representativeness, and methodological origin. Data integration and the related concept of data fusion refer to the process of combining heterogeneous data sources to create a more complete and meaningful representation of mobility trends. As such, integration is not just a technical process but rather a methodological challenge because the way in which datasets are combined can significantly influence the identified mobility trends.

A strong approach to combining data from multiple sources is the use of a shared spatial-temporal reference, allowing different datasets collected at different levels of detail to be compared or linked within a common analytical framework (Loidl, Werner, Füssl, Kratochwil, & Resch, 2025). This is important in mobility analysis as different datasets typically represent movement in different ways, such as point-based counts, trajectory records, aggregated flows, or contextual layers. Simple overlay analysis, in some cases, may be sufficient for visual interpretation, for example, when comparing observed flows with infrastructure characteristics. More advanced integration or homogenisation would be required if datasets are intended to be analytically combined, compared, or used to derive mobility indicators.

Many studies have explored the use of modelling, algorithms, and frameworks to merge data from multiple sources (Rodrigues, Boukerche, Silva, Loureiro, & Villas, 2017), (Caceres, Sierra-Alonson, Cuesta, Vela, & Cavero Barca, 2020). Fusion methods can be employed to combine multisource data and create more robust representations of mobility trends (Fadhel, et al., 2024). Despite this, research gaps remain in best practice for mobility data integration. This is especially evident when linking trajectory-based or crowdsourced data with stationary count data. Previous work has highlighted that no established method exists beyond map-matching trajectories and calculating correlation coefficients at selected locations (Loidl & Witzmann-Müller, 2021), suggesting that while individual analytical methods exist, there remains a lack of standardised workflows for connecting mobility datasets with different formats.

A further challenge lies in that many mobility models and algorithms depend on specific data structures, indexes or system architectures. Because of this, integrating methods from literature into new contexts can prove problematic when common data systems are lacking (Sakr, Ray, & Renso, 2022). This is of relevance to local-scale mobility studies when available datasets are commonly fragmented, varying in format, and intended for different original purposes. An example of this is how stationary sensors provide reliable counts at selected points whilst GPS tracks provide route information for a specific user group, and open data provides contextual information about the surrounding environment. Each source provides valuable information, yet the process of

combining them requires consideration of the scale, format, reliability and meaning of each dataset.

There are known limitations to implementing data fusion within smart city contexts, including missing data, data accuracy, and fusion accuracy challenges. “Diversified and extensive datasets can enhance the accuracy and robustness of information fusion systems” (Fadhel, et al., 2024), but arguably, this is only possible when the quality and compatibility of the datasets are fully understood. The combining of more datasets does not automatically produce a better analysis; on the contrary, the value of data fusion is dependent on whether the datasets complement each other and whether their uncertainties are taken into consideration during interpretation. The consideration of the relationship between trajectory data and stationary count data demonstrates this challenge. Factors influencing the correlation between tracks and counts include technical, temporal, spatial and population characteristics as visualised in Figure 2. Count data should not be treated as truths, as they may be affected by measurement errors, and similarly, track data could be affected by sampling biases, positional uncertainty, and biased user participation. It is also unclear how spatial distribution, observation period, and temporal aggregations influence correlations derived from mobility datasets (Graser, Stutz, & Loidl, 2021). With consideration of such uncertainties, correlations between datasets must be interpreted carefully as opposed to a direct validation of reality.

Data integration and fusion can provide opportunities for improving the interpretation of mobility patterns; however also introduce methodological complexities. Different datasets contain different assumptions, limitations, and levels of reliability. Because of this, integration and fusion should take into consideration how the weaknesses of each dataset can influence analytical findings, especially in cases where results are influenced by how heterogeneous datasets were harmonised, compared and subsequently communicated.

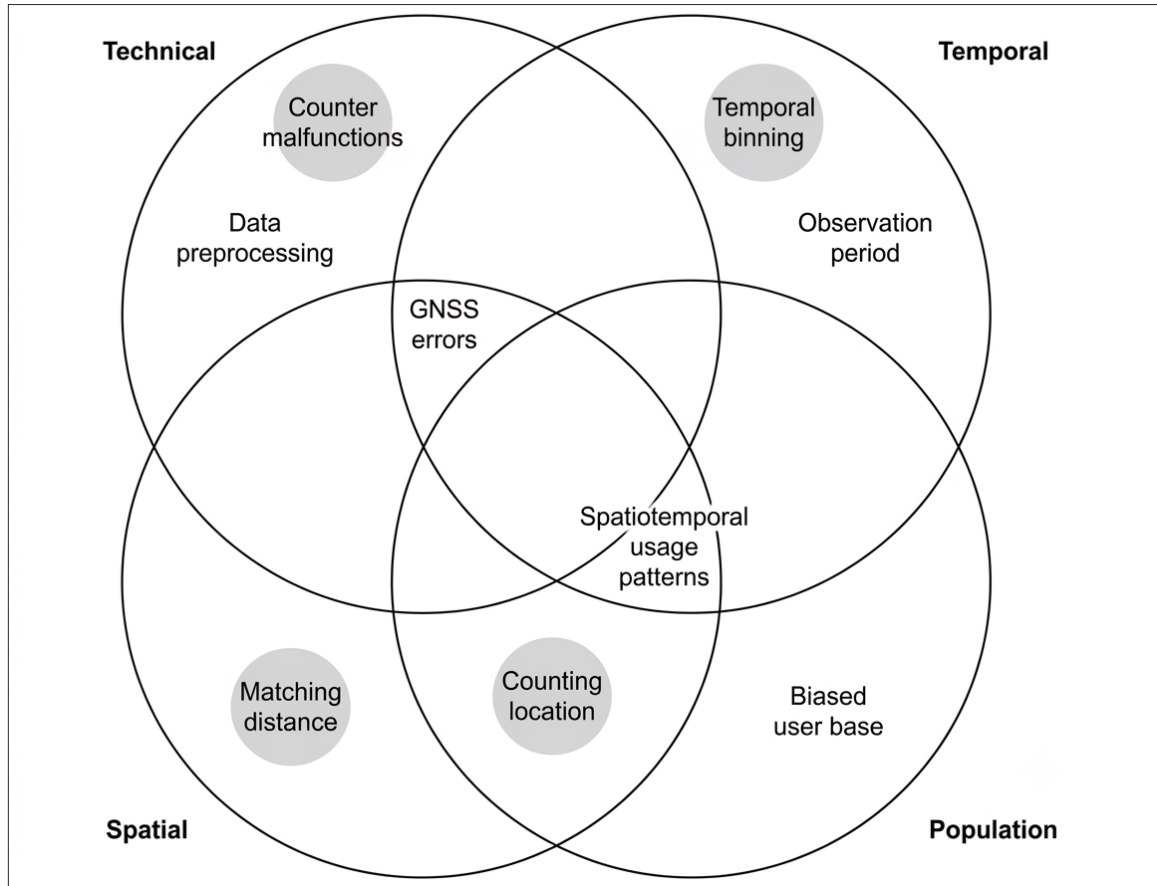


Figure 2: Factors influencing the correlation between tracks and counters, from (Graser, Stutz, & Loidl, 2021)

2.5 Identification of Mobility Patterns

Mobility patterns can be identified through the analysis of spatial, temporal and network characteristics of movement data. Depending on the dataset being used, this may involve examining flows between locations, repeated trajectories, variations in count intensity or the use of parts of a transport network. These approaches transform mobility data from simple individual observations into interpretable patterns of movement. This systematic classification of mobility patterns is important, as analytical methods are required to identify patterns such as convergence, divergence, repetition, encounters, flows, or route similarities (Dodge, Weibel, & Lautenschütz, 2008).

Flow-Based Pattern Identification

This approach focuses on movements between locations and can be applied to OD pairs, MPD, commuting datasets or datasets from BSPs. The quality of results is dependent on the spatial resolution and level of aggregation. Flow analysis can be used to identify movement direction, intensity of connections between areas, and the distribution of movement across a study area. It is usually most suitable for identifying general trends rather than precise analysis because flow-based data generally represents movement between zones rather than exact routes taken.

This approach is valuable for defining broader mobility trends such as commuting flows or movements between municipalities. For example, MPD has been used to visualise intermunicipal commuting patterns in Czechia (Burian, Žejdlík, & Rypl, 2025).

Trajectory-Based Pattern Identification

Movement paths can be analysed to identify how people, vehicles or objects move through space. The use of GPS tracks, GPX files, or application-based movement records can be analysed to identify common routes, stopping behaviours, speed variation, and deviation from expected routes. If a full trajectory record is available, it can provide more detailed information about the nature of movement than what point-based counts or aggregated flows can provide.

A common process within this analysis is map matching, where recorded GPS points are linked to the most likely location on a transport network to allow for movement traces to be interpreted in relation to network features. Similar trajectories can be grouped to identify the most and least used segments. For example, methods such as a hidden Markov Model approach can be used for this purpose because of how they account for both the measurement noise and structure of the road network when estimating the most likely route (Newsom & Krumm, 2009).

Identifying trends using trajectory-based data is susceptible to positional uncertainty, sampling frequency and user bias issues, reducing the reliability of identified trends.

Count-Based Pattern Identification

Traffic volumes recorded at fixed locations can be analysed to identify temporal patterns at different temporal aggregations, directional differences, and changes in intensity over time. This data format is particularly useful for the comparison of monitored locations and identifying where movement is concentrated.

Count-based datasets can support the interpretation of other data sources; for example, previous studies have shown how citizen-generated Telraam count datasets can complement ILC datasets, demonstrating their potential value in local mobility analysis (Janež, Verovšek, Zupančič, & Moškon, 2022). Similarly, Strava data has previously been found to correlate well with official counts, suggesting that app-based data has the potential to provide valuable insights into active mobility trends when interpreted carefully (Davies, 2019). Count-based pattern identification approaches, however, remain limited, unable to identify complete routes, determine trip purposes, or define relationships between origins and destinations.

Network-Based Pattern Identification

Mobility and its relation to the structure and characteristics of its surrounding network can be assessed; this is particularly of relevance to studies exploring active modes of transport where route choice is influenced by not only distance and travel time, but motor-vehicle traffic, turn frequency, infrastructure quality and environmental factors (Hrncir, Song, Zilecky, Nemet, & Jakob, 2014). This pattern identification, therefore, can identify preferred routes, missing links in the network, mobility barriers, and overall desired movement trends.

Route modelling can support network-based pattern identification in cases where complete trajectory data is unavailable. Methods include route interpolation, least-cost path analysis, and cost-function modelling to estimate likely routes through a network. The reliability of these outputs, however, relies on the complexity of the model and how well modelled costs reflect real-world conditions and actual user behaviours.

In conclusion, the chosen methodology to identify mobility patterns is, therefore, dependent on matching the analytical method to the structure of the available dataset.

Flow-based methods are suitable for identifying relationships between locations, and trajectory-based methods support analysis of routes and corridors, count-based methods quantify intensity and temporal variation, and network-based methods interpret movement in relation to infrastructure.

These approaches, together, provide a basis for the analysis and subsequent visualization of mobility trends, supporting the interpretation of datasets.

2.6 Visualization of Mobility Patterns

Cartography has a vital role in the communication of information. Maps and dashboards do not display data neutrally but rather present a particular interpretation or narrative within the data. In mobility studies, this is especially important to consider as visualization choices influence how movement patterns, gaps in data, intensities in trends, and how relationships are understood. Dashboards can support this interpretation by combining maps with additional information such as charts, filters, indicators or contextual layers, which assist the user in the interpretation of mapped data and identifying potential biases and limitations.

The ability to harmonise and integrate different datasets into a uniform format for geovisualization has the potential benefit of reducing the effects of data participation inequality, data coverage gaps, and quality differences. By presenting multiple datasets within a shared spatial framework, geovisualization supports more informed conclusions about mobility trends within a given study area, which is particularly relevant where mobility patterns are derived from heterogeneous datasets.

Interactive visual displays can support human perception, cognition and reasoning, especially when supported by databases and computational methods that can handle big data (Andrienko, Andrienko, & Wrobel, 2007). Building upon this, visual movement analysis provides a methodological basis for the exploration of trajectories, events, places, time periods, and derived movement patterns through interactive visual and computational methods (Andrienko G. , Andrienko, Bak, Keim, & Wrobel, 2013). In this way, the value of visualization within mobility studies lies in the effective addition of semantic context to numerical data. Visualization allows for patterns such as flows, concentrations, frequently used routes, and spatial and temporal variations to be interpreted more effectively as opposed to only presenting counts or coordinates.

Visualization can also support the identification of previously unknown movement patterns and form part of dynamic simulation systems (Dodge S. , Weibel, Ahearn, Buchin, & Miller, 2016). Data dashboards are commonly employed to inform decisions made at the city level to support governance of complex urban dynamics (Kourtiti & Nijkamp, 2018). They can also act as tools for communicating mobility information to citizens. Although such approaches are often applied at a city-scale, they could also be relevant for smaller areas of interest where there is a requirement for detailed local interpretation.

Different forms of mobility data are better suited to different visualization approaches. Point-based count data can be represented through proportional symbols, charts or temporal dashboards, whilst trajectory and track data can be visualised as lines, routes or aggregated corridors.

Flow data can be represented using origin-destination lines, desire lines, or flow maps, while animated trajectories can be used to show movement over time. Dense point or trajectory datasets could also be generalised through hexbin aggregations, whilst network heatmaps can show movement intensity along segments. Contextual datasets can then be used as semantic information to explain how infrastructure, land use, or environmental characteristics influence mobility patterns. As such, the choice of visualization method influences the readability of the output and the conclusions which the user is likely to draw from it.

Intra-city data visualizations have been found to focus predominantly on expert systems, which support the display of mobility patterns and congestion analysis (Clarinval & Dumas, 2022). For mobility visualizations to be useful beyond expert interpretation, however, the communication of data and trends should consider clarity, comprehensibility, and the intended user group. This applies to dashboard-based environments where visual outputs may be used not only for analysis but also for communication, planning and decision-making purposes.

2.7 Applications of Mobility Data

Mobility data has a wide range of applications, including transport planning, sustainable mobility, and smart city development. Identifying where, when, and how people move through mobility data supports a better understanding of how space is utilised and where interventions are required. This information can also explain why some locations are used more or less frequently than others; it may be related to efficiency, accessibility, directness, perceived safety and/or perceived emotions. Approaches such as emotion mapping support a more user-centred interpretation of mobility trends and identify areas where actions can be taken to improve the mobility environment.

Mobility data is also relevant to sustainability goals because sustainable transport is connected to the social, economic, and environmental dimensions of urban development. Mobility data can be utilised to monitor progress, evaluate whether sustainable travel modes are being supported, and where subsequent changes may be required. As such, the analysis of mobility trends can support sustainable transport planning, as well as wider goals relating to accessibility, quality of life, and dependence on private car use.

Within the context of smart cities, mobility data can be integrated with other urban systems, including open data, smart parking, environmental monitoring and traffic management (Fadhel, et al., 2024). This integration can support more responsive and evidence-based decision-making. Similar applications can be seen in the EnCLOD project, where installations across Europe have demonstrated the use of mobility monitoring for road traffic safety alongside public participation in the form of surveys (Hrudkay, Čulík, Cingel, & Madleňák, 2025), highlighting how sensor-based data can be successfully combined with social or observational information to support practical planning and safety-related applications.

At a local scale, mobility data can be utilised to support institutional sustainable mobility planning. The UPOL Action Plan for the Implementation of UP's Sustainable Development Strategy for 2024-2025 (Palacký University Olomouc, 2024) states, “the

goal is to support staff and students in using sustainable modes of transport for commuting and moving around the city, specifically walking, cycling, and public transport” (author’s translation). It also aims to prepare recommendations for business travel in line with sustainable mobility principles. This is further reinforced by the 2026-2027 Action Plan (Palacký University Olomouc, 2025), which highlights active mobility modes as an area with significant development potential and is an ongoing institutional priority. Mobility data, therefore, can provide evidence of existing movement patterns, evaluate barriers to sustainable travel, and encourage more sustainable mobility choices.

From a wider sustainable development perspective, sustainable mobility is particularly relevant to the United Nations (UN) Sustainable Development Goals (SDGs) (United Nations General Assembly, 2015). Specifically, SDG 3 “Ensure healthy lives and promote well-being for all at all ages” through the promotion of active mobility, road safety, and healthier travel behaviour, SDG 11 “Make cities and human settlements inclusive, safe, resilient and sustainable” through supporting more inclusive, safe and resilient cities, and SDG 13 “Take urgent action to combat climate change and its impacts” through the reducing transport-related environmental impacts.

Mobility data is evidently not only important for describing mobility trends but also for monitoring progress towards meeting sustainability goals and identifying areas for intervention.

Cycling infrastructure planning represents another valuable application of mobility data; the increasing popularity of cycling as a mode of transport has led to greater investment in cycle infrastructure, making it important to understand how cyclists move through urban networks and whether infrastructure investments respond to actual mobility patterns. Monitoring and modelling cyclists' movement is therefore commonly used to support infrastructure planning decisions (Łukawska, 2024). Despite this, modelling of route choices remains challenging, despite being an important component in predicting traffic conditions and network use (Prato, 2009). This reflects how cyclist route choices are influenced by multiple variables, including distance, duration, traffic, turn frequency and environmental factors such as noise and pollution (Hrncir, Song, Zilecky, Nemet, & Jakob, 2014).

Route modelling and interpolation methods support the estimation of likely cycling paths where complete trajectory data is unavailable. Cost functions are frequently used in cycle route modelling studies, with older models mostly considering the value of distance (VoD) to be of the highest priority to cyclists, with newer models focusing more upon the value of time (VoT), incorporating desired speeds and anticipated delays from intersections (Hrncir, Song, Zilecky, Nemet, & Jakob, 2014) (Liu, Johansson, Kristoffersson, & Rydergren, 2025).

A previous local study found that two-wheeled mobility within the city of Olomouc was primarily for commuting, leisure, and recreation. The study highlighted that perceptions of safety, comfort, and environmental quality are as important as physical infrastructure. Despite the favourable geographic conditions of the area, there is a sense of mobility injustice because of car-oriented planning, and subsequent policy recommendations focus on filling network gaps, improving infrastructure quality and integrating with other transport systems (Ritterová & Pánek, 2026). This demonstrates how mobility data and user-centred interpretation can support more targeted and equitable sustainable mobility planning approaches.

2.8 Uncertainty in Mobility Data and Visualization

Uncertainty visualization is important due to how visual outputs can make data appear more certain than it is. In mobility studies, this is especially relevant because datasets often contain uncertainty from positional error, sampling bias, aggregation, incomplete coverage, or the integration of heterogeneous data sources. As such, uncertainty visualization is not limited to showing data but also assists users in understanding how reliable the displayed mobility patterns are.

In the context of mobility data, this is important due to how maps and dashboards may display patterns that appear clear even when the underlying data contains positional errors, sampling biases, aggregations, incomplete coverage or uncertainty from integrating heterogeneous data sources. The term "signal suppression" refers to a visualization designed to prevent false conclusions, in which the signal (i.e., the collective take-away from the estimates) is suppressed by the noise (i.e., the variance in those estimates). Current standards in visualization suggest that uncertainty visualizations designed for decision-making should not be considered uncertainty visualizations at all. Effective signal suppression, therefore, requires communicating the signal and the noise as a single "validity of signal" variable, and doing so proves to be difficult with existing methods.

For mobility analysis, this is particularly relevant for where visualizations are used as evidence for planning, infrastructure recommendations, or communication with stakeholders. Maps and dashboards should, therefore, communicate not only where mobility trends occur but also how reliable or uncertain these trends are likely to be.

3 METHODOLOGY

3.1 Area of Interest

Olomouc is a statutory city situated in the eastern part of the Czech Republic, with a population of approximately 100,000 (Czech Statistical Office, 2025). The city is strongly influenced by the presence of UPOL, which contributes a student population of ~23,000 (Palacký University Olomouc, 2026). As such, student mobility forms an important part of the city's everyday movement patterns.

The AOI presented in Figure 3 is in the south-eastern part of the city, bounded by 17. Listopadu, Trída Kosmonautů, Masarykova Trída and the Morava River, covering an area of approximately 0.17 km². The AOI is characterised by CORINE as mostly discontinuous urban fabric, as well as green urban areas (European Union's Copernicus Land Monitoring Service Information, 2018), containing a mixture of university dormitories, teaching and study facilities and public spaces, plus roads, cycle and pedestrian ways throughout.

The AOI is relevant for this case study in how it concentrates several different mobility functions within a relatively small area. It is used by students, university employees, residents, commuters and visitors, whilst also acting as a connecting space between the university campus, surrounding neighbourhoods, and the wider city centre. This creates a complex mobility environment where pedestrians, cyclists, and motor vehicles interact closely. The multifunctional nature of this area and its importance within UPOL make it a relevant case study for analysing mobility as a location experiencing commuters and residents, and as a connecting area to the surrounding city. Additionally, the range of available mobility datasets makes the project feasible.

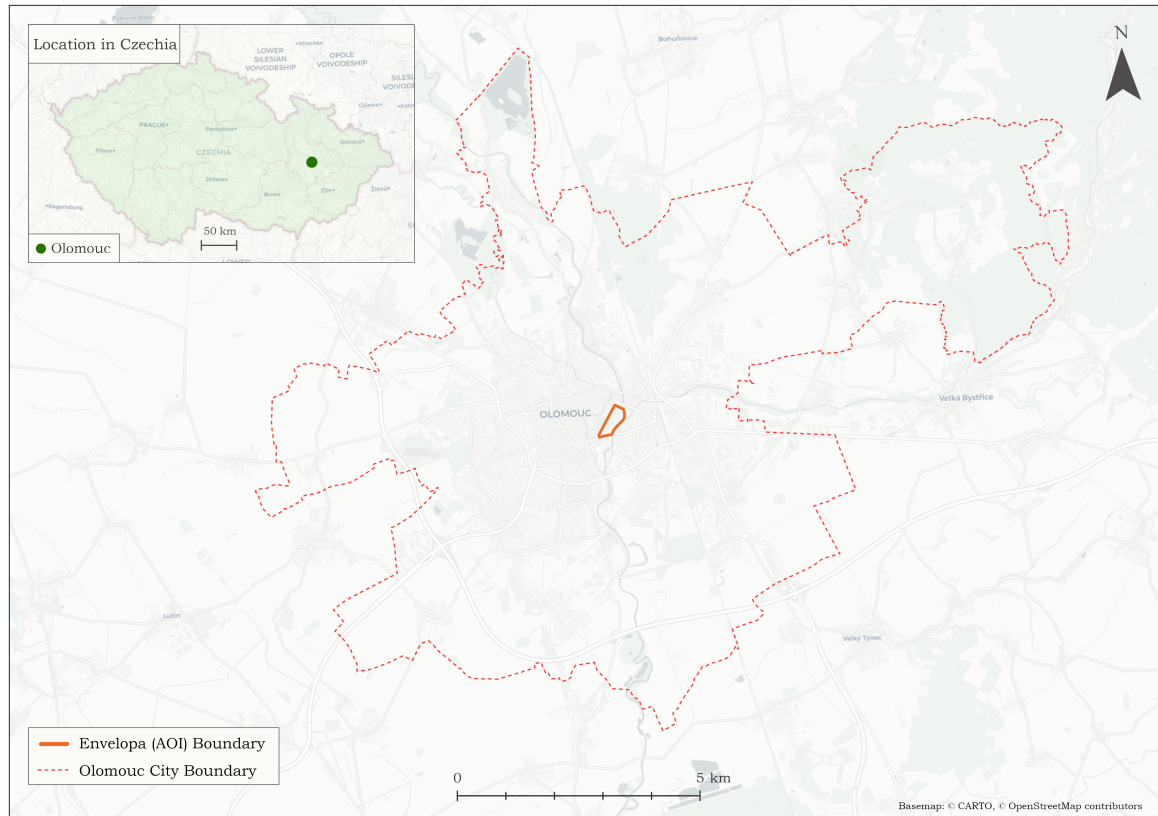


Figure 3: Location of the AOI within Olomouc, including context within Czechia

3.2 Data Sources

Nextbike

Nextbike is a bikeshare programme (BSP) company with rental services across Europe. Bicycles can be rented and dropped off at docking stations or random locations across the city. These bicycles are equipped with GPS receivers, recording data regarding their pickup and drop-off locations, plus supplementary data on the time of trip commencement and duration.

Data was acquired from Nextbike covering the period from 12/05/2025 to 30/11/2025. The dataset included information regarding the start and end location of trips (origin-destination pairs) and journey duration, but no detailed trajectory. Four official Nextbike stations are located within the AOI: Menza UPOL (the canteen), Právnická Fakulta UPOL (Faculty of Law building), Přírodovědecká Fakulta (Faculty of Science Building), and Koleje Generála Svobody (Dormitories), however trips can also start and end outside these locations.

EnCLOD

Enhancing Governance Capacities of Local Authorities Using Open Data (EnCLOD) is supported by the Interreg Central Europe Programme (Interreg Europe, 2025), which aims to “support data-driven decision-making and local development planning.” The EnCLOD project in Olomouc is an example of an open-data initiative supporting local public governance, and in practice overlaps strongly with open government data in how it enables the public authority to collect, publish, and reuse openly accessible urban data. Olomouc is one of the 10 project partners, primarily targeted at monitoring heat islands in the city through a network of Internet of Things (IOT) sensors (Digital Olomouc, 2025). As of June 2026, there are 38 traffic sensors actively monitoring in the city area.

The author participated in two EnCLOD-related events in October 2025 and May 2026 to further familiarise themselves with the project and the datasets generated within its scope. These events also provided an opportunity for in-person discussions with project experts, supporting the development of a deeper understanding of the project background, data characteristics, and analytical uses.

As part of EnCLOD, Olomouc employs traffic-classifier magnetometers, which are manufactured and supplied by CITIQ. These sensors are installed directly into the centre of the road where vehicles will pass over. The sensor is cylindrical, installed to a depth of 150mm with a diameter of 100mm. The installation process is presented in Figure 4. The sensor is autonomous and communicates to the cloud through a low-power IoT network. These sensors function by sensing the change in the surrounding geomagnetic field caused when vehicles pass over the sensor; embedded algorithms then classify the length and speed of the vehicle and then send this to the cloud every five minutes (CITIQ s.r.o, 2021). For Olomouc, the data can be acquired from the API at a 15-minute resolution.

Although CITIQ magnetometers provide continuous 24/7 monitoring of traffic, their counts should be interpreted as estimates rather than exact ground-truth observations; potential sources of error include congestion, stop-start traffic, slow vehicles, interference from the adjacent lane, and unusual vehicle types. Manufacturer documentation states an approximate error of 5%; however, an independent study found deviations of up to approximately 15% (Mráčková, 2025).



Figure 4: Installation process of traffic sensor magnetometers (CITIQ s.r.o, 2021)

Eight EnCLOD sensors are located within the AOI and are used for the analysis of traffic volumes in this diploma thesis. The data is aggregated into four categories based on vehicle length (4-7m, 7-14m, 14-21m, and uncategorised), which is used as a proxy for vehicle type (car, van, bus/truck, uncategorised). Data were acquired from EnCLOD covering the period from 12/05/2025 to 10/05/2026.

Telraam

Two traffic-counting Telraam S2 sensors were mounted on the inside windows of the first floor of the building of the Faculty of Science in October 2025. These sensors are produced and maintained by Rear Window BV (Belgium), measuring approximately 65 x 99 x 30 mm, containing a wide-angle camera, a purpose-built AI chip, capability for cellular communication, and use a USB-C power supply. The sensor performs object detection and classification on the device, then sends anonymised aggregated count data to the Telraam database. No images or videos of traffic are stored or transmitted. The sensors continuously count pedestrian, two-wheeler, car, and heavy-vehicle flows during the daytime and provide a general count during nighttime. (Telraam, 2018).

The device was installed in a suitable location following the requirements set out on the Telraam website to allow for optimal performance. Manufacturer documentation reports a typical daytime accuracy of ~90-95% for motorised traffic under suitable installation conditions. The accuracy may be lower for pedestrians and cyclists, particularly if the road users are partially obscured, at a distance from the camera, in groups or when the viewing angle and street geometry are suboptimal (Telraam, 2023).

Within this diploma thesis, Telraam data is employed as multimodal counts, split into pedestrians, bicycles, large vehicles, night totals and overall totals. Telraam data covers the period from 31/10/2025 to 10/05/2026.



Figure 5: Telraam Sensor observing traffic at the front of the Palacký University Faculty of Science Building

CHMI

Meteorological data were recorded by the Czech Hydrometeorological Institute (CHMI) at the station in Holicе, approximately 2 km southeast of the AOI. The station belongs to the national meteorological monitoring network and therefore represents official meteorological observations rather than citizen-science or third-party sensor measurements. Details on the specific apparatus used to measure meteorological conditions are not available online from CHMI; therefore, the exact certainty and reliability of this data are also unknown. The data was acquired from CHMI in 10-minute intervals and then aggregated to hours for use within this diploma thesis. The variables selected are mean temperature and total precipitation.

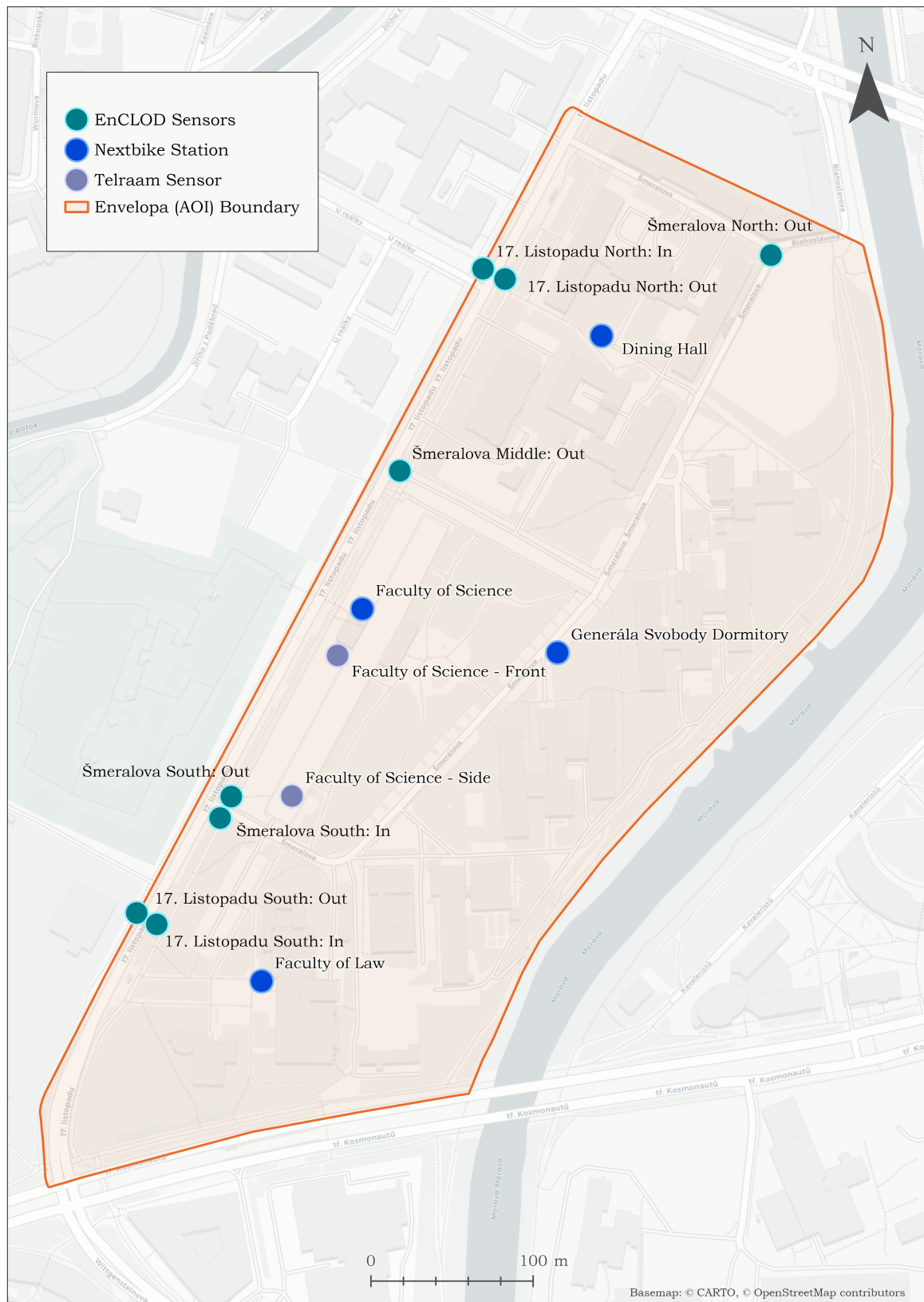


Figure 6: Location of all employed mobility sensors within the AOI

Strava Metro

Strava is an application used by individuals for sharing physical activities (e.g. walking, running, cycling) in a social networking setting. Data is recorded using a GPS-enabled device, such as smartphones, sports watches, and cycling computers and then uploaded to the platform. Records typically contain spatial and temporal information such as the route geometry, distance, duration, speed, elevation, and the time of activity.

Access to Strava activity records is not freely available; instead, Strava provides Strava data without identifiers and aggregation applied to provide a dataset of general trends through Strava Metro.

Access to Strava Metro is restricted to larger academic projects or active transportation infrastructure planning applications. As such, it has not been possible to acquire data for usage in this study. A further considered option was to manipulate the readily available heatmap to utilise as a base layer; however, “the heatmap is normalised to improve the legibility of the visualization, so techniques such as raster depth analysis will not produce reliable results.” (Strava, 2024). Therefore, whilst Strava was considered a potentially valuable source of active-mobility data, it has been excluded from the final analysis due to access limitations and the analytical limitations of the public heatmap.

Copernicus ERA5

Hourly gridded model-based weather estimates, comprising temperature at 2m, 10m U and V components of wind, and total precipitation, were obtained from the Copernicus Data Store via the CDSAPI in GRIB format. The data is produced through climate reanalysis, which combines observations from several sources and a numerical weather prediction model through data assimilation to create a consistent estimate of atmospheric conditions (Copernicus Climate Change Service (C3S), 2023).

The dataset was available at a suitable temporal resolution and file format; however, its spatial resolution of $0.25^\circ \times 0.25^\circ$ (approximately 31 km) was considered too coarse for the AOI and therefore excluded from the final analysis.

Mobile positioning data (MPD)

Previous studies have used and manipulated MPD; however, they rely on the availability of data on a volunteer basis or a specific smartphone application, both of which are not feasible for this diploma thesis. Alternatively, MPD or GSM is available directly from mobile operators; however, the resolution of this data is of varying granularity, but generally coarse, with cells ranging from 500 m in urban locations to several kilometres in rural areas (Goves, Hemmings, & North, 2016).

Given the scale and objectives of this diploma thesis, these data sources were not considered suitable for further inclusion. The AOI is relatively small, meaning that the spatial resolution of operator-based mobile phone data would be too coarse to reliably identify movements into, out of, or within the AOI.

3.3 Methods

3.3.1 Data Acquisition and Management

EnCLOD and CHMI data were acquired using their respective APIs, whilst Nextbike was acquired directly from the company, and Telraam from the online user interface.

The Python scripts for data acquired via APIs are included in Attachment 1.

All data was stored locally before processing, and then subsequently stored on the project GitHub repository as a secure backup and for subsequent integration into the interactive web map dashboard.

3.3.2 Data Processing

All data processing was executed locally using Python scripts. ArcGIS Pro ModelBuilder was not used because it would have been inefficient at handling the volume of data involved in the workflow. Python was adopted as a more efficient and reproducible approach, enabling immediate outputs throughout the workflow. This supports quality control and enables results to be verified statistically and visually at each stage of processing.

Temporal Aggregation

Data were aggregated by day, week, month, days of the week within the month, and categories representing divisions of the academic year. This was applied with consideration that a significant proportion of the movement within the AOI is likely to be by students or those employed by the university. The selected categories are as follows:

Academic Year 2024 - 2025

- Summer Break and Exam Period: 12/5/2025 – 30/6/2025
- Main Holidays: 1/7/2025 – 31/8/2025

Academic Year 2025 - 2026

- Winter Semester: 22/9/2025 – 19/12/2025
- Winter Break and Exam Period: 5/1/2026 – 6/2/2026
- Summer Semester: 9/2/2026 – 7/5/2026, (Palacký University Olomouc, 2026)

Note: Winter Semester and Summer Semester are teaching periods. All other categories are non-teaching periods.

Terms were selected based on the availability of data. It is acknowledged that there is a limitation in the data coverage: Nextbike data is available until 30/11/2025, while Telraam data became available only from 31/10/2025.

Pre-processing the time series and compressing the data provided a more manageable and interpretable dataset for online representation. It is acknowledged that smaller bins are more likely to result in random correlations, whilst large bins result in fewer values, which would not be suitable for correlation analysis (Graser, Stutz, & Loidl, 2021), hence, the complete range of temporal aggregations is included.

Data Fusion (DF) and Integration

Due to the differences in sensor measurement methods and segment coverage, it is not possible to ‘fuse’ or truly integrate the available mobility data. Rather, the challenge

of this diploma thesis lies in combining multimodal data and employing statistical analysis, which avoids the risk of ‘multi-counting’ journeys. Chapter 6: Comparative Analysis of Telraam and EnCLOD Datasets explores the differences between EnCLOD and Telraam counts for the same location, exemplifying how the application of DF or data integration would produce weak outputs.

Analysis

The statistical procedures applied to each data set are further detailed in Chapter 5: Mobility Patterns in The Envelopa Campus, and Chapter 6: Comparative Analysis of Telraam and EnCLOD Datasets.

3.3.3 Visualization

Techniques discussed in Section 2.6: Visualization of Mobility Patterns directly inform the practical methodology adopted by the diploma thesis. Rather than applying a single method to all datasets, different visualization techniques have been applied based on the spatial structure, temporal characteristics, and analytical purpose of each data source. As such, sensor counts, modal composition, estimated cycling routes and temporal trends are represented using different but complementary methods as described below.

Geovisualization

Sensor-based data is provided as a count for one specific location. From this, it can be assumed that vehicular traffic (i.e., not pedestrians or cyclists) continues along that section of road until the next junction. Based on this principle, polylines are used to visualise EnCLOD data. For Telraam data, proportional doughnut charts are used as an intuitive tool for showing the modal split of traffic at each point. For Nextbike data, a least cost path algorithm was applied (further detailed in Section 4.4: Preparation.) to create possible linear routes.

Spatial data is presented within an interactive web map dashboard application using Leaflet. The methodology for this is expanded upon in Chapter 7: Web Application Development.

Non-Spatial Visualization

The inclusion of graphs and diagrams alongside the main map as part of the final output of a web application was deemed crucial, as using purely visual mapping methods can fail to thoroughly convey the analysis of movements of different inputs over extended periods of time (Andrienko, Andrienko, & Wrobel, 2007).

Methodology, which was not utilised

A least generalised cost path approach was selected for the creation of cycling routes instead of using ArcGIS Pro Network Analyst Tools, as it allows for the incorporation of index values rather than solely physical distances. Furthermore, conducting all data processing entirely in Python also ensures that the workflow remains repeatable and reproducible. Additionally, spatial aggregations of the Nextbike data, such as hexbins, would require additional assumptions (such as using an appropriate grid and managing uneven observation density); therefore, they would not add meaningful value and are not considered further for use in this diploma thesis.

The use of Space-time cubes (STCs) was considered because they are an established method for the simultaneous visualization of several trajectories and identifying

movement patterns; however, their effectiveness in presenting trends in data reduces when presenting larger amounts of data, where visual clutter, occlusion and reduced interpretability become problematic (McArdle, Demšar, van der Spek, & McLoone, 2014). Given the required volume of data for the web application and the length of the study period, it was determined that STCs would be an unsuitable method for use in this diploma thesis.

3.4 Software

ArcGIS Pro (v3.6.1) was used for the creation and export of GeoJSONs of sensor locations as points or polyline segments and the AOI boundary, and the creation of maps presented in Figure 3 and Figure 6. Python (v3.13.5) was used for the acquisition and preprocessing of mobility and meteorological data. This included the retrieval of data from the EnCLOD API and the CHMI API, the creation of the least-generalised cost paths for Nextbike data, as well as applying pre-processing and statistical analysis to all datasets. Python scripts are included within Attachment 1. Docker (v4.41.2) was used to run NetAScore within the containerised environment. Microsoft Excel (v.2605) was used for visual inspection of raw datasets and CSV outputs from Python scripts, i.e. formatting and filtering of data to check for missing records, dataset anomalies, and general viewing of the dataset. GitHub was used as a remote repository for the storage of all scripts as well as hosting of the interactive web map dashboard.

Within the interactive web map dashboard, HTML, CSS, and JavaScript were used for the creation and styling of the dashboard interface. Leaflet was used for the deployment of interactive web map elements. The associated scripts are included in Attachment 3. Affinity (v3.2.2) was used for the creation of the processing procedure flow chart presented in Figure 7, the diploma thesis poster, which is included in Attachment 5, and the Key Findings Infographic, which is included in Attachment 6. Grammarly (v1.2.280.1927) was used throughout the preparation of this diploma thesis to identify typographical errors.

3.5 Processing Procedure

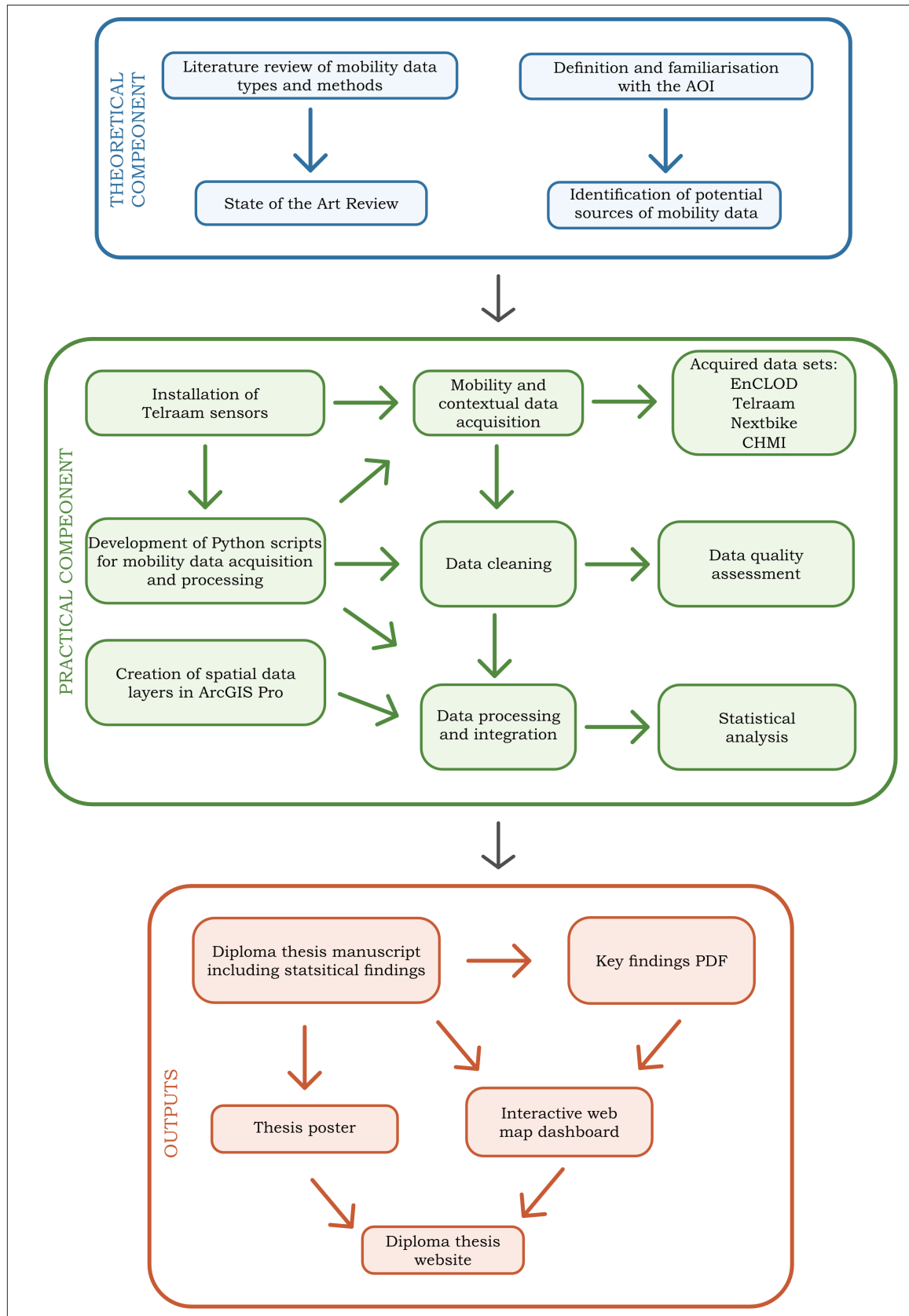


Figure 7: Flow chart of the processing procedure

4 DATA ACQUISITION, QUALITY ASSESSMENT, AND HARMONISATION

4.1 Data Acquisition

As previously stated within Chapter 3: Methodology, EnCLOD and CHMI weather data were acquired from their respective APIs, Telraam data from the online user interface, and Nextbike data provided directly by the company. All were obtained in CSV file format.

4.2 Data Evaluation

Nextbike

The dataset was cleaned to retain only start and/or end points located within the AOI. Trips with the same start and end coordinates within 30 m of each other were also removed from the dataset, as no trip can be inferred from these records. From the original dataset of 39,342 records, 2,082 (5%) were removed due to the origin and destination coordinates being within 30m of each other. Of the remaining 37,260 trips, a further 32,140 (86%) were removed because neither the origin nor the destination coordinate was located within the AOI. This resulted in a final dataset of 5,120 (13% of the original dataset).

Overall, the data in the format of OD pairs lacks spatial context, such as midpoints of the journey, which would have added value to the analysis in allowing for more accurate inferences. Furthermore, there is uncertainty regarding the accuracy of the GPS points; upon visual inspection of the original dataset within ArcGIS Pro, many points were located considerably outside of the Olomouc City area, and there is no direct available method to validate the accuracy of trips which remain within the dataset following the filtering procedures.

EnCLOD

The acquired dataset was observed to contain a large proportion of incomplete hourly records due to technical issues, as shown in Table 1. Rather than all sensors recording a complete hour of observations, many hourly records contain only partial 15-minute intervals. This was particularly evident for the Šmeralova sensors, where full coverage is substantially lower. As such, EnCLOD results should be interpreted with caution, especially when comparing volumes between locations.

Table 1: Hourly data completeness across EnCLOD sensors, presented as a percentage of all records

	No data	15 minutes	30 minutes	45 minutes	Full hour
17. Listopadu North: In	1.13	0.37	1.39	10.02	87.09
17. Listopadu North: Out	1.11	0.37	1.1	8.31	89.11
17. Listopadu South: In	1.12	0.27	0.98	7.71	89.92
17. Listopadu South: Out	1.18	0.21	0.92	7.38	90.31
Šmeralova South: Out	1.7	4.82	14.87	20.23	58.38
Šmeralova South: In	1.97	6.15	14	18.54	59.35
Šmeralova Middle: Out	2.04	7.86	22.44	27.6	40.06
Šmeralova North: Out	1.81	7.51	27.84	26.16	36.68

Telraam

The acquired dataset was mostly complete, with only three hourly records for each dataset below 60% uptime, defined as the percentage of time within the hour actively observing traffic. The main observed limitation in the dataset is the nighttime count, which aggregates all detections during dark hours without classification. Despite estimates being possible based on the proportion share of mobility counts during the daytime, this does not provide a fully accurate classification. This limitation was especially relevant during the winter months when daylight hours were reduced.

Telraam states within their user guide that sensor performance can also be affected by extreme light situations, obstructions to the view caused by weather, or atypical traffic such as crowding (Telraam, 2026). These circumstances are largely unavoidable but may have influenced the quality of the collected data.

CHMI

The acquired dataset was complete; however, the station is located approximately 2 km from the AOI, meaning that recorded values may not fully capture the localised weather conditions. Furthermore, the specific measurement apparatus used at the station is unknown; therefore, its accuracy is also unknown. However, as the data originates from an official CHMI measurement site, they are considered sufficiently reliable for this diploma thesis.

Overview

Across the datasets employed in this diploma thesis, there are recurring issues related to the accuracy, uncertainty and data completeness. This is something which is communicated within the interactive web map dashboard to ensure users interpret the presented values with appropriate discretion; values should therefore not be treated as absolute truths but rather general indicators of observed mobility patterns. The precise level of uncertainty is difficult to quantify and therefore cannot be meaningfully visualised. For this reason, uncertainty is addressed through discussion rather than represented directly in the dashboard maps or charts.

4.3 Data Processing

Separate processing scripts were developed for each dataset to account for differences in initial structure and format as follows:

- EnCLOD: data was initially retrieved from the API as daily 15-min CSVs, then compiled into a single CSV for all eight sensors. For readability, the sensors are referred to using descriptive names based on their location and movement direction.
- Telraam: two separate CSVs were downloaded from the online user interface for each sensor, then compiled into a single CSV.
- Nextbike: the initial dataset consisted of origin-destination pairs of coordinates. These were processed to produce the least generalised cost paths, i.e. the assumed routes.
- CHMI: hourly values were retrieved from the API and saved as a CSV.

All datasets were further processed to create temporal bucket aggregations and calculate the morning and afternoon peaks, and the raw and average hourly counts. These outputs were then used to generate the dynamic graph on the interactive web map dashboard, presenting the hourly counts for the selected sensor and bucket type.

The development of the data processing scripts was supported by ChatGPT 5.5 as an assistive tool; this included the structuring of functions, identifying syntax issues, and troubleshooting the scripts. Despite this, all final inclusion and implementation decisions were completed by the author.

All processing scripts and the associated environment YAML are provided in Attachment 1.

4.4 Preparation of Visualizations

Production of Segments

Once the representative segments and sensor points had been determined, as discussed in Section 3.3.3: Visualization, they were created within ArcGIS Pro and stored as a GPKG. The same CARTO basemap utilised in the interactive web map dashboard was used to ensure visual alignment. Segments were then exported in the format of GeoJSON for easy integration into Leaflet.

NetAScore

The NetAScore toolset (v1.1.1) was employed to create a bikeability index for the city of Olomouc. This software is open and extendible for segment-scale bikeability analysis. The software uses OSM data and considers variables such as cycling infrastructure, speed limits and greenness. The software outputs a cycling network consisting of edges and nodes, where each edge includes information on the segment length and bike preference index value, where 1 is strongly preferred, and 0 is the least preferred (Werner, et al., 2025). This was then used as an input for the least generalised cost-path generation. Required files were downloaded from the project repository on GitHub (Werner, et al., 2025) and run using Docker. In the 'settings_osm_query.yml' file, the 'case_id' was amended to 'olomouc', after which the index output was generated as a GPKG.

Cycling Least Generalised Cost-Path Creation

To add greater visual meaning to the Nextbike data, potential cycling routes were inferred using network analysis. The routing was based upon a cost function derived from the NetAScore bikeability index. This method was developed specifically for this diploma thesis because no satisfactory approach was identified in the literature for the available data structure. Existing route choice models often rely on more detailed trajectory information, including mid-journey points, whereas the Nextbike data only provides OD pairs.

The general framework applied to the Nextbike data treats journeys as paths through the network, evaluated according to a generalised cost function based on segment length and the bikeability index value. The resulting link cost is seen to represent the generalised inconvenience which a cyclist may face. Routes identified as the least-cost paths are selected and visualised. Origin and destination points were snapped to the nearest edge in the network to allow for a complete hypothetical journey to be represented.

The cost function is defined as:

$$c(e) = L(e) \cdot (1 + k \cdot (1 - I(e)))$$

Where:

- $L(e)$ is equal to the segment length in meters;
- $I(e)$ is equal to the bike preference index; and
- k is equal to the strength of the preference, which is set to 2.0 as a moderate preference scenario.

This approach is consistent with existing route choice models, which generate possible routes and then determine the likelihood of choice using link attributes such as bicycle facilities, comfort, and stress, represented through generalised costs or coefficients. They are typically operationalised through shortest-path searches on weighted networks, (Bekhor, Ben-Akiva, & Ramming, 2006) as previously discussed in the Chapter 2: State of The Art.

The method does not account for time of day or directionality to maintain computational simplicity. This limitation is considered acceptable for visualization, particularly considering the relatively small AOI. It is also acknowledged that inferring a complete route from OD points is inherently assumptive, as the potential intermediate stops are unknown; however, because the visualization is focused upon the AOI, the routed geometries are considered suitable as estimated likely paths rather than confirmed observed journeys. The routed geometries, therefore, represent the estimated likely paths between recorded origin and destination points.

Temporal Aggregation

As previously stated in Chapter 3: Methodology, datasets were grouped into several temporal aggregations to analyse how traffic patterns differ throughout the year. In addition to providing a clearer understanding of overall patterns, temporal aggregation helps to reduce the influence of short-term outliers or anomalies, which could distort the interpretation of underlying trends.

5 MOBILITY PATTERNS IN THE ENVELOPA CAMPUS

5.1 Identification and Analysis

This section analyses the general mobility patterns within the AOI, exploring daily cycles, term-based temporal variations, and differences between locations. The purpose of this analysis is to establish a baseline understanding of “normal” mobility patterns in the AOI, specifically identifying whether mobility patterns reflect the structure of the academic calendar and whether any anomalies or unreliable data are present.

The establishment of a baseline is important in that it provides context for later comparative analysis within Chapter 6: Comparative Analysis of Telraam and EnCLOD Datasets. Without an initial understanding of the general spatial and temporal structure of movement in the AOI, it would be difficult to interpret whether the observed differences between the datasets represent a meaningful pattern or rather just a result of data limitations.

Due to the different spatial structures of the datasets, the analysis was conducted in two ways: for Telraam and EnCLOD data, mobility patterns were analysed at the sensor level, allowing for differences between locations to be assessed. For Nextbike, however, this analysis was carried out at the AOI level using all trips within the temporal aggregation. This was necessary as the trips do not correspond to a fixed location, and so more spatially detailed aggregation would produce sparser and less meaningful results.

Additionally, the consideration of weather is a key part of mobility analysis, as weather conditions significantly affect how and when people move, especially for active mobility methods. Because the study period spans a year, it is possible to explore how mobility modes and weather interact. This section uses weather data from CHMI and applies statistical methods to identify trends and correlations in the data.

Research Questions

To structure this chapter of the diploma thesis, six questions were posed:

- Do mobility volumes and peak periods vary across semester periods and sensor locations?
- Do average 24-hour mobility profiles, aggregated by semester periods, differ between locations?
- How many days experience deviation from typical volumes, and can this be attributed to specific events?
- Are pedestrian and cycling mobility volumes more sensitive to weather conditions than motor vehicle volumes?
- Do academic terms explain additional variation in daily mobility volumes after accounting for weather conditions and weekday effects?
- What is the observed traffic difference on rainy, warm, and cold days?

These questions were designed to assess both the overall level of mobility and its temporal distribution. The aim was not only to identify where movement volumes are highest but also to assess whether different locations display similar daily mobility patterns or whether distinct temporal behaviours are visible across the AOI, as well as how mobility, weather, and events interact within the AOI.

5.2 Analytical Approach

Distribution statistics (KPIs) were calculated for each aggregation type, using mean values. These measures were used to assess the spread and variability of mobility patterns across temporal aggregations. This was useful for recognising short-term periods of concentrated movement during the day, such as during commuting hours and timetable transitions.

The morning (AM) and evening (PM) peak times were derived using fixed windows (06:00 to 10:00, then 15:00 to 19:00, respectively); the identified hour was that with the highest mean value. Due to data availability, EnCLOD is processed to 15 mins whereas the other two sensors are hourly aggregations.

Hourly average values were exported separately to support the visualization of 24-hour mobility graph within the interactive web map dashboard. This graph could then be used to compare the overall shapes of daily mobility patterns across locations rather than just their total values.

KPIs were calculated across all temporal aggregations to allow for the assessment of mobility intensity at various levels of temporal detail. However, within the analysis here, only term data is discussed; this level of aggregation reduces the effect of short-term daily variations and provides a clearer basis for comparing the broader mobility patterns across the academic year.

For the comparison of days with significant deviation from typical volumes, a baseline value was calculated for each day as a ± 6 moving window, excluding the given day. From this, the raw difference and percentage change to the baseline were calculated. A z-score was also calculated, as the observed day minus the baseline, over the baseline standard deviation.

From these, a shortlist was made of records with a z-score exceeding 2, a percentage change of at least $\pm 20\%$, and a raw count difference of at least ± 20 , as this was deemed to be meaningful changes as opposed to minor day-to-day variations. The shortlisted records are included in the 'significant_daily_deviation' CSV for each sensor type. These were then assessed by ChatGPT 5.5 against local events and national holidays to identify dates where the traffic flow deviations could be accounted for. This included the Flora exhibition, the Olomouc Half Marathon, UPOL graduation ceremonies, the opening day of the Christmas market, and the weekends preceding the start of the winter and summer semesters.

Daily and hourly aggregations remain important for identifying the peak periods and short-term fluctuations. Still, they are more sensitive to external factors such as events, weather conditions, incomplete data, and general irregular travel behaviour. By contrast, focusing on semester-level aggregations provides a more stable overview of general mobility patterns in the AOI.

To examine the relationship between weather conditions and mobility volumes, Spearman's rank correlation and generalised linear modelling (GLM) were applied. Spearman's correlation used daily mean temperature and daily precipitation total as continuous weather variables, whilst GLM used these variables converted into operational weather indicators: rainy, warm and cold days. Mobility variables included total EnCLOD counts for all sensors as well as groupings of sensors on 17. Listopadu and Šmeralova,

Telraam for all sensors and combined for bicycles, pedestrians, and motor counts, and Nextbike trip counts.

Spearman's rank correlation was used to assess whether the daily mobility volumes exhibited a monotonic relationship with weather conditions, overall indicating how sensitive mobility is to weather. This was calculated using all available daily observations, as weather sensitivity was not dependent on academic calendar classifications. This statistical method was appropriate because the relationship between weather and mobility is unlikely to be strictly linear.

The Spearman coefficient was calculated as:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

Where d_i is the difference between the ranks of the two variables for observation i , and n is the number of paired observations. Positive values indicate that mobility volumes tend to increase as weather variables increase; on the other hand, a negative coefficient would indicate a tendency to decrease. The absolute coefficient value was then used to compare the strength of association between modes

$$S = |\rho|$$

A higher S value indicates stronger weather sensitivity and was then used to compare between modes. Observed correlations are interpreted as associations rather than evidence of causation, as the analysis is observational and does not account for all possible confounding factors.

A GLM was used to identify the adjusted influence of weather conditions and academic term periods on daily mobility volumes. The analysis used only dates within the predefined academic term periods. As the daily mobility counts were used as the dependent variable, both Poisson and a negative binomial model were fitted as likelihood-based count models; they are the standard models for count data, and the standard alternative for when count data is over-dispersed (respectively). The GLM is run separately for each sensor and mode type rather than pooling features; therefore, does not need to take into consideration the sensor or location within the model.

$$Y_i \sim \text{Poisson}(\mu_i)$$

or:

$$Y_i \sim \text{Negative Binomial}(\mu_i, \alpha)$$

where Y_i is the observed daily mobility count, μ_i is the expected daily count, and α is the overdispersion parameter. A Gaussian model was not tested because it would assume continuous values, normally distributed residuals, constant variance and possible negative values, all of which are inappropriate for the nature of mobility data.

A log-link function was used:

$$\log(\mu_i) = \beta_0 + \beta_1 R_i + \beta_2 W_i + \beta_3 C_i + \gamma D_i + \delta T_i$$

R_i represents rainy days (days with ≥ 1 mm of precipitation), W_i warm days (mean temperature above 20 °C), C_i cold days (mean temperature below 5 °C), D_i weekday controls (because it can be anticipated that mobility differs between workdays and weekends, and this is something which the model is sensitive to), and T_i academic term controls.

To assess whether academic terms improved model performance beyond weather and weekday effects, two model structures were compared. The first excluded academic terms, and the second included them.

The model selection was then based on the Akaike Information Criteria (AIC):

$$AIC = 2k - 2 \ln(L)$$

Where k is the number of estimated parameters, and L is the model likelihood. Lower AIC values indicate a better balance between the model fit and complexity. For each mobility grouping, Poisson and negative binomial models were compared, and the model with the lowest AIC value was selected; if the difference was small, then the simpler model was preferred.

To further assess the contribution of academic terms, an additional contribution to the academic term was assessed using:

$$\Delta AIC = \Delta AIC(\text{no term}) - \Delta AIC(\text{with term})$$

A positive value indicates that including terms improves the model performance, and values greater than ~ 2 are interpreted as evidence that academic terms improve the model, whilst values below this suggested a weak or uncertain improvement; contrastingly, negative values indicate that the model was stronger without the inclusion of academic terms.

To then quantify the explanatory power of the model, McFadden's pseudo- R^2 was calculated

$$R^2_{McFadden} = 1 - \left[\frac{\ln(L_{\text{model}})}{\ln(L_{\text{null}})} \right]$$

L_{model} is the likelihood of the fitted model, and L_{null} is the likelihood of the intercept-only model. It indicated the improvement of the fitted model relative to the null model.

To then allow for easier interpretation, the GLM coefficients were converted into percentage changes:

$$\% \text{ change} = [\exp(\beta) - 1] * 100$$

This allowed for results to be expressed as an estimated percentage increase or decrease in daily mobility volume on rainy, warm or cold days whilst holding other variables constant. Academic term coefficients were interpreted in the same way.

The script included QC outputs to assess how the weather had joined to the mobility datasets, as well as indicating which terms had incomplete coverage and therefore should be seen as representing the observed periods rather than a full term.

Weather thresholds were used in this analysis as operational definitions rather than strict meteorological classifications to enable a simpler, more consistent comparison across all sensors, modes, and data sources. Overall, thresholds were selected to prioritise interpretability; these boundaries affect statistical outputs, and therefore findings should be interpreted as indicative of general weather effects as opposed to exact threshold-based responses.

5.3 Comparative Findings

To reflect the way in which each dataset differs in spatial structure and sensor types, they are treated here as complementary sources rather than directly interchangeable measurements. As such, results here are presented separately by data source, and then interpreted together where comparable patterns are identified.

Mobility volumes across academic terms

The total mobility volumes across the main academic and non-academic periods provide an overview of the relative scale of movement recorded by each dataset and sensor location. Table 2 presents values that have been normalised to an average daily count, as the length of these periods differs. Values show how EnCLOD sensors peak during the Winter Semester, suggesting that the regular teaching periods are most responsible for generating the highest daily mobility intensity. Troughs do, however, differ by location: Šmeralova mostly fall to their lowest values during the Main Holiday, whilst 17. Listopadu sensors are lowest during the Summer Exam Period and remain relatively active during the Main Holiday.

As such, it could be interpreted that Šmeralova is more sensitive to university routines, whilst 17. Listopadu functions more as a mobility corridor. When assessing Telraam data, however, this data behaves slightly differently: both peak during the Summer Semester, although this comparison is somewhat limited due to missing Telraam data for the earlier periods. Similarly, the highest Nextbike normalised count was observed during the Summer Exam Period and lowest during the Main Holiday; however, the size of the dataset and its temporal coverage are too small to identify true trends in volume changes over the study period.

Table 2: Normalised traffic counts as per day trips across terms

Sensor	Summer Exam Period (50 days)	Main Holiday (62 days)	Winter Semester (89 days)	Winter Exam Period (33 days)	Summer Semester 91 days)
Telraam: 17. Listopadu	-	-	5,992	8,069	8,752
Telraam: Šmeralova	-	-	1,459	2,110	2,612
Nextbike: All	26	21	23	-	-
Šmeralova South: In	905	649	972	813	889
17. Listopadu South: In	4,797	5,380	6,411	5,672	5,943
Šmeralova North: Out	311	199	335	246	307
17. Listopadu North: Out	4,212	4,856	5,642	4,967	5,172
Šmeralova South: Out	633	535	687	578	655
17. Listopadu South: Out	4,535	5,481	5,703	5,346	5,536
17. Listopadu North: In	4,602	5,358	5,694	5,272	5,483
Šmeralova Middle: Out	283	156	313	222	271

Variation in peak-period timing by academic terms

Values in Table 3 show that the PM peak timing is more consistent than AM peak timing, with most PM peaks occurring close to the start of the afternoon window between 15:00 and 16:00, whilst for AM the peaks vary noticeably both temporally and spatially.

Telraam sensors are the most temporally stable, at 17. Listopadu, the AM peak remains fixed at 07:00 across all aggregations, whilst the PM peak shifts later from 16:00 in the winter semester to 17:00 in the winter exam period and 18:00 in the summer semester, suggesting stable morning traffic levels but a gradual delay in the strongest mean flows. The Telraam sensor on Šmeralova is also relatively consistent, with one hour of variation in both the AM and PM peaks (07:00 to 08:00 and 15:00 to 16:00, respectively).

Nextbike data shows a distinct shift in AM timing, moving from 10:00 during the summer exam period to 08:00 during the main holidays and 07:00 during the winter semester, suggesting that bike-share use is more sensitive to the effects of the academic calendar. In contrast, the PM peak remains stable between 15:00 and 16:00.

With consideration of the EnCLOD sensors, PM peaks are relatively consistent with most peaks at or close to 15:00, except for the winter exam period, where all sensors shifted later to 16:30 to 16:45, indicating a delay in afternoon activity when compared to regular semester and holiday periods. On the other hand, AM peaks for the EnCLOD sensors are much more variable. For example, Šmeralova North: Out ranges from 06:00 during the main holiday to 09:15 during the winter exam period. Similarly, 17. Listopadu North: Out also vary from 06:15 during the summer exam period to 09:00 during the main holiday, suggesting that outbound movements are less stable and may reflect more flexible patterns in commuting, visits to campus and general local trips.

Overall, there is no clear pattern in the shift of AM PM peaks across sensors and terms; however, it is noticeable that the regular semester periods exhibit earlier AM peaks, specifically for Telraam and Nextbike and that the winter exam period often presents later AM and PM peaks, especially for EnCLOD sensors. Overall, morning activity is more sensitive to term variations and locations, whilst afternoon activities present more stable peaks but are often later during exam periods.

Table 3: Peak AM and PM times per sensor across terms

Sensor	Summer Exam Period	Main Holiday	Winter Semester	Winter Exam Period	Summer Semester
Telraam: 17. Listopadu	-	-	07:00 16:00	07:00 17:00	07:00 18:00
Telraam: Šmeralova	-	-	07:00 15:00	08:00 15:00	07:00 16:00
Nextbike: All	10:00 15:00	08:00 16:00	07:00 15:00	-	-
Šmeralova South: In	06:15 15:30	06:00 15:00	06:30 15:45	07:30 16:30	07:00 15:00
17. Listopadu South: In	06:30 15:00	08:15 15:00	08:30 15:30	07:00 16:30	07:00 16:00
Šmeralova North: Out	09:00 15:00	06:00 15:00	08:45 15:00	09:15 16:45	08:45 15:00
17. Listopadu North: Out	06:15 15:30	09:00 15:00	08:30 15:00	07:00 16:45	08:00 15:00
Šmeralova South: Out	06:15 15:45	06:00 15:15	08:30 16:00	09:00 16:30	07:45 15:00
17. Listopadu South: Out	06:15 15:15	08:15 15:15	08:45 15:30	09:00 16:30	09:30 15:00
17. Listopadu North: In	06:15 15:00	07:00 15:00	08:45 15:15	09:00 16:45	08:00 15:00
Šmeralova Middle: Out	08:00 15:00	08:15 16:00	08:30 15:45	08:45 16:45	07:00 15:00

Daily deviations

The identified deviations presented in Table 4 represent a relatively small share of all daily observations within the datasets. EnCLOD contained 196 recorded deviations out of 3,000 observations, equivalent to 6.5% of observations. Telraam contained 32 recorded deviations out of 384 observations, equivalent to 8.3%. Nextbike contained 11 recorded deviations out of 203, equating to 5.4%.

When assessed against known events, a small number of events could be associated with these specific dates. EnCLOD showed the highest level of alignment, with 20 out of 70 deviations being accounted for as a mix of local events and national holidays. Telraam had 6 out of 25 deviation days accounted for, all of which were national holidays. Only one Nextbike deviation could be accounted for as a local event. The overlap of deviation dates was also assessed. No date was shared across all three datasets. EnCLOD and Telraam shared 12 dates, whilst EnCLOD and Nextbike shared four dates. Telraam and Nextbike had no overlapping dates. Deviations being inconsistently observed indicates that variations are likely a result of sensor-specific or mode-specific variation as opposed to an external calendar effect.

Table 4: Summary of shortlisted daily deviations matched to local events and Czech public holidays

Sensor	Number of recorded deviations	Total records identified as deviations (%)	Number of unique deviation days	Days accounted for by event or public holiday	Days unaccounted for (%)
EnCLOD	196	6.5%	70	20	71.4
Telraam	32	8.3	25	6	76
Nextbike	11	5.4	11	1	90.9

24-hour mobility profiles across academic terms

Figure 8 presents how the average 24-hour mobility profiles vary across the academic terms for both EnCLOD and Telraam sensors, using the average daily volume across all EnCLOD sensors on each respective road, and the average values for Telraam incorporating all transport modes. Nextbike data is not presented here due to the limitations in the size of the sample data, meaning that trends would not be identifiable.

EnCLOD generally shows a smoother, bell-shaped daily profile with mobility increasing in the morning, remaining relatively stable throughout the day and then decreasing again in the evening. This pattern is visible for 17. Listopadu and Šmeralova, however, volumes are considerably higher on 17. Listopadu. The pattern exhibited by EnCLOD suggests a more continuous flow of traffic rather than distinct commuting peaks. On the other hand, Telraam sensors show a more distinctive morning and evening peak during the typical commuting periods. Considering that this pattern is consistent with the sensor type and not the geographic location, this difference is likely to be related to the modes of transport counted by each sensor; EnCLOD records only motorised vehicles, and the smoothest curve visible on 17. Listopadu is likely related to the function of this road as an important entrance/exit to the city, meaning that the traffic here is more related to general urban movement and not so strongly tied to university routines. Contrastingly, Telraam, by capturing multiple modes including active transport methods, means it is more likely to capture a larger proportion of university-related commuting activity, as students are more likely to rely on active transport modes such as walking and cycling due to typically lower levels of car ownership amongst students, partly due to financial constraints.

The exhibited profiles for all sensors show some variation across the academic calendar, supporting the idea that the observed mobility in the AOI is influenced by university activity; despite this, the continual presence of daytime movements during non-teaching periods suggests that the streets also have broader urban function.

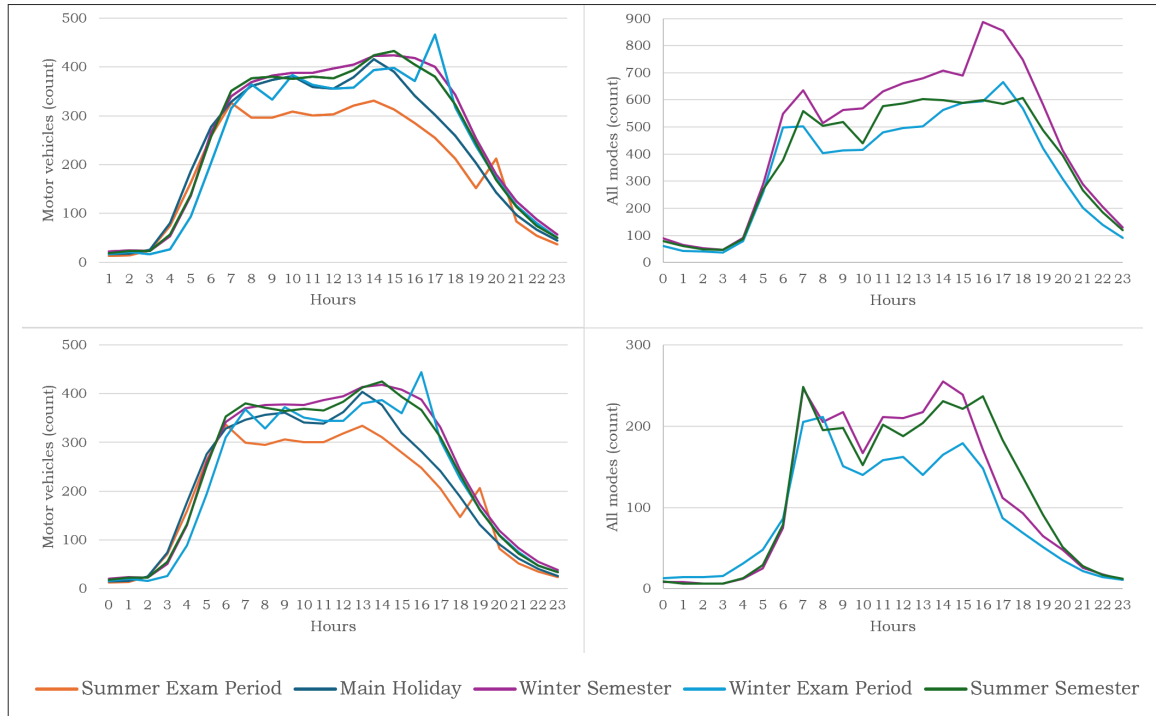


Figure 8: Average 24-hour mobility patterns across academic terms. Top left: all EnCLOD sensors on 17. Listopadu; top right: Telraam on 17. Listopadu, all modes; bottom left: all EnCLOD sensors on Šmeralova; bottom right: Telraam on Šmeralova

Sensitivity of modes to weather

Mode-level weather sensitivity is presented below in Table 5, summarised from all available sensor/source-level Spearman tests. Values summarise the strength of monotonic associations between sensor counts and the weather variables. A higher value, therefore, indicates a strong association with weather conditions, independent of direction. This included 4 pedestrian tests, 6 bicycle tests, and 20 motor vehicle tests across the 3 sensor types.

Overall, active travel modes showed a stronger weather sensitivity than motor vehicles. Bike counts had the highest mean absolute correlation of 0.305, followed by pedestrians of 0.296. Motor vehicles showed a much weaker overall association of 0.117, suggesting that motor vehicle flows were less affected by weather conditions than walking or cycling activities.

The highest individual correlation was observed for bikes (0.744), almost double that for pedestrians and motor vehicles (0.486 and 0.370, respectively). This indicates that whilst both active modes are weather sensitive, cycling showed a stronger single association with the weather.

Results separated by individual weather variables show that temperature was the main driver of weather sensitivity. For pedestrians, the mean temperature correlation was 0.476 compared to 0.116 for precipitation. For bikes, the mean temperature correlation was 0.415 compared with 0.195 for precipitation. Motor vehicles exhibited the same pattern but with weaker values of 0.175 for temperature and 0.059 for precipitation.

Table 5: Weather sensitivity by transport mode based on absolute Spearman correlations

Mode	N tests	Mean	Median	Max
Overall				
Pedestrians	4	0.296	0.299	0.486
Cyclists	6	0.305	0.235	0.744
Motor Vehicles	20	0.117	0.106	0.370
Temperature				
Pedestrians	2	0.476	0.476	0.486
Cyclists	3	0.415	0.444	0.744
Motor Vehicles	10	0.175	0.128	0.370
Precipitation				
Pedestrians	2	0.116	0.116	0.132
Cyclists	3	0.195	0.189	0.281
Motor Vehicles	10	0.0594	0.0438	0.174

Term influence upon mobility volumes when accounting for weather

GLMs were fitted separately for each sensor and mode type; AIC identified that negative binomial models were consistently preferred, indicating overdispersion in daily mobility counts and that the Poisson assumption of equality between the mean and variance was over-restrictive.

To avoid overemphasis of individual sensor-level mode results, the term influence models were summarised by mode.

As presented in Table 6, the academic term control improved the GLM performance across nearly all tests after weather and weekday effects were accounted for. The term inclusion improved by 100% for both pedestrian and bicycle modes, and 90% for motor vehicle modes. The size of improvement varied by mode type; pedestrian models showed the greatest improvement with a median ΔAIC of 68.26. Motor vehicles also showed a notable improvement with a median ΔAIC of 32.38. Bike models showed a slightly weaker but an improvement nonetheless in the median ΔAIC of 7.36. Overall, the results can be understood to mean that academic terms added explanatory value across all observed mode types, although the strength was much greater for pedestrians and weakest for bicycles. A dataset-level breakdown showed that the contribution of academic terms was not uniform across all sources. The greatest observed improvements were observed for Telraam pedestrian and enclosed motor vehicles, whilst the Telraam motor vehicle model showed a less consistent, weaker improvement. Bicycle models improved across both Telraam and Nextbike sources, although the size of improvement was larger for Telraam than Nextbike, suggesting that the academic term effects were present across all datasets but did vary by sensor types.

It should be noted that the Telraam dataset did not cover any warm days.

Table 6: Improvement in GLM performance following the addition of academic term controls by transport mode

Mode	N tests	Improvement (% of tests)	Median Δ AIC
Pedestrians	2	100	68.26
Cyclists	3	100	7.36
Motor Vehicle	10	90	32.38
EnCLOD (Motor Vehicles)	8	100	34.73
Nextbike (Cyclists)	1	100	5.53
Telraam (Cyclists)	2	100	20.13
Telraam (Motor Vehicles)	2	50	5.91
Telraam (Pedestrians)	2	100	68.75

Observed percentage change during specific weather conditions

Table 7 presents that the clearest weather effect was found for cyclists on cold days, with a median decrease of 26.82% and statistical significance in 100% of tests, indicating that cycling was particularly sensitive to low temperatures. Similarly, cold days were also associated with lower pedestrian volumes, with a median decrease of 9.60%, although not significant. In contrast, motor vehicles showed a small median increase on cold days of 7.03%, but the significance was limited, suggesting a less consistent effect.

Days with precipitation were associated with reduced cycling volumes, with a median decrease of 12.97%, although only 33.33% of tests were statistically significant. Effects for motor vehicles and pedestrians were small and barely or non-significant (10% and 0% respectively).

Warm-day effects were the weakest overall, with motor vehicles showing a slight decrease of -3.55% on warm days, whilst cyclists showed -6.01%; however, this was based on only one test and was not significant.

Overall, the results show that cold weather has the strongest adjusted effect on mobility volumes, notably for cyclists, whilst precipitation and warm-day effects were much weaker and less consistent.

Table 7: GLM effects separated by mode, expressed as percentage changes in daily mobility volumes

Mode	N tests	Median change (%)	Mean change (%)	Significance (%)
Cold days				
Pedestrians	2	-9.60	-9.60	0
Cyclists	3	-26.82	-31.33	100
Motor Vehicles	10	7.03	2.71	30
Warm days				
Motor vehicles	8	-3.55	-4.12	12.5
Cyclists	1	-6.01	-6.01	0
Days with precipitation				
Pedestrians	2	-0.86	-0.866	0
Cyclists	3	-12.97	-15.85	33.33
Motor Vehicles	10	1.83	2.07	10

6 COMPARATIVE ANALYSIS OF TELRAAM AND ENCLOD DATASETS

6.1 Identification of Datasets and Comparison Objectives

Context

The two Telraam sensors cover the same comparison location as the EnCLOD sensors (17. Listopadu South: front location and Šmeralova South: side location), thus allowing for a comparison in measured values.

Research questions

To structure this chapter of the diploma thesis, four questions were posed:

- Does disagreement between Telraam and EnCLOD counts increase with traffic volume?
- Are Telraam or EnCLOD counts consistently higher?
- Are there extreme disagreement periods between Telraam and EnCLOD?
- Do larger aggregation periods improve agreement between the Telraam and EnCLOD datasets?

6.2 Analytical Approach

Data was filtered to dates where both datasets had values available – 31/10/2025 to 10/05/2026. Temporal harmonisation was then performed using the shared bucket structure present in both datasets from initial processing for use in the interactive web map dashboard. Records were matched using ‘bucket_type’, ‘bucket’, ‘date_start’, and ‘date_end’, with comparisons carried out separately for each temporal aggregation (daily, weekly, monthly, weekday-in-month, and term). Only records present in both datasets were used for the statistical comparison, while coverage checks were produced separately to confirm whether any unmatched periods existed. In the final harmonised dataset, all comparison periods matched successfully between the Telraam and EnCLOD datasets.

The main comparison value for EnCLOD was ‘total_sum’, representing the total motor-vehicle count.

For Telraam, a direct comparison using only ‘car_total’ and ‘large_vehicle_total’ was considered potentially incomplete, because Telraam groups non-daylight detections into a nighttime count without vehicle-type classification. To account for this, a weighted night adjustment was applied. First, the daylight motor-vehicle share was calculated as the proportion of cars and large vehicles within all classified daylight detections. This motor share was then applied to the nighttime count to estimate the likely motor-vehicle component of night traffic. The final Telraam comparison value was therefore calculated as daylight motor vehicles plus the estimated motor-vehicle share of night detections. This approach prevented ignoring night traffic, while also avoiding the assumption that all night detections were motor vehicles.

The daylight classified total was:

$$C_i = \text{pedestrian_total} + \text{bike_total} + \text{car_total} + \text{large_vehicle_total}$$

The daylight motor-vehicle share was:

$$S_i = \frac{M_i}{C_i}$$

The Telraam comparison value was calculated as:

$$T_i = M_i + (\text{night_total}_i \times S_i)$$

Statistical methods and justification

The comparison between EnCLOD and Telraam datasets was based upon matched observations where both datasets provided a value for the same location and the same aggregation period. Neither dataset can be assumed to represent a ground truth, and therefore, all employed methodologies avoid using EnCLOD or Telraam as a reference dataset.

The signed value (SPD_i) was used to assess bias and direction, while $ASPD_i$ was used to measure the size of disagreement between the datasets, regardless of which dataset was higher. This was applied instead of a standard percentage error because it would require one dataset to be treated as the reference denominator, which was not possible, as neither can be assumed to be a 'true' value.

The signed difference was calculated, with positive values indicating that EnCLOD was higher and negative values indicating that Telraam was higher.

$$D_i = E_i - T_i$$

The absolute difference was also calculated to measure the size of the raw difference in values without consideration of which dataset was higher.

$$|D_i| = |E_i - T_i|$$

Symmetric percentage difference (SPD) was employed as the main relative error percentage measure to assess whether the EnCLOD or Telraam dataset tended to be higher:

$$SPD_i = \frac{2(E_i - T_i)}{E_i + T_i} \times 100$$

The absolute symmetric percentage difference (ASPD) form was then used to measure the magnitude of disagreement between the datasets, regardless of which dataset was higher:

$$ASPD_i = |SPD_i|$$

Extreme disagreement periods were flagged using:

$$ASPD_i \geq 30\%$$

Agreement was summarised by location and aggregation type using mean and median absolute symmetric percentage difference:

$$\overline{ASPD} = \frac{1}{n} \sum_{i=1}^n ASPD_i$$

$$\widetilde{ASPD} = \text{median} (ASPD_i)$$

This comparison between datasets is made over many observations rather than just single observations. The mean identifies the overall level of disagreement, whilst the median indicates typical disagreement between the datasets, as it is less affected by extreme values.

Bias was summarised using the mean and median signed symmetric percentage difference to assess whether one dataset was consistently higher or lower than the other:

$$SPD = \frac{1}{n} \sum_{i=1}^n SPD_i \quad \widetilde{SPD} = \text{median}(SPD_i)$$

Threshold-based classifications were made to create an easier-to-interpret finding. Each observation is classified based on which dataset was higher. Observations were classified using a $\pm 5\%$ similarity threshold:

$$p_E = \frac{\#(SPD_i > 5)}{n} \times 100 \quad p_T = \frac{\#(SPD_i < -5)}{n} \times 100 \quad p_S = \frac{\#(|SPD_i| \leq 5)}{n} \times 100$$

where p_E is the percentage of observations where ENClod was higher, p_T is the percentage where Telraam was higher, and p_S is the percentage where the two datasets were similar.

The level of disagreement between the datasets was assessed with respect to traffic volume sensitivity. The mean of the two datasets was used as a neutral volume estimate:

$$V_i = \frac{E_i + T_i}{2}$$

The relationship between traffic volume and disagreement was then assessed using a Spearman correlation:

$$\rho_V = r(\text{rank}(V_i), \text{rank}(ASPD_i))$$

A positive ρ_V indicates that disagreement tends to increase at higher traffic volume, while a negative value indicates that disagreement decreases as volume increases. Pearson's wasn't employed here, as a linear relationship is unlikely for mobility data.

To assess whether increased temporal aggregation improved agreement between datasets, each aggregation type was assigned an ordinal value:

$$\text{daily} = 1, \text{weekday in month} = 2, \text{week} = 3, \text{month} = 4, \text{term} = 5$$

For each aggregation level (j), the median absolute symmetric percentage difference was calculated:

$$M_j = \text{median}(ASPD_i)$$

The aggregation effect was assessed using Spearman correlation between aggregation order and median disagreement:

$$\rho_A = r(\text{rank}(A_j), \text{rank}(M_j))$$

where A_j is the aggregation order. A negative ρ_A indicates that agreement improves with greater aggregation, while a positive value indicates that disagreement increases with aggregation.

Overall, the methodology assessed the direction, magnitude, bias, similarity, volume sensitivity, aggregation effects, extreme disagreement and data coverage of the two datasets.

6.3 Comparative Findings

Nighttime adjustment of Telraam data

The weighted night adjustment substantially improved agreement between Telraam and EnCLOD, as shown in Table 8. This indicated that the Telraam unclassified nighttime detections were an important source of disagreement. After applying the adjustment, the number of extreme disagreement periods decreased for both comparison locations, although the improvement was much more pronounced at the side location.

For the front location, the number of daily extreme observations decreased from 276 to 171, representing a decrease of 38%. However, EnCLOD remained consistently higher than Telraam counts, and large disagreements were frequent. In contrast, the side location showed a much greater improvement, with daily extreme observations decreasing from 138 to 17, equating to a decrease of 88%. This suggests that the weighted nighttime adjustment was particularly effective for the side location, while the front location is likely influenced by additional spatial or sensor-specific factors.

Table 8: Difference in extreme period occurrence between daytime and weighted nighttime values

Location	Original extreme periods (count)	Weighted nighttime extreme periods (count)	Raw Change (count)	Percentage change (%)
Front	276	171	-105	-38
Side	138	17	-121	-88

Aggregation-related trends

As presented in Table 9, systematic bias remained across temporal aggregation levels after the nighttime adjustments were applied. Particularly at the front location, EnCLOD generally reported higher values than Telraam. At this location, EnCLOD values were higher in 98.95% of daily observations and in 100% of weekly, monthly, term-level, and weekday-in-month aggregations. The same pattern was also present at the side location, although not as noticeably. EnCLOD reported higher values in 72.92% of daily observations, 71.43% of weekly observations, 75% of monthly observations, 66.67% of term-level observations, and 68% of weekday-in-month observations, indicating that the direction of bias was consistent at both locations, although more pronounced at the front location.

Table 9: Percentage of readings within the aggregations where EnCLOD had higher values

Location	Day	Weeks	Months	Terms	Weekdays in months
Front	98.95	100	100	100	100
Side	72.92	71.43	75	66.67	68

Temporal aggregation affected the two locations differently; the side location aggregation generally improved agreement between the datasets, with the strongest agreement observed at the term level and the weakest agreement at the daily level. In comparison, the aggregation increased disagreement at the front location. Here, the best agreement was observed at a monthly resolution, whilst the weakest was at the term level.

Overall, the results suggest that increased temporal aggregation reduced random variation at the side location, whilst at the front location it resulted in an amplification of the bias.

Extreme periods

Extreme disagreement periods, i.e. where the level of disagreement exceeded 30%, were observed consistently at the front sensor location across all temporal aggregation levels. They accounted for 57% of daily observations, 68% of both weekly and weekday-in-month observations, 75% of monthly observations, and all term-level observations. In contrast, extreme disagreement at the side location appeared only at smaller aggregation levels, representing 7% of daily observations and 6% of weekday-in-month observations. No extreme disagreement was observed at this location at a weekly, monthly, or term aggregation level.

General trends

The median absolute symmetric difference, as presented in Table 10, supports that the disagreement between the two data sets was not spatially uniform. The side location showed relatively low median disagreement across all aggregation levels, ranging from 8.1% to 10.9%. In contrast, the front location exhibited substantially higher disagreement, with median values ranging from 32.8% to 36.8%.

The results suggest that the observed differences were not caused solely by the temporal aggregations, but rather that location- specific factors may have influenced the comparison. Possible explanations may include, but are not limited to, sensor placement, field of view, directional coverage, misclassification, occlusions, local road geometry, and specifically the presence of an intersection, pedestrians crossing, and parked cars near the front location.

Table 10: Median absolute symmetric difference (%)

Location	Day	Week	Month	Term	Weekdays in Months
Side	10.9	10.4	9.7	8.1	8.8
Front	33.2	35.7	32.8	36.8	33.5

Volume-related trends

The relationship between traffic volume and disagreement was not consistent at either location or across temporal aggregation levels, as presented in Table 11 and summarised in Table 12, suggesting that the volume of traffic alone does not explain the observed differences in the datasets.

For the side location, disagreement decreased with higher traffic volume at the daily level, while no strong relationship was observed for weekly, monthly, or weekday in-month aggregations. At the term level, disagreement increased with higher traffic volume, and similarly, the front location showed no consistent pattern. Disagreement decreased

at higher traffic volume at the weekly level but increased at the monthly, term and weekday in-month aggregations. For daily aggregations, no strong relationship was found.

Overall, the results indicate that the disagreement between the two sensors was not a result of volume; the inconsistency in Spearman values suggests that other factors likely played a more influential role.

Table 11: Spearman's correlation between traffic volume and disagreement

Location	Day	Week	Month	Term	Weekdays in Months
Side	-0.41	0.24	0.14	0.50	-0.17
Front	-0.05	-0.31	0.43	0.50	0.30

Table 12: Summary interpretation of volume-related disagreement patterns

Location	Aggregation levels where disagreement decreased with volume	Aggregation levels where disagreement increased with volume	Aggregation levels with no strong relationship
Side	Day	Term	Week, Month, Weekdays in months
Front	Week	Month, Term, Weekdays in months	Day

7 WEB APPLICATION DEVELOPMENT

The interactive web map dashboard was developed as the interactive output of the diploma thesis, allowing for the processed mobility datasets to be visualised and explored interactively by a non-specialist audience. The dashboard was designed to communicate the mobility patterns identified within the AOI in a clear and accessible manner, whilst still retaining analytical detail to achieve the research objectives of the diploma thesis. Special attention was paid to the usability, visual clarity, and avoidance of overly technical terminology, as the audience may include users who do not have a background in geoinformatics or mobility analysis.

The application prioritises an intuitive layout with interactive elements which allow users to explore the data without needing to understand the processing workflow supporting it. Context panels and information buttons are used throughout the dashboard to expand upon the meaning of filters, charts, map layers, and indicators. By embedding these short explanatory texts within the interface, the application assists users in correctly interpreting the content and reduces the risk of misunderstanding the outputs.

The dashboard has six sections: project information, main dashboard, time comparison, sensor comparison, other findings, and a help page. This structure allows for the separation of the general project context from the more analytical functions whilst supporting a more logical user journey; the user experiences general orientation with the project and its employed data sources, moving to interactive exploration of the findings, and then to more analytical comparison and interpretation of the data.

The development of the web-application scripts was supported by ChatGPT 5.5 as an assistive tool; this included assistance in structuring, refining and troubleshooting the scripts. All final implementation decisions and script validation were completed by the author.

The scripts and data files used for the dashboard implementation are provided in Attachment 3.

7.1 Static Data Integration

The application uses a static data structure based on pre-processed CSV and GeoJSON files, which are directly loaded into the application. This approach was selected because it is well-suited for web-based dashboard hosting through GitHub Pages, where all files must be served statically. The resulting framework from this is lightweight and easier to maintain than a database-driven system.

The preprocessing of data, as discussed in Chapters 3 and 4 produced CSVs with a consistent format of temporal schema and fields to use in the application, allowing front-end scripts to handle all datasets with similar logic; for example, EnCLOD values are linked to road segments, Telraam values to sensor point locations, and Nextbike values to assumed route geometries. This separates any analytical processing from the web application.

7.2 Front-end Development

The front end of the interactive web map dashboard was developed using HTML, CSS, and JavaScript. These technologies were chosen due to the way in which they are widely supported by web browsers and allow for the application to run without the requirement for users to install additional software. As such, the dashboard is freely available online through a standard web browser and is suitable to be viewed on large and small screens.

The HTML files define the main components of the application, including the navigation bars, map containers, information and filter panels, and data visualizations. CSS was implemented to control the visual design, layout and styling of the dashboard. A consistent visual structure is applied to ensure that the application remains readable and navigable, and for users to easily distinguish between the capabilities of different components.

JavaScript was used to provide the interactive functionality of the web dashboard. This controls the loading of data, interactive filtering of records, and subsequent updating of map and panel records. Data is loaded client-side, utilising PapaParse for CSV parsing, whilst Leaflet is used for the embedded maps. Data handling operations are performed client-side once static files are loaded.

The front-end was developed to ensure that users receive responsive visual feedback when interacting with the dashboard through dynamic updates based on the users' data selections. This supports the exploratory analysis of the data and allows users to explore both spatial and temporal mobility patterns within one environment.

7.3 Visualization Methods

Different visualization methods were utilised for each sensor type; this was informed by Section 2.6 and based upon the varying structure and level of detail of the mobility data. A single visualization method would not have communicated all datasets effectively, and so instead, each source is visualised in a way which matches the characteristics of the data.

EnCLOD data is represented using graduated line symbology to represent motor vehicles along road segments. The use of graduated lines allows users to identify which road sections experience lower or higher motor vehicle observations, and reflects the linear nature of a road network, therefore supporting intuitive interpretation of traffic intensity.

Telraam data is visualised using proportional doughnut chart markers. This was selected due to records detailing modal splits; a single location contained multiple categories of movement. This symbology allows for the map to communicate both the total volume of traffic as well as the relative composition of different modes.

Nextbike data is represented as a heatmap-style line layer, with the lighter colour representing fewer trips and the more intense colour representing more frequently used areas. This was selected as a standard way to visualise bike trips, for example, as a method commonly utilised by Strava. The GeoJSON is processed as a single line object with different values along segments of the line to visualise the intensity of trips. This allows for the file size to stay small in comparison to what individual trips would be and would thus reduce the responsiveness of the interactive web map dashboard.

Employing different visualization methods for each data type assists users in distinguishing the source, reducing ambiguity and supporting easier, accurate interpretation of the dashboard's contents. Additionally, all lines and points can be clicked upon, and a pop-up presents more detailed information on exact count values and the split between types/modes, thus allowing users to gain more information should they seek it, but preventing unnecessary initial cognitive overload.

In addition to the geovisualization, the dashboard includes temporal visualization of annual mobility trends and 24-hour mobility patterns. These allow users to explore broader temporal patterns as well as daily rhythms. The combination of spatial and temporal visualization enables the dashboard to communicate mobility patterns at different scales simultaneously.

7.4 Presentation of Analysis

The presentation of analytical findings within the interactive web map dashboard was designed to focus on the findings most suitable for interactive communication rather than presenting all analytical outputs which were produced within this research. This approach reduces the overall cognitive load whilst ensuring that the dashboard remains relevant and accessible to the intended audience.

The About the Project page, as shown in Figure 9 provides contextual information regarding the location and use of the dashboard. It introduces the spatial and temporal scope of the application and explains its main interactive functions. This information supports usability whilst communicating important analytical context and limitations, including the need to interpret mobility counts as estimates rather than exact values.

Key findings are presented on the About page as a downloadable PDF, allowing users to access a concise written summary of the analysis while interacting with the dashboard. This combination supports exploratory engagement with the data whilst also providing a more traditional presentation of the analytical results. The Key Findings PDF is included in this diploma thesis as Attachment 6.

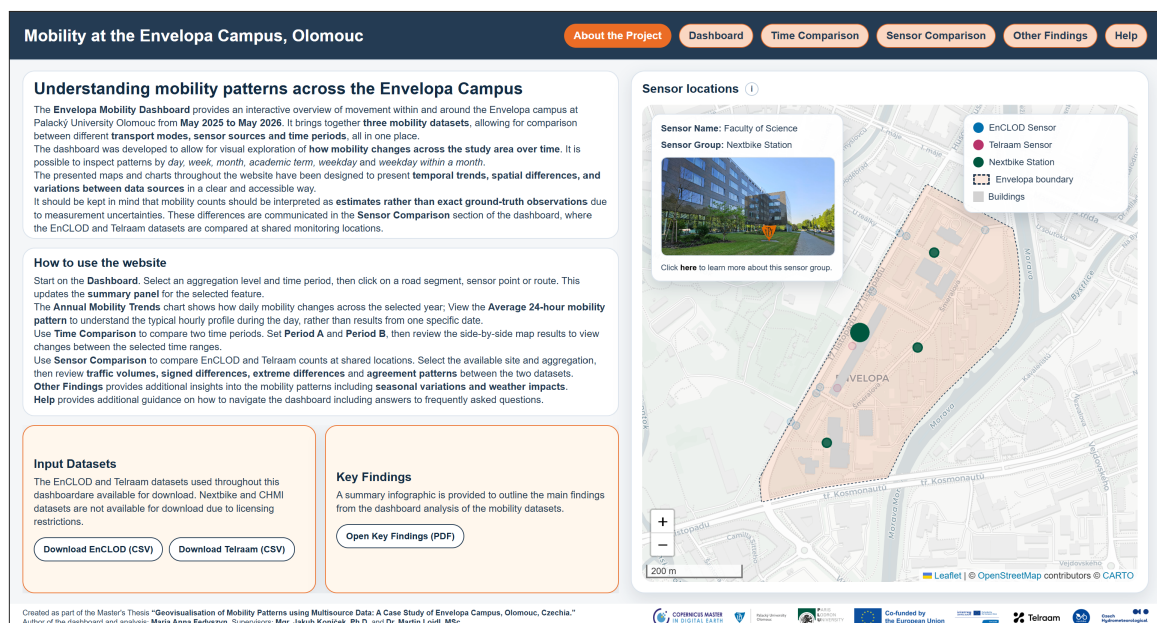


Figure 9: About the Project page, providing dashboard guidance, dataset information and access to downloadable datasets and key findings summary

The Dashboard page, as shown in Figure 10, presents four KPIs: mean hourly value, maximum hourly value, morning (AM) peak and evening (PM) peak. These KPIs were selected because of how they provide a concise and easily interpretable summary of mobility intensity and daily rhythm. The presented values update dynamically according to the selected data source and temporal aggregation and are visually supported by the annual mobility and 24-hour trend charts.

Together, these analytical outputs provide a complementary temporal perspective on the data. The annual mobility chart supports the identification of longer-term patterns and variations whilst the 24-hour trend chart illustrates typical daily mobility rhythms. Presenting these outputs alongside the interactive map allows users to identify spatial and temporal patterns quickly, therefore making the analytical findings more accessible.

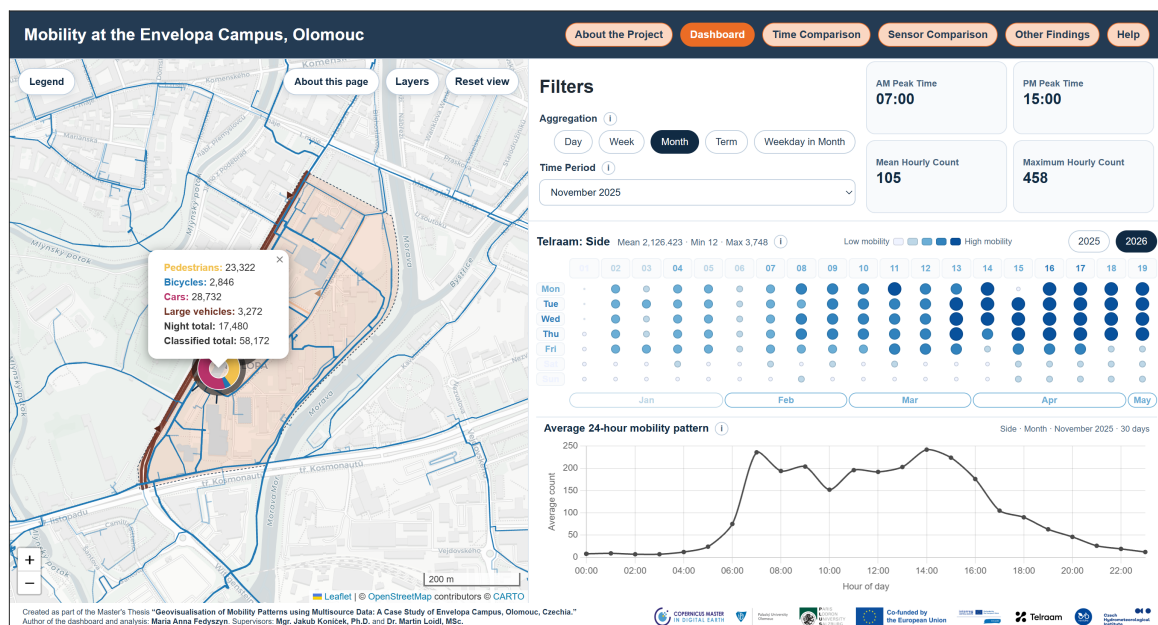


Figure 10: Main dashboard, presenting interactive mobility mapping, summary KPIs and temporal mobility trends

The Time Comparison page, as shown in Figure 11, allows users to compare these KPIs across two selected periods. This allows for quick identification of which period has higher or lower mobility values and whether peak times occur earlier or later.

The side-by-side presentation supports the interpretation of temporal variation by allowing users to directly compare selected periods rather than viewing them independently. This functionality therefore supports the exploration of differences within individual datasets and, where appropriate, between different temporal selections and aggregations.

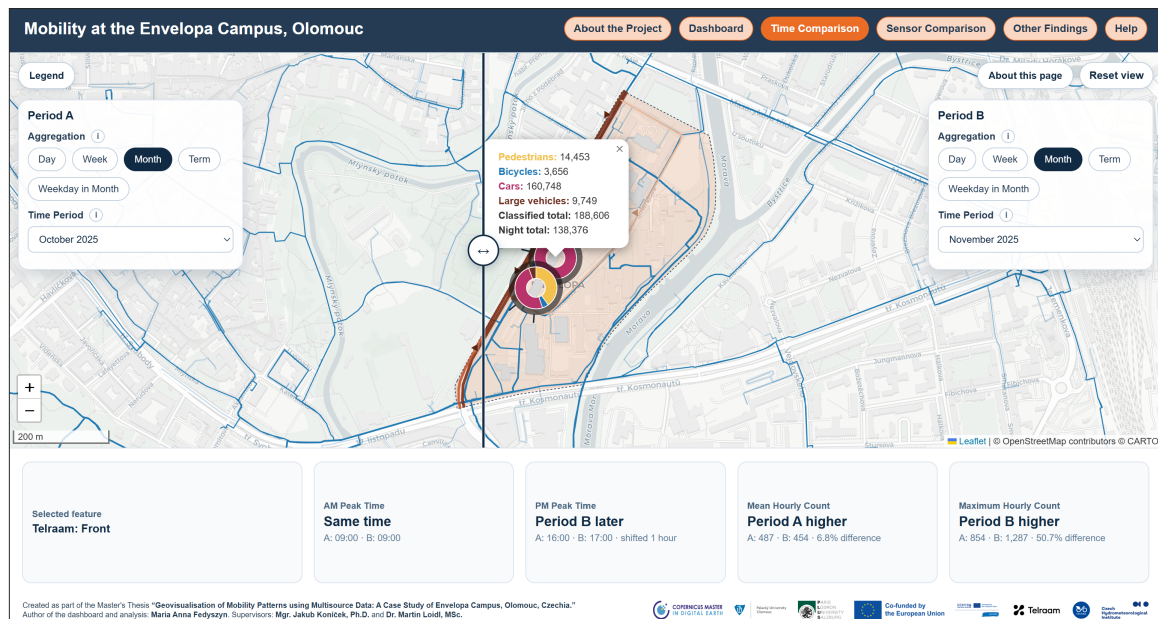


Figure 11: Time comparison page for side-by-side comparison of mobility patterns and summary KPIs across two selected periods

The Sensor Comparison page, shown in Figure 12, provides a more detailed analytical function by allowing the user to compare Telraam and EnCLOD data. This interaction allows the user to gain a deeper understanding of how the two datasets differ and develop a deeper understanding of how mobility patterns may vary according to the sensing system being used. The purpose of the comparison is not to determine which dataset represents an absolute ground truth but rather to demonstrate that measurements can differ. This page reinforces the need to interpret the Telraam and EnCLOD datasets as separate representations of mobility rather than as directly interchangeable measurements.

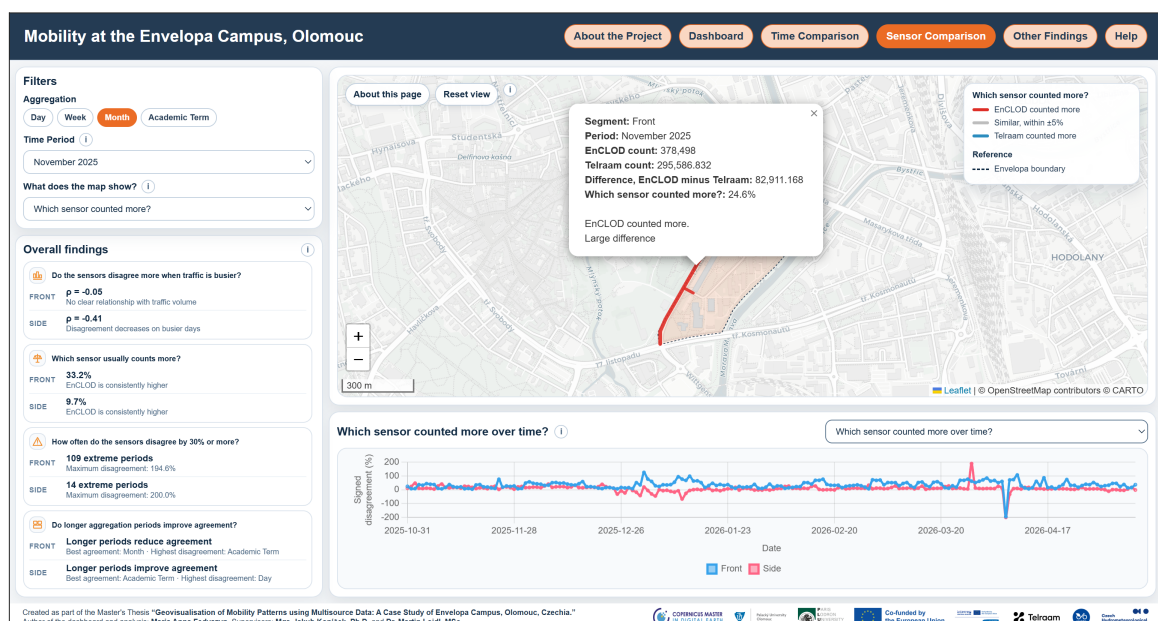


Figure 12: Sensor Comparison page for interactive analysis of differences between EnCLOD and Telraam mobility counts

The Other Findings page, shown in Figure 13, provides analytical findings relating to weather sensitivity and effects upon mobility, and the influence of specific events and academic terms on mobility volumes. Findings are presented as a combination of bar charts and accompanying text.

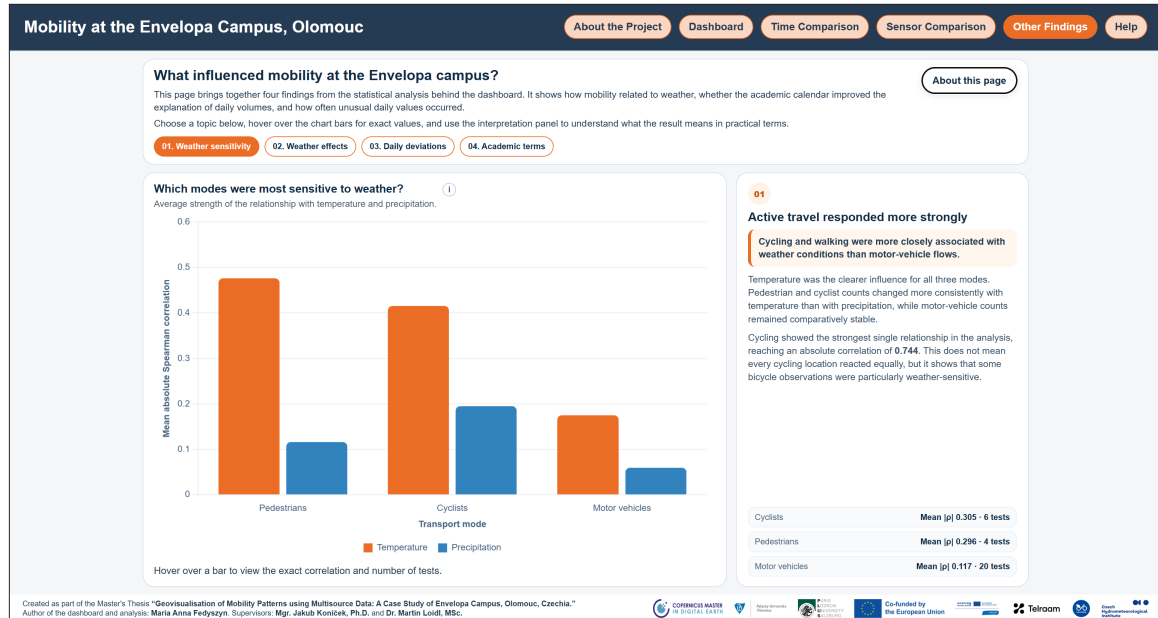


Figure 13: Other Analysis page presenting weather and event analytical findings

The Help page, shown in Figure 14, provides a demonstration video of each page on the website and summarises the purpose and function of each page. The page also includes 'Frequently Asked Questions' to address the most likely questions which users may have, whilst also addressing matters such as how terminology should be understood within the context of the dashboard.

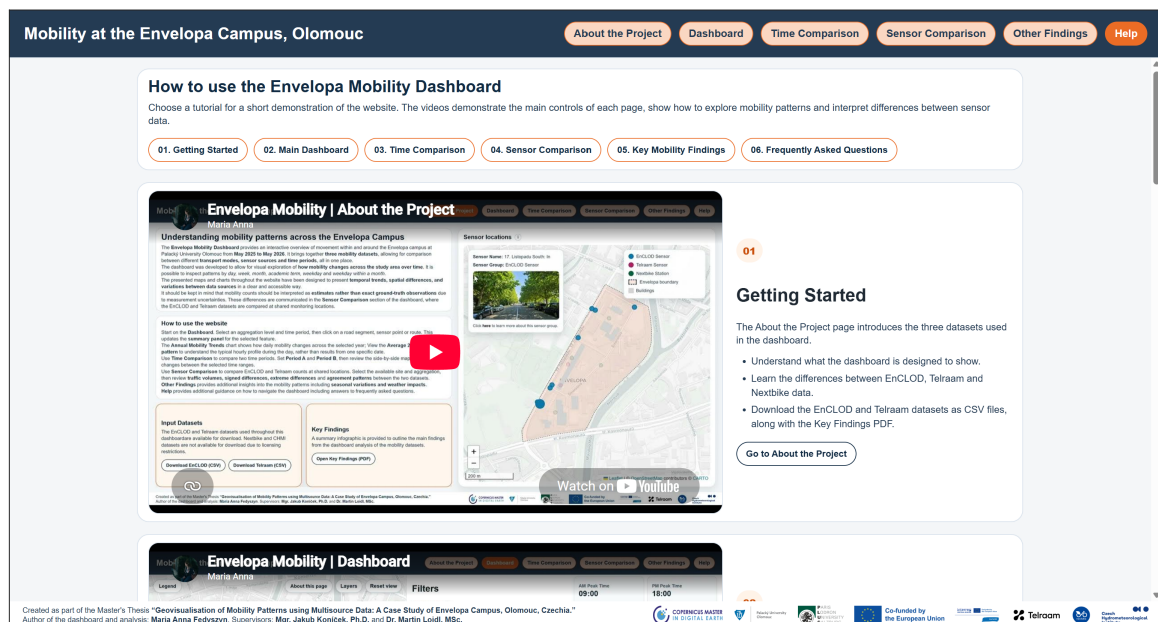


Figure 14: Help page presenting demonstration videos for each page and a 'Frequently Asked Questions' section

Together, these six pages provide a structured presentation of the analytical findings. The pages progress in their level of detail and complexity, helping to maintain an accessible and user-focused interface whilst allowing users to engage with increasingly detailed aspects of the analysis and including a help section to ensure users can navigate the website with ease.

7.5 Reproducibility

Reproducibility was considered throughout the development of the interactive web map dashboard. The project relies on input data in the form of CSVs from their respective sources, as discussed in Section 3.2: Data. These files were processed using Python scripts and then converted into standardised CSV and GeoJSON outputs for use in the web dashboard. As a result of the dashboard using static files, reproducibility is dependent on maintaining a consistent schema; if new data is utilised which employs the same matching identifiers, then the dashboard would be capable of supporting alternative data with minimal changes to the scripts, making the approach adaptable to updating the data or for adding other locations.

Reproducibility is further strengthened by the use of CSVs and GeoJSON file format as open and widely supported formats, and the use of HTML, CSS and JavaScript means that the dashboard has no reliance on specialised proprietary software. GitHub's data storage, structure, and version control further encourage reproducibility by tracking changes over time and documenting how the dashboard evolved.

7.6 Sustainable Hosting

The web application is hosted using GitHub Pages, which was selected as a free and accessible publishing platform. This approach also provided the additional benefits of Git-based version control and straightforward project management. As GitHub Pages is free to use for public repositories, it allowed the application to be deployed without additional hosting costs. The site will remain hosted indefinitely, provided that the repository and GitHub Pages services remain active; as such, this is a sustainable long-term hosting solution for the project. Furthermore, access to the web application through a standard web browser improves accessibility to the interactive web map dashboard, without requiring the need for additional software or an account, and as the underlying code and data structure are stored alongside the deployed application

ESRI Experience Builder was considered as an alternative because it offers a user-friendly interface and simplifies the process of building web applications. However, it was not selected due to several limitations. These included the potential costs associated with using the platform, concerns that hosting and serving large volumes of data could consume a significant number of credits, and the risk of losing access to the application after graduation.

For these reasons, GitHub Pages was considered the most appropriate choice. It supports a more sustainable and open-source approach while ensuring that the application remains accessible beyond the duration of the project.

8 RESULTS

This chapter synthesises the achieved results, organised by the main outputs of the diploma thesis: the review and methodological framing of multisource mobility data, the acquisition and harmonisation of heterogeneous mobility datasets, the analysis of mobility patterns in the AOI, the comparison of Telraam and EnCLOD data, and the development of the interactive web map dashboard.

Methodological Framing of Multisource Mobility Data

The first objective of the diploma thesis was to review existing methods for combining and visualising multisource mobility data with varying spatial and temporal resolutions. This was achieved through Chapter 2: State of The Art, which reviewed methods of mobility monitoring, sensor types and their limitations, data integration and fusion methods, and geovisualization methods for mobility data. The review identified that heterogeneous mobility datasets cannot typically be combined directly without consideration of their differences in spatial coverage, temporal resolution, the recorded transport mode, and data collection assumptions. As such, this provided the methodological basis for the processing and comparison of mobility data within this diploma thesis, specifically in that the datasets were to be treated as complementary sources of mobility data rather than directly interchangeable measurements. This finding was later supported by the sensor comparison presented in Chapter 6: Comparative Analysis of Telraam and EnCLOD Datasets, where Telraam and EnCLOD data showed sizeable disagreements in values for measurements corresponding to the same road sections.

Data Acquisition, Quality Assessment, and Harmonisation

The second objective was to collect, process and harmonise the heterogeneous mobility datasets for the AOI. This was achieved through the successful acquisition and preparation of Telraam, EnCLOD, Nextbike and CHMI data. The original datasets differed in their structure and contents; as such, separate processing workflows were created for each dataset before the harmonisation, analysis and visualization of data. As discussed in Section 4.1 and 4.3, EnCLOD and CHMI data were acquired from APIs, Telraam data was downloaded from the online user interface, and Nextbike data was provided directly from the company.

A key result of the data preparation phase was the production of cleaned dashboard-ready datasets. The Nextbike dataset was filtered, as shown in Section 4.2 to retain only trips with a start and/or end point within the AOI and remove records where the origin and destination were within 30m of each other, as no meaningful trip could be inferred from them. After this filtering procedure, the dataset was reduced from 39,342 original records to 5,120 relevant trips, equating to approximately 5% of the original dataset, but producing a smaller but more spatially relevant dataset for this analysis.

An evaluation of EnCLOD data identified that the dataset contained many incomplete hourly observations, especially for sensors located on Šmeralova. As shown in Table 1, the 17 Listopadu sensors had substantially higher full-hour completeness, ranging from 87.09 to 90.31%, whilst Šmeralova sensors showed much lower completeness, ranging from 36.68 to 59.356%. The lowest completeness was observed at Šmeralova North: Out, where only 36.68% of hourly records represented a full hour of observations. This was important to identify because it would have directly implicated the count of traffic and,

as such, affected the interpretation of motor-vehicle volumes and comparisons between locations. On the other hand, Telraam data was mostly complete in terms of hourly uptime, with only three hourly records per sensor with 60% uptime; however, the main limitation was the classification of nighttime detections, where traffic was recorded without mode separation. The CHMI dataset was complete, with the meteorological station being located approximately 2km outside the AOI; this meant that the data represented nearby weather conditions rather than being localised to AOI conditions.

As part of the data processing, harmonised temporal aggregations were produced, including daily, weekly, monthly, weekday-in-month and academic term aggregations. This allowed for mobility patterns to be compared between consistent time frames despite differences in the original temporal resolution of datasets. Harmonised outputs were produced as CSV and GeoJSON to be used for statistical analysis and the basis for dynamic charts and map layers within the web dashboard, as described in Chapter 7: Web Application Development.

A further result of this processing stage was the successful creation of estimated Nextbike route geometries from origin-destination coordinates within the original dataset. To allow for this, a bikeability index was created for Olomouc using the NetAScore toolset, and then this index was used to infer likely cycling paths based on the segment length and bicycle preference values, as discussed in Section 4.4. The geometries do not represent observed journeys but rather provide a meaningful spatial representation of potential bike-share movements within the AOI, rather than simple straight lines between origins and destinations.

Mobility Patterns at the Envelopa Campus

The third objective was to analyse mobility patterns within the AOI, including an evaluation of the utilised data and methodological limitations. Analysis showed that mobility within the AOI varied both across space and time; normalised daily values indicated that mobility was generally higher during regular semester periods, and this was especially visible for the EnCLOD data set, where most sensors had their highest average daily values during the Winter Semester. As presented in Table 2, Listopadu South: In increased from 4,797 average daily counts during the Summer Exam Period to 6,411 during the Winter Semester, whilst 17. Listopadu North: Out increased from 4,212 to 5,642. Similar increases were visible for several Šmeralova sensors; for example, Šmeralova South: In increased from 905 to 972 average daily counts. Spatial differences were identified between the two main observed streets, with Šmeralova being more sensitive to the academic calendar, with lower mobility during the Main Holiday period, and, in contrast, 17. Listopadu remained relatively active during non-teaching periods. For example, Table 2 presents how Šmeralova Middle: Out decreased to 156 average daily counts during the Main Holiday, whilst 17. Listopadu South: In remained high at 5,380 during the same period. This suggested that Šmeralova is more strongly connected or influenced by university-related movements and activities, while 17. Listopadu functions as a broader urban mobility corridor. The findings reflect that the AOI should not be interpreted as purely a university campus but more so as part of wider city mobility.

Peak period times are presented in Table 3 showed that evening (PM) peaks were more stable than morning (AM) peaks. Most PM peaks occurred between 15:00 and 16:00, while AM peaks varied more between sensors, locations, and academic periods. Telraam 17. Listopadu showed a stable AM peak across the available academic periods of 7:00, whilst its PM peaks shifted from 16:00 in the Winter Semester to 17:00 in the Winter

Exam Period and 18:00 in the Summer Semester. EnCLOD sensors showed greater AM variation; for example, Šmeralova North: Out ranged from 06:00 during the Main Holiday to 09:15 during the Winter Exam Period, reflecting more flexibility in travel routines during exam periods and breaks, when compared to regular teaching weeks.

Overall, the findings support that mobility patterns in the AOI are not only influenced by university-related activity but also broader urban movement; the academic calendar did influence mobility volumes and daily rhythms; however, the continual presence of daytime movement during non-teaching periods shows that the AOI also serves wider city functions.

The analysis of 24-hour profiles further identified differences between datasets and mobility modes; EnCLOD generally produced smoother daily profiles with mobility increasing in the morning, remaining relatively stable throughout the day and then declining in the evening, reflecting the motor-vehicle focus of these sensors. In contrast, Telraam showed more distinct morning and afternoon peaks, which are likely connected to its inclusion of active transport modes of pedestrians and cyclists, which are more likely to reflect university-related commuting, and are especially relevant for students who may have lower access to private cars and therefore rely more strongly upon active transport methods. The result showed that sensor type and the recorded mobility mode can influence the visible shape of daily mobility pattern trends. These patterns are visible in Figure 8 where EnCLOD profiles for 17. Listopadu and Šmeralova show smoother daily curves, whilst Telraam have clearer commuter-correlated peaks.

Daily Deviations and Contextual Events

Concerning the recorded daily deviations, these represented a small proportion of the total observations across all three datasets, ranging from 5.4% for Nextbike to 8.3% for Telraam. When assessing these dates against known events which could explain the variation, only a minority of observations could be associated with local events or national holidays. EnCLOD had the highest level of contextual matching, with 20 out of 70 deviation days accounted for, compared to 6 of 25 for Telraam and 1 of 11 for Nextbike. There was no deviation date which was shared by all three datasets; however, EnCLOD and Telraam overlapped on 12 dates and EnCLOD and Nextbike overlapped on four dates. This analysis suggested that the deviations were not consistently a result of events but rather may reflect dataset-specific, sensor-specific or mode-specific variations.

Effects of Weather and Academic Periods

Concerning weather effects, the adjusted GLM results identified that cold days had the largest effect on mobility volumes, especially for cyclists; cycling volumes decreased substantially on cold days, whilst precipitation was also associated with lower cycling volumes, but to a lesser extent and less consistently. Spearman correlation results in Table 5 show how cyclists had the highest mean absolute weather sensitivity value of 0.305, followed by pedestrians at 0.296, whilst motor vehicles had the lowest value. 0.117. Temperature showed a stronger association than precipitation for all modes, with temperature correlations of 0.476 for pedestrians, 0.415 for cyclists and 0.175 for motor vehicles. Pedestrians and motor vehicles also presented weaker and less consistent influence from weather effects. Overall, the results indicated that cycling was the most weather-sensitive mode in the observed data, whilst motor vehicles were comparatively less affected.

The GLM model comparison presented in Table 6 further showed that academic term controls improved model performance in 100% of the pedestrian tests, 100% of the cyclist tests and 90% of motor-vehicle tests. The greatest improvement was found for pedestrians

with a median ΔAIC of 68.26%, followed by motor vehicles with a median ΔAIC of 32.38. Cyclist models showed a smaller but still consistent improvement with a median ΔAIC of 7.36, indicating that academic terms explained additional variation in mobility volumes even after accounting for weather and weekday effects.

The weather effects presented in Table 7 identify that cold days were associated with a median cycling decrease of 26.82%, with a statistical significance of 100% of cyclist tests. Precipitation was associated with a median cycling decrease of 12.97%, although this was only statistically significant in 33.33% of cyclist tests. Pedestrians showed a median decrease of 9.60% on cold days, whilst motor vehicles showed a median increase of 7.03%, although with limited statistical significance. Warm-day effects were weaker overall, with motor vehicles showing a median decrease of 3.55% and cyclists showing a decrease of 6.01%.

Comparative Analysis of Telraam and EnCLOD Datasets

Another key analysis was the comparison of Telraam and EnCLOD datasets, possible at two locations where both sensors covered the same road sections. The inclusion of a weighted nighttime adjustment for Telraam data accounted for unclassified nighttime detections, allowing for better comparison between the datasets. Despite this, the result showed an improvement in the agreement between datasets, especially at the side location; however, for the front location, the disagreement between datasets remained high. Table 8 shows how the weighted nighttime adjustment reduced the number of extreme disagreement periods from 276 to 171 at the front location, representing a decrease of 38%, whilst at the side location, the number of extreme disagreement periods decreased from 138 to 17, representing a decrease of 88%.

The comparison identified EnCLOD values as being generally higher than Telraam for the same time periods. At the front location, EnCLOD was higher across almost all temporal aggregation levels, whilst the side showed lower levels of disagreement and notably better agreement when the data was aggregated into larger temporal periods. As shown in Table 9, EnCLOD was higher in 98.95% of daily observations at the front location and in 100% of weekly, monthly, term-level and weekday-in-month aggregations. At the side location, EnCLOD was also more often higher but less consistently, ranging from 66.67% of term-level observations to 75% of monthly observations. The median absolute symmetric percentage difference was much lower at the side location than at the front, indicating that the sensor disagreement was not spatially uniform. Table 10 presents how median disagreement at the side location ranged from 8.1% to 10.9% across aggregation levels, whilst the front location ranged from 32.8% to 36.8%, indicating that the front location experienced consistently higher occurrences of disagreements even after temporal aggregation.

Analysis also identified that disagreement between the datasets did not increase consistently with an increase in traffic volume, and instead, the relationship between traffic volume and disagreement varied by location and aggregation levels, meaning that traffic volume alone was not responsible for the observed differences between the datasets. As shown in Table 11, the Spearman correlation between traffic volume and disagreement ranged from -0.41 to 0.50 at the side location and from -0.31 to 0.50 at the front location, depending upon the temporal aggregation level. Table 12 summarises this inconsistency, presenting how disagreement decreased, increased or showed no strong relationship in different cases. Larger temporal aggregation did improve agreement at the side location, but not at the front, suggesting that some disagreement can be reduced by

aggregation when the differences are caused by short-term variation; systematic sensor and location-specific differences can persist even at broader aggregation levels.

The results exemplify how datasets with similar spatial coverage should not be automatically treated as equivalent to each other, even when observing the same location. Their values may differ because of sensor placement and accuracy, coverage, and classification logic. Comparative analysis, therefore, fulfilled this diploma thesis objective by identifying where comparison between heterogeneous datasets can be meaningful and where it may be misleading.

Web Application Development

The fourth objective of the thesis diploma was the development and implementation of an interactive web map dashboard to communicate mobility patterns in the AOI. This was achieved through the creation of a static web application which presents the processed mobility datasets, analytical indicators and selected findings in an interactive format. The dashboard includes a project information page, a main dashboard, a time comparison page and a sensor comparison page. These sections allow users to explore spatial mobility patterns and temporal trends in the AOI, plus differences between the Telraam and EnCLOD datasets.

The dashboard visualises each dataset with different cartographic methods to reflect its spatial and thematic structure; these visualization choices allow the dashboard to present multiple heterogeneous datasets without giving the impression that all datasets measure the same phenomenon in the same way. The dashboard not only displays statistical data but also includes analytical results through charts and KPI cards, allowing for the communication of key findings and data limitations.

A further result from this portion of the diploma thesis was the implementation of an accessible and reproducible dashboard technical structure. The approach of utilising HTML, CSS, and JavaScript hosted through GitHub Pages and static CSV and GeoJSON files reduced hosting requirements and the need for additional software dependencies for users, making the application accessible through a standard browser. Using open and supported file formats in this way supports overall reproducibility and future adaptations of the workflow.

Overall Synthesis and Contributions

Overall, the work produced harmonised mobility datasets, identified spatial and temporal mobility patterns in the AOI, evaluated weather and academic-term period relationships, and compared sensor based datasets which were then developed into an interactive web map dashboard to communicate the results and identified that heterogeneous mobility datasets can provide valuable insight to campus-level mobility however special attention must be paid to the differences, limitations, and uncertainties within each dataset. Analytically, the diploma thesis provides new insights into the mobility patterns within the Envelopa Campus, including the effects of academic periods and weather sensitivity. Methodologically, the work demonstrates a transferable workflow for processing, harmonising, comparing and visualising heterogeneous mobility datasets. The resulting dashboard provides a practical example of how such data can be communicated to users in an accessible form whilst still conveying the importance of data limitations.

9 DISCUSSION

The results of the diploma thesis demonstrated how heterogeneous mobility datasets can provide valuable insights into mobility patterns within the AOI but also showed how such datasets can't be interpreted or combined without thorough consideration of their limitations. The value in this work lies not only in identifying the mobility patterns, but also in demonstrating what different mobility datasets can (and cannot) reliably represent. This is of high relevance in the context of sensor-based geographic data, where recorded values may initially appear objective but are in fact influenced by the sensor type and accuracy, classification logic, and data completeness.

The most significant methodological decision in the diploma thesis was that of treating Telraam, EnCLOD, Nextbike and CHMI data as complementary datasets rather than merging them into a single unified mobility dataset. This decision was supported by the literature reviewed within Chapter 2: State of The Art where multisource mobility data integration was shown to require careful harmonisation of spatial and temporal resolution, transport mode representation and general uncertainty. The results of this diploma thesis confirmed this issue in practice within Chapter 6: Comparative Analysis of Telraam and EnCLOD Datasets, which identified substantial disagreement between the datasets with the same spatial and temporal coverage. Direct data fusion would have introduced a high level of uncertainty; such assumptions would have created a misleading impression of the data's accuracy. As such, the decision to harmonise, compare, and visualise the datasets separately was arguably more appropriate than producing a single combined mobility count.

The comparison of Telraam and EnCLOD data within Chapter 6: Comparative Analysis of Telraam and EnCLOD Datasets was one of the key findings within the diploma thesis. Although both datasets describe mobility in the same location during the same period, they did not record similar values. The inclusion of a weighted nighttime adjustment for Telraam data did improve the agreement, especially at the side location, but did not remove the systematic disagreement at the front location, suggesting that sensor disagreement was not caused simply by the unclassified counts in Telraam data but also by additional location and sensor specific factors; this may include but is not limited to differences in sensor placement, the field of view, occlusions, local road geometry, nearby intersections, stationary cars, directional coverage and classification methods. The finding is important in how it exemplifies that sensor datasets should not be treated as a ground truth despite being produced by established monitoring systems. Future work could consider quantifying the reliability of such comparisons through the integration of manual validation counts, temporary reference sensors or video-based ground-truth observations.

Limitations were faced in relation to data completeness and temporal coverage. EnCLOD data included many incomplete hourly observations, especially on Šmeralova, where several sensors had much lower full-hour completeness than those on 17. Listopadu, affecting the reliability of direct comparisons between locations, because their lower observed counts may partly reflect incomplete observation periods rather than an actual reduction in traffic intensity. Telraam data was mostly complete in terms of sensor uptime; however, the nighttime detections did not include any classification of mode type, which was especially relevant during winter months with shorter daylight periods. Nextbike data was limited by the detail of the dataset, with only origin and destination

coordinates available, with no detail on the actual route taken or mid-journey points. CHMI weather data was complete, but the monitoring station is located ~2 km from the AOI, meaning that it may not fully represent microclimatic conditions within the AOI. All utilised datasets are 'flawed' in some regard; however, this is where the challenge of this diploma thesis lies in overcoming these weaknesses to derive meaningful analytical outputs.

The filtering of Nextbike data to include only trips starting and/or ending within the AOI to focus the analysis on trips relevant to the AOI, and the removal of all trips with start and end coordinates within 30 m of each other, because no meaningful journey could be inferred from these. This substantially reduced the size of the dataset; however, it was necessary to focus on relevant trips which are suitable for exploratory analysis and visualizations, but this did result in a dataset which is less suitable for deriving strong statistical conclusions regarding cycling trends. The application of the least generalised cost-path approach arguably improved the spatial representation of Nextbike trips as estimated cycling routes rather than simplistic straight lines from origin to destination. These routes can only, however, be interpreted as estimated paths and not observed trajectories. A more accurate analysis would require the integration of GPS trajectory data, higher-resolution bike-share data, or direct information on the actual routes taken. Net balance calculations were initially considered for the analysis of the Nextbike data, defined as arrivals minus departures, interpreted from start points within the AOI and those outside, respectively; however, due to the limited size of the dataset, these statistics were considered insufficiently robust and, as such, were excluded from the final analysis.

Academic terms were selected as appropriate temporal aggregations due to the AOI being strongly connected to the university environment. This provided meaningful temporal structure for interpreting trends within the campus area, and results showed that term periods explained additional variation in daily mobility volumes after accounting for weather and weekday effects. Similarly, this coarse aggregation weakened the influence of anomalies within the datasets. This aggregation also has its limitations in how academic terms naturally overlap with seasonal variations of temperature and daylight conditions, making it challenging to truly separate the effects of university activity from weather and seasonal effects. The GLM analysis did assist in addressing this by including weather and weekday variables; however, a one-year period is not sufficient to confirm whether these trends persist over longer time scales. The ability to acquire mobility datasets spanning several academic years would enable stronger, more certain conclusions about recurring academic-calendar effects.

Analysis was mostly based on aggregated data; hourly aggregation was used to create 24-hour profiles, while daily and broader temporal aggregations were used to support clearer visualizations and reduce noise presented in the dashboard. This aggregation was necessary due to how the employed datasets differed in temporal resolution, and furthermore, very detailed data could risk increasing visual complexity and backend load in the dashboard; this aggregation inevitably reduces detail. Short events, sudden traffic changes, or temporary disruptions may appear diminished or hidden. Employing academic term aggregations is useful for identifying broader patterns; however, it limits the ability to identify and explain short-term variations caused by specific events, timetable changes, construction works, weather extremes, or irregular travel behaviour trends.

Analysis of the influence of weather upon mobility showed that active modes, specifically cycling, were more sensitive to weather conditions than motor-vehicle movements. This is consistent with broader literature on active mobility, where walking and cycling are often more affected by temperature, precipitation and general comfort conditions than motor travel. Temperature showed stronger associations with mobility than precipitation, which may reflect both the direct comfort effects and broader seasonal patterns. The weather indicators utilised in the GLM were simplified into rainy, warm and cold days, which made results easier to interpret and compare across datasets; however, this reduced the complexity of real conditions. For example, precipitation intensity, snow, wind, humidity, daylight duration and road-surface conditions were not included. Future analysis could further explore how more detailed meteorological variables can be integrated to understand how specific weather conditions affect different mobility modes.

Development of the dashboard involved practical compromises. The application was intended to be understandable for users who do not have a technical background in geoinformatics or mobility analysis. For this reason, the number of indicators and interactive options was limited to avoid excessive cognitive overload. The dashboard, therefore, communicated the most important trends through maps, charts, KPI cards and comparison pages rather than presenting every analytical output produced during the diploma thesis. This improved accessibility but meant that the dashboard was a simplified representation of the full analysis. Advanced uncertainty visualization could have been included, but the uncertainty within each dataset was arguably too complex to precisely quantify. For this reason, uncertainty was mainly communicated through explanatory text and the discussion of limitations, rather than through visual uncertainty layers.

The choice of GitHub Pages and a static web structure was suitable for meeting the aims of the diploma thesis; it allowed for the dashboard to be hosted freely, accessed by the user through a standard web browser, and maintained without a complex server-side backend. This supports reproducibility and long-term accessibility beyond the completion of the diploma thesis. Despite this, a static dashboard has its limitations. Specifically, it is less suitable for live API connections, large datasets, advanced database queries, or real-time sensor updates. Alternative solutions more suited for these integrations could include ArcGIS Experience Builder, Dash, R Shiny, PostGIS with a web-specific frontend, or a cloud-hosted database-driven application. These alternatives would support more advanced filtering, live updates, and larger datasets, but would also introduce costs, the need for more technical maintenance, possible access restrictions for users, and a greater risk of the application not being maintained after graduation. For these reasons, the static open-web approach was deemed a reasonable balance between functionality, sustainability, and accessibility.

The results of this diploma thesis may provide value for future campus mobility research and local mobility planning; they provide the first multisource overview of mobility patterns in the AOI and identify how 17. Listopadu and Šmeralova have different mobility functions. Results also demonstrate how university-related mobility is visible in data trends; the AOI also acts as part of the wider urban area. The dashboard supports communication with stakeholders by presenting complex mobility data in an accessible format; however, the results should only be used as indicators of mobility patterns as opposed to exact measurements of total mobility trends.

Future research could develop the findings made here in several directions. Firstly, the monitoring period could be extended across several academic years to assess whether observed trends persist over time. Secondly, manual validation of traffic counts or temporary reference sensors could be utilised to evaluate the accuracy of Telraam and EnCLOD counts. Thirdly, additional mobility datasets could be incorporated if they were to become available, such as public transport data, Strava Metro data, mobile phone data, parking data, or pedestrian counts if ethically appropriate. The inclusion of such sources would support broader city-scale analysis, although issues surrounding data privacy, access, cost and spatial resolution would need to be considered. Fourth, Nextbike route estimates would be improved by using more complex routing models, observed actual cycling trajectories and user preference calibration. Finally, the dashboard could be extended with additional uncertainty communication, integration of live data updates, or scenario-based tools for evaluating the effects of infrastructure changes.

Overall, this discussion has highlighted that the strength of this diploma thesis lies in its multisource data approach, transparent processing workflow, critical comparison of the available sensor data and the practical geovisualization output. Simultaneously, the work is limited by unequal data coverage, sensor-specific uncertainties, estimated as opposed to observed routes, simplification of weather indicators, and the constraint of a one-year study period. These limitations should not be seen to undermine the value of the results, but rather, clarify the conditions under which the results should be interpreted. The diploma thesis, therefore, not only contributes findings of mobility trends in the AOI but also provides a critical example of how heterogeneous mobility datasets can be responsibly utilised for campus-scale mobility analysis.

10 CONCLUSION

The diploma thesis identified and communicated mobility patterns within the Envelopa Campus of Palacký University, Olomouc, using heterogeneous mobility data. The work used Telraam traffic counts, EnCLOD municipal sensor data, anonymised Nextbike journey records and CHMI weather data to analyse how mobility varies spatially and temporally, with a focus on the influence of academic periods and weather conditions. Furthermore, the diploma thesis critically evaluated the quality, usability, and limitations of the employed datasets and then communicated the findings through an interactive web map dashboard.

The diploma thesis first reviewed existing approaches to mobility monitoring, sensor-based data collection, data integration, data fusion, mobility visualization, and uncertainty. This provided the methodological basis for working with datasets that differ in spatial and temporal resolution, recorded transport modes, technical assumptions, and dataset structure. The review showed that heterogeneous mobility datasets cannot typically be combined without careful harmonisation and critical interpretation of each dataset. This principle guided the later stages of the diploma thesis when datasets were processed, compared and visualised as complementary sources of mobility information for the AOI.

The practical component of the diploma thesis focused on the acquisition, cleaning, evaluation, and harmonisation of the four employed datasets. Separate workflows were created for Telraam, EnCLOD, Nextbike and CHMI data as each source had a different initial structure, purpose, and level of detail. The processed outputs were manipulated into consistent temporal aggregations and prepared as CSV and GeoJSON files for further analysis and integration into the dashboard. For Nextbike data, filtering was applied to isolate relevant trips to the AOI and then processed into estimated cycling routes using a least generalised cost-path approach based on the NetAScore bikeability index, allowing for the visual representation of probable bike-share movement through the campus rather than simple origin-destination lines.

The analysis of data identified that mobility within the AOI varied across time and space; teaching academic periods were generally associated with higher mobility volumes, especially for EnCLOD data, where most sensors reached peak average daily values during the Winter Semester. Differences were also identified between 17. Listopadu and Šmeralova, where the latter appeared to be more strongly influenced by the academic calendar, whilst 17. Listopadu remained highly active during non-teaching periods, suggesting that this street functions not only as a campus-related street but also as a broader urban mobility corridor. The analysis of daily rhythms identified that afternoon peak times were generally more consistent than morning peak times, which varied more depending on the location, academic period, and dataset. Regarding 24-hour trends, EnCLOD data presented smoother daily curves whilst Telraam showed more notable morning and afternoon peaks, likely a result of the dataset's multimodal structure.

Weather sensitivity analysis identified that active mobility modes were more sensitive to weather conditions than motor vehicles; cyclists were the most weather-sensitive mode in the observed data, particularly during cold conditions when volumes decreased substantially. GLM analysis quantified how academic-term periods explained additional variation in daily mobility volumes after accounting for weather and weekday effects. This identified that mobility patterns in the AOI were influenced by both environmental conditions and the academic calendar. It should be noted that results should be

interpreted with caution due to the one-year study period and the unequal coverage of the individual datasets.

Comparative analysis of Telraam and EnCLOD data was possible due to sensors covering the same road segments (17. Listopadu South: front location and Šmeralova South: side location); however, the analysis identified that the datasets cannot be treated as equivalent despite their same spatial coverage. The use of weighted nighttime adjustment on the Telraam dataset improved the agreement between the datasets, especially at the side location, but substantial disagreements remained at the front. Overall, EnCLOD values were generally higher than Telraam values, and the degree of disagreement varied by location and temporal aggregation, highlighting the importance of critically evaluating sensor data before utilising it for comparisons, integration with other datasets, or supporting decision-making.

The dashboard, produced as the final practical output of the diploma thesis, presents processed datasets, analytical indicators, and selected results in an accessible format. Users can explore spatial mobility patterns, temporal trends, 24-hour profiles and selected KPIs, as well as explore the differences between Telraam and EnCLOD measurements. Findings are intentionally presented in an easily interpretable form, allowing users to understand the main mobility patterns without the need for prior technical knowledge. The use of HTML, CSS, JavaScript, CSVs and GeoJSON files hosted on GitHub Pages provides an open, reproducible and browser-friendly example of how heterogeneous mobility datasets can be communicated through a combination of geovisualization and non-spatial static visualizations.

The contribution of the diploma thesis is analytical and methodological. Analytically, the work provides new insights into mobility patterns within the AOI, including the influence of academic periods, daily rhythms, weather sensitivity and disagreement between sensor datasets. Methodologically, it demonstrates a transferable workflow for the acquisition, processing, harmonising, analysing and visualising of heterogeneous mobility datasets in a campus-scale environment. The work shows how multisource mobility data provides a richer understanding of mobility than a single dataset alone; however, only when uncertainty, data quality, and comparability are considered.

Overall, the objectives of this diploma thesis have been met; existing methods for working with multisource mobility data were reviewed, heterogeneous mobility datasets were collected and harmonised, mobility patterns and data limitations were explored, and an interactive web map dashboard was created to communicate findings. As such, the work provides a foundation for future mobility research at UPOL whilst providing a practical example of how multiple mobility datasets can be visualised and communicated to support a greater understanding of mobility for a given location.

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ATTACHMENTS

LIST OF ATTACHMENTS

Free attachments

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|--------------|---|
| Attachment 1 | Folder containing Python scripts for data acquisition and data processing, and the associated YAML environment file |
| Attachment 2 | Folder containing datasets used for analysis within the diploma thesis |
| Attachment 3 | Folder containing interactive web map dashboard scripts |
| Attachment 4 | Folder containing thesis website |
| Attachment 5 | Thesis Poster (A2 PDF file) |
| Attachment 6 | Key Findings Infographic (A2 PDF file) |

All the digital data used was provided for the elaboration of the diploma thesis.
Their further use is possible only with the consent of the administrator of this data.