

Article

A New Perspective on Urban Mobility Through Large-Scale Drone Experiments for Smarter, Sustainable Cities

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Highlights

What are the main findings?

- We present large-scale drone deployments conducted across five cities to capture high-resolution, multimodal mobility data.
- The paper demonstrates the flexibility and scalability of drone monitoring in varied topographies and stakeholder needs.

What is the implication of the main finding?

- Vehicle, bicycle, and pedestrian trajectories were extracted and analyzed to support simulation approaches, emissions assessments, and safety analyses.
- Insights emphasize privacy-preserving methods and close collaboration with public authorities to enable next-generation smart city applications.

Abstract

European cities are increasingly turning to data-driven solutions to tackle the complex challenges of urban mobility, yet many still lack high-resolution, multimodal data to make fact-based interventions. This paper presents the aims and initial findings of large-scale drone-based experiments conducted across five European cities—Athens, Madrid, Mykonos, Limassol, and Helsinki. Designed in close collaboration with local stakeholders, each deployment targeted city-specific objectives ranging from traffic congestion and safety to changing multimodal behaviour. Using GDPR-compliant computer vision techniques, we extracted privacy-preserving trajectory data that reveal detailed insights into flow dynamics, modal interactions, and behavioural patterns. Around 1.5 million trajectories were extracted in total. This paper offers a comparative analysis of findings across contexts and key lessons around stakeholder engagement, operational scalability, and ethical data practices. Our results demonstrate the potential of drone-based mobility monitoring as a powerful, flexible tool for supporting sustainable and inclusive urban transport planning across Europe.

Keywords: urban mobility; traffic analysis; multimodality



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1. Introduction

Urban mobility systems worldwide are facing unprecedented challenges. Rapid urbanization, rising environmental concerns, and increasing demands for equitable access

are placing pressure on cities to transition toward more sustainable, inclusive, and efficient mobility models [1–4]. However, one of the most persistent barriers to evidence-based urban transport planning remains the scarcity of high-resolution, multimodal, and context-specific mobility data. At the same time, traffic monitoring and data collection have long been central pillars of urban mobility research and planning [5,6].

While conventional approaches—ranging from loop detectors [7,8] and roadside cameras [9] to GPS traces [10,11] and Bluetooth sensors [12,13]—have enabled significant advances in traffic modelling, they come with fundamental trade-offs in privacy, spatial resolution, coverage, scalability, and cost. For example, loop detectors provide data aggregated over fixed time intervals [14], and CCTV cameras face challenges such as occlusion and privacy concerns [15]. Thus, the limitations of fixed-location sensors, coupled with the sparse penetration of floating car data, hinder the ability to analyse mobility dynamics in complex, multimodal, and rapidly evolving urban environments at scale.

In recent years, unmanned aerial vehicles (UAVs)—commonly referred to as drones—have emerged as a promising tool to bridge this gap [16–20]. Compared to traditional fixed sensors and monitoring systems, drones offer a flexible, rapidly deployable solution capable of capturing high-resolution, multimodal data over large and complex urban areas, complementing existing infrastructure rather than replacing it. This combination of flexibility, spatial coverage, and multimodal trajectory extraction makes UAVs particularly well-suited for experimental deployments across diverse city environments.

Additionally, their ability to capture wide-area, top-down video data enables the extraction of detailed trajectories of vehicles, bicycles, and pedestrians with minimal infrastructure investment and low operational disruption. Moreover, when integrated with computer vision and privacy-preserving algorithms, drones can deliver robust, GDPR-compliant insights into urban mobility patterns [21–23]. While UAV-based experiments have demonstrated promising results [17,22,24–26], applying drone swarms in large-scale, multimodal traffic environments has remained largely unexplored in real-world conditions. Compared to the existing trajectory datasets collected with drones that mainly focus on vehicles [17,24–26], our approach tackles diverse urban mobility challenges.

To operationalise this potential at scale, MobiLysis, an EPFL spin-off, led a series of large-scale drone-based experiments across five European cities: Athens, Madrid, Mykonos, Limassol, and Helsinki. These efforts were conducted under the umbrella of three major EU-funded research projects—ACUMEN [27], DELPHI [28], and metaCCAZE [29]—which collectively aim to push the boundaries of urban mobility research through novel data collection and analytics approaches. The five cities where drone experiments were performed represent various environments with different target audiences and were selected in agreement with all consortium members as part of larger pilots and use cases.

Each city deployment was co-designed with local authorities and stakeholders to ensure alignment with real-world challenges and planning priorities of the different requirements set by the projects—ranging from congestion analysis in dense corridors to vulnerable road users (VRUs') safety monitoring near transport hubs and to infrastructure usage around tourist areas or port-driven environments. The experiments used various tools and techniques to generate multi-resolution trajectory datasets that support diverse use cases.

The contribution of this paper is threefold. First, we provide an overview of the design, implementation, and lessons learned from these field experiments, which span different urban typologies, regulatory environments, and data use cases. Second, we explore the versatility of drone-collected data in supporting a wide array of research and policy objectives. Finally, we critically examine the technical, legal, and logistical barriers

that remain in operationalising drone-based traffic monitoring as a mainstream practice in urban analytics.

The remainder of this paper is structured as follows. Section 2 outlines the motivation and objectives of the drone-based traffic monitoring experiments in each of the five cities, emphasizing the role of local stakeholders in shaping context-specific goals. Section 3 describes the experimental design and methodologies deployed, including flight logistics, data capture setups, and processing pipelines. Section 4 presents initial results, highlighting both the capabilities and limitations of drone-based monitoring in diverse urban environments, accompanied by a comparative analysis and visual insights. Section 5 discusses cross-cutting lessons learned, including challenges related to privacy, ethics, and regulatory constraints. Finally, Section 6 explores future research directions, with a focus on integrating drone-derived data into digital twins, network-level models for traffic congestion, emissions and safety, and next-generation traffic management systems across European and international contexts.

2. Urban Challenges and Collaborative Objectives

Each drone-based experiment was co-designed in close collaboration with local stakeholders to address context-specific urban mobility challenges. Leveraging the authors' expertise in traffic data analysis [22,30–32], multimodal monitoring, and systemic urban dynamics, the deployments extended beyond isolated technical demonstrations. Instead, they were integrated, policy-relevant initiatives that responded directly to local needs and strategic priorities. These efforts were firmly embedded within each city's broader agenda for sustainability, safety, and digital transformation, ensuring both operational relevance and long-term applicability of the insights generated.

The following list outlines the five drone-based experiments and the particular objectives in each one:

- **Athens (ACUMEN):** In one of Europe's most congested capitals, the drone experiment focused on understanding congestion dynamics and traffic flow efficiency along key arterial corridors. The experiment was designed in collaboration with the National Technical University of Athens (NTUA) and the City of Athens IT Company (DAEM SA). By capturing detailed vehicle trajectories, stop durations, and illegal on-street parking behaviour, the goal was to identify micro-disruptions that cumulatively impact flow efficiency. The high-resolution data supported a granular analysis of how intermittent obstructions and stop-and-go dynamics shape traffic patterns in dense urban settings.
- **Helsinki (ACUMEN):** In the Finnish capital, drone operations were integrated into the city's digital twin development and simulation modelling efforts. MobiLysis collaborated with Aalto University and Forum Virium Helsinki to collect multimodal traffic data—particularly focusing on pedestrians and VRUs around multimodal transit hubs. Another aim of the data collection was to validate and enrich sensor fusion processes with existing infrastructure. The experiment also supported sustainability evaluations by analysing the balance and safety of soft modes (walking, cycling) in dense, high-flow environments.
- **Madrid (DELPHI):** This experiment involved collaboration between partners with diverse areas of expertise, including public transportation (Metro de Madrid S.A.) and logistics (KOIKI HOME S.L.U. and DHL Exel Supply Chain Spain). The objective in Madrid was mainly to support VRUs involved in last-mile delivery by identifying safe, low-emission, and efficient routing options. The rich movement data captured by drones enabled fine-grained validation of last-mile optimization models, especially around pedestrian–vehicle interaction zones.

- Mykonos (DELPHI): On this seasonal island with a high influx of visitors and minimal existing sensing infrastructure, MobiLysis deployed drones to assess the impact of ferry arrivals and port operations on vehicular congestion. The experiment was designed in collaboration with the Mykonos Bus Service, the port authority of Mykonos, and the Institute of Communication and Computer Systems, a research brand of NTUA. It targeted key bottlenecks that occur during peak disembarkation times, offering rare, data-driven visibility into how port-related activity disrupts traffic. These insights aim to inform adaptive traffic management and future infrastructure planning in tourism-heavy island environments.
- Limassol (metaCCAZE): In this experiment, drones were used to collect data on traffic conditions and multimodal flows around high-demand zones for on-demand ride services. The experiment was designed together with the municipality of Limassol and MaaSLab, a research-based institute focusing on passengers and freight. Its objective was to analyse congestion patterns and identify safe, efficient pick-up/drop-off points for shared mobility, especially in areas not currently served by fixed sensors. By fusing spatial and temporal data on vehicle interactions and pedestrian proximity, the study seeks to reduce safety risks and operational inefficiencies around these dynamic urban hotspots.

It can be seen that these deployments were executed in close partnership with local partners, such as universities, governments, and urban mobility departments. The co-creation model ensured that each drone mission addressed real-world, actionable challenges, and that results could feed directly into city strategies on sustainable mobility, safety, and data-driven urban governance.

3. Methodologies and Experimental Design

This section outlines the methodologies and experimental setup from the drone-based deployments across the five aforementioned European cities.

3.1. Methodological Framework

Figure 1 offers a flowchart of the methodological framework and processes used in each drone experiment, from the deployment of drones to the extraction of mobility analytics through computer vision. After collecting the videos, the computer vision pipeline we used consisted of three main steps (Figure 1), following the standard tracking-by-detection paradigm: object detection, object tracking, and stabilization.

The object detection step is performed by running a deep convolutional neural network on each frame independently. We use networks from the YOLOv8 family [33], a common choice across many industrial sectors as they offer good performance with satisfying run times. They are based on models pre-trained on large-scale aerial traffic datasets, which achieve mean average precision (mAP) detection results of 95% for vehicles and 61% for pedestrians. We then optionally fine-tuned the models on a representative subset of our own data we annotated to specialize the models to our needs and further increase their performance.

Next, the tracking step uses standard algorithms BoT-SORT [34] and OC-SORT [35] from the literature, as we found them to achieve good results, boosting the recall of all trajectories to more than 90%. Finally, stabilization is performed for each frame by computing a homography to a reference frame using ORB keypoints [36]. Following this pipeline, post-processing includes geo-registration of the trajectories and fitting an Extended Kalman Filter (EKF) to smooth the trajectories and estimate their speeds. The whole pipeline is run offline after the videos are collected, meaning there is little runtime constraints, and we are

free to choose the image resolutions, video frame rates, and network sizes that yield the best results.

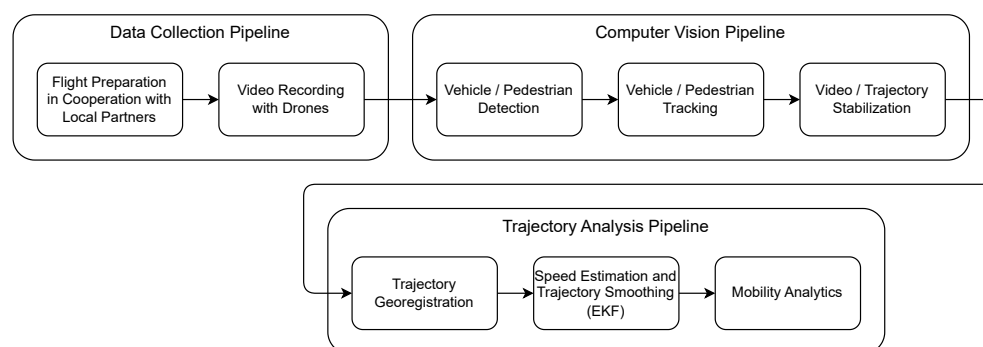


Figure 1. Flowchart of the methodologies from data acquisition to trajectory analysis.

3.2. Experimental Design

Each case study combined researchers' expertise in traffic analytics and stakeholder co-creation to tailor data collection efforts to local mobility challenges. The campaigns targeted critical urban locations, selected in coordination with city authorities and transport agencies to ensure alignment with policy goals and data needs. Table 1 summarizes the key operational information of each experiment and the total recording.

Table 1. Key figures of the drone experiments.

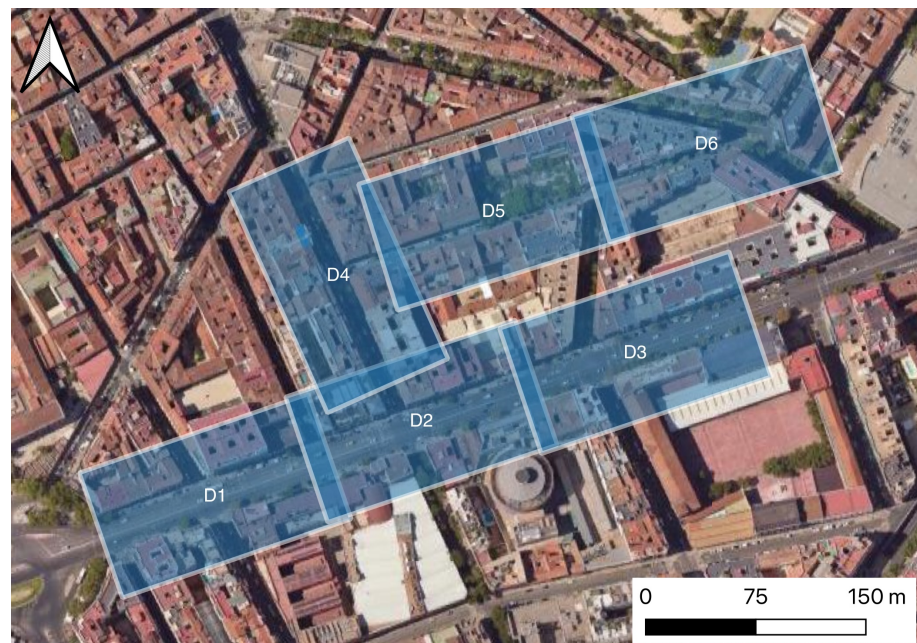
	Athens	Helsinki-1	Helsinki-2	Mykonos	Madrid	Limassol
HEU Project	ACUMEN	ACUMEN	ACUMEN	DELPHI	DELPHI	metaCCAZE
No. of drones	8	3	6	4	6	5
No. of days	5	3	3	3	4	3
Dates	20/05/2023					
	21/05/2023	11/09/2023	16/09/2024	30/09/2024	23/09/2024	26/03/2025
	22/05/2023	13/09/2023	17/09/2024	01/10/2024	24/09/2024	27/03/2025
	23/05/2023	15/09/2023	18/09/2024	02/10/2024	01/10/2024	27/03/2025
	24/05/2023				02/10/2024	28/03/2025
Road User Detection	Vehicles	Vehicles & Pedestrians	Vehicles & Pedestrians	Vehicles & Pedestrians	Vehicles	Vehicles
Recording hours	133 h	33 h 25 min	60 h 15 min	41 h 35 min	52 h 40 min	50 h 35 min
No. of trajectories	~840 k	~21 k	~64 k	~135 k	~128 k	~270 k

The design of two example experiments (Helsinki-2 and Madrid) is presented next. Figure 2 illustrates the drone configurations for each example, where each rectangle represents the field of view of a drone operating at an altitude of 120m. In the case of Helsinki-2, Figure 2a shows a large spatial coverage, as 6 drones were spread out covering the road entrances to the Jätkäsaari peninsula (drones D3 and D4), closest metro station (D5) and the ferry terminal (drones D1, D2) for passengers and vehicles, respectively. This setup can allow us to gain a good understanding of the mobility situation in the entire peninsula without the need to install additional sensors in its internal part. In contrast, a smaller coverage area was planned in the drone experiment in the city centre of Madrid. As shown in Figure 2b, 6 drones were placed close to each other near the Embajadores area, allowing for a spatially continuous monitoring of traffic flows. With this experiment, we are able to follow vehicles that move from one drone to the other as the aim is to maximize the length of individual trajectories. These two examples showcase the versatility of how drone

technology can be applied to mobility monitoring covering different requirements without any interference in their hardware but only in the placement and experimental setup.



(a)



(b)

Figure 2. Drone setup during the experiment in (a) Helsinki-2 (ACUMEN). (b) Madrid (DELPHI).

In order to accommodate varied urban forms and objectives, both fixed-point and mobile drone operations were employed in all experiments. All deployments were executed under GDPR-compliant frameworks, with privacy-preserving computer vision techniques used to extract detailed yet anonymous multimodal trajectory data, including vehicles, cyclists, and pedestrians [22]. GDPR compliance is ensured through the bird's-eye view

perspective and the drone altitude, which prevents the identification of vehicle plates or faces. The data were processed through MobiLysis' proprietary analytics pipeline, allowing for high-resolution behavioural and flow analysis.

With regards to the experimental design and although each experiment addressed context-specific challenges, a consistent logistical framework was employed to ensure standardization across our processes. At each location, professional local drone pilots were hired to operate C0-class drones, such as the DJI Mini 4. They were responsible for requesting all necessary local flight permissions and were provided with a clear list of instructions to ensure videos were recorded in the right format: 4 K video (3840×2160) at 25 frames per second (FPS) using the bird's-eye view at an altitude of 120 m. For C0-class drones, a key regulation in the open category is to fly within a visual line of sight (VLOS) and below a 120 m altitude.

Considering the limited battery life of the drones used and the need for extended recording duration, each pilot was equipped with a sufficient number of batteries or on-site charging facilities. Depending on the experiment's scale, multiple drones were used simultaneously and flight operations were conducted repeatedly over several consecutive days as presented in Table 1. Moreover, to mitigate the impact of unforeseen adverse weather, additional buffer days before and after the planned drone flights were reserved as contingency. Finally, recent research indicates that while continuous drone monitoring may be optional, it offers substantial benefits when implemented, such as better traffic flow prediction [20].

4. Case Study Analyses: Findings

Each city-specific subsection below details the experimental design—including drone setup, data extraction protocols, and coordination mechanisms—as well as selected initial insights that illustrate the analytical value of the data collected.

4.1. Athens

The drone experiment in Athens in 2023 represents the biggest effort in terms of drone traffic monitoring that MobiLysis has ever conducted by the time of the experiment. Eight static drones were used to monitor several parts of the congested city centre, which is characterized by high traffic volumes. The drones hovered over key locations in the city centre during the morning and afternoon peak hours during 5 consecutive days (20–24 May 2023). As a result, over 130 h of traffic recordings were collected.

A distinctive characteristic of Athens road traffic is the high presence of taxis, buses, and motorcycles as well as frequent illegal stops, creating frictions in the shoulder lanes especially [17,31]. Thus, the drones' bird's-eye view provides a unique opportunity to study traffic dynamics and driver behaviour in urban environments with mixed traffic conditions. In this direction, Figure 3 shows a scatter plot of the vehicle stops in the western side of Syntagma square, right in the heart of Athens.

Each point marks a stopping event, with its colour reflecting the duration—red indicating prolonged stops of 80 s or more. Longer stops are predominantly observed in the rightmost lane, where designated taxi and bus stops are located. In contrast, yellow-marked stops—indicating 40 to 50 s duration—are frequently seen just upstream of the traffic lights on the left side of the image. Meanwhile, the traffic light situated before the pedestrian crossing in the centre of the image appears to result in shorter stop durations. The visualization in Figure 3 provides a quick overview of congestion problems too: queues propagate for vehicles turning left that come from the vertical street while vehicles entering from the left side of the image do not appear to encounter immediate congestion ahead.



Figure 3. Locations and durations of vehicle stops around Syntagma Square, Athens. Each point marks a stopping location, with colour indicating stop duration—red for longer stops and green for shorter ones.

4.2. Helsinki

Under the ACUMEN project, three rounds of drone flights were programmed in Helsinki, Finland, for 2023, 2024, and 2025. The first two rounds were conducted in September 2023 and September 2024 as shown in Table 1. In both rounds, key intersections were monitored around the Jätkäsaari area and the West Ferry Terminal, where the boats to Tallinn depart from.

The collected videos were then processed to observe pedestrian behaviour and mode choice around the entrance to the West Ferry Terminal. For that purpose, virtual gates were installed in the tramway platforms, in the parking entrances, in the ferry terminal, and in the sidewalks. As a result, pedestrian ODs were extracted as shown in Figure 4. Each colour represents an origin–destination pair, being able to recognize the flows from the ferry terminal to the tramway platforms or the parking lots.

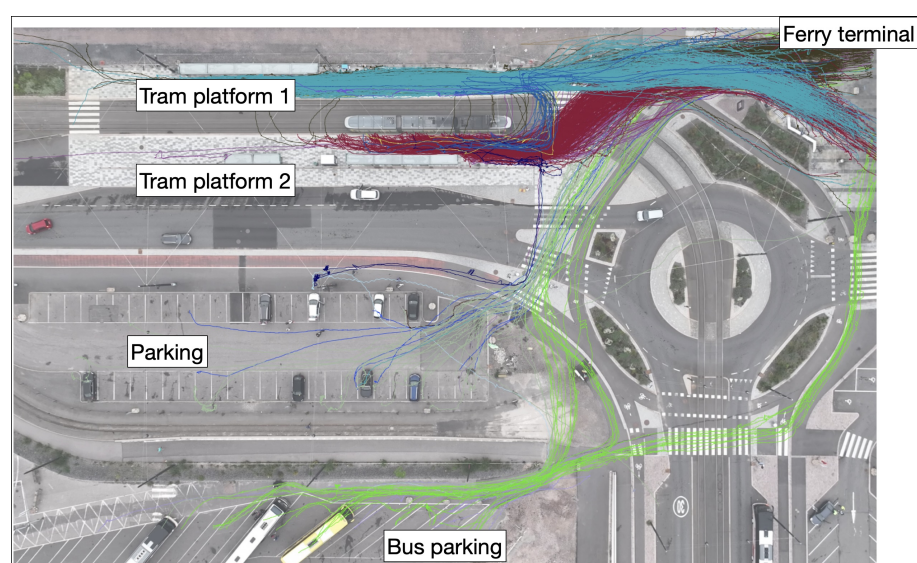


Figure 4. Pedestrian trajectories in front of the Helsinki ferry terminal, colour-coded by origin–destination (OD) pair.

Moreover, as the roads nearby the ferry terminal were also monitored, traffic peaks could be observed following the disembarkation of vehicles after a ferry's arrival. Figure 5 shows the evolution of the vehicle flow coming out of the Terminal's vehicle exit and the arrival times of the boats (orange dashed line). Two peaks can be observed in the morning around 08:20 and 09:40, following the arrival of boats from Tallinn at 08:15 and 09:30. Another peak is detected in the afternoon around 15:40, after the boat's arrival at 15:30. These peaks correspond to the disembarkation of vehicles from ferries arriving at Helsinki.

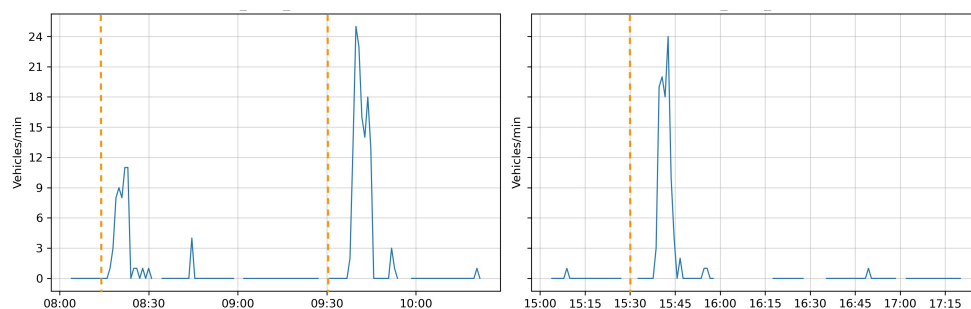


Figure 5. Vehicle flow exiting the ferry terminal during the morning and afternoon recording sessions, shown in one-minute intervals. Orange dashed lines mark ferry arrival times.

4.3. Mykonos

A drone monitoring campaign was conducted in the island of Mykonos, Greece, which experiences a sharp increase in population during the summer months, driven by a high volume of tourist arrivals, particularly via ferry. The island is also characterized by a lack of monitoring infrastructure. In this context and under the DELPHI project, MobiLysis used three drones to monitor traffic and VRUs in the port dock of Mykonos and one drone to monitor two roundabouts in the island. The drones flew for several hours in the morning for three consecutive days (30 September, 1–2 October 2024). Over 30 h of recording was collected in the port and around 11 h in the two roundabouts. Despite high winds in the area, data collection was successful and the extracted trajectories were of high quality.

Videos captured from the Mykonos port dock were processed to detect and track both vehicles and VRUs present in the scene. Figure 6 shows a distinctive aerial perspective of pedestrian trajectories (green lines) observed during a 20 min period. These trajectories not only clearly outline a boat's docking location but also offer valuable insight into pedestrian movement patterns around the terminal.

Building on the analysis of pedestrian activity during a boat's arrival, Figure 7 shows the detected pedestrians during the arrival of two consecutive boats. Through the installation of virtual counters, Figure 7 illustrates the trajectories of embarking and disembarking passengers for two boats. Utilizing a consistent colour palette, Figure 8 presents the temporal evolution of passengers embarking and disembarking for each vessel at 1 min intervals.

The data indicate that boat 1 arrives at approximately 12:35, with passengers beginning to disembark via the left ramp. Approximately one minute later, embarking commences through the right ramp simultaneously. In contrast, boat 2 is equipped with a single access ramp. As shown in Figure 8, disembarkation is completed before embarking begins, indicating a sequential use of the ramp for passenger movement.



Figure 6. Pedestrian trajectories (represented in green lines) at the Mykonos port dock recorded between arrival and departure of two boats.



(a)



(b)



(c)



(d)

Figure 7. Pedestrian trajectories of embarking and disembarking boats at the Mykonos port dock during arrival and departure. (a) Pedestrians disembarking (leaving) boat 1. (b) Pedestrians embarking (entering) boat 1. (c) Pedestrians disembarking (leaving) boat 2. (d) Pedestrians embarking (entering) boat 2.

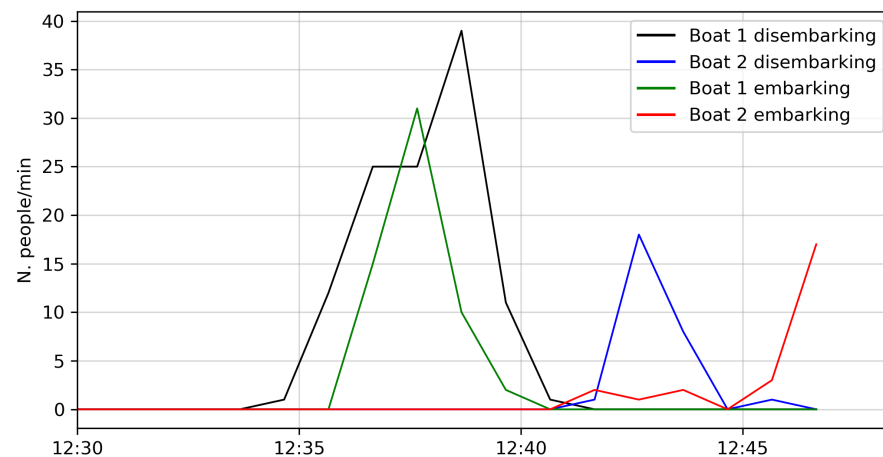


Figure 8. Minute-by-minute counts of pedestrians embarking and disembarking from two boats at the Mykonos port dock. The four coloured lines represent embarking and disembarking flows for each boat.

4.4. Madrid

The goal of the data collection in Madrid was to record traffic streams across a variety of road types, including large avenues and small streets, to understand the exposure to traffic-related emissions and unsafe events. To this end, two areas in the city centre—Embajadores and Plaza de España—were monitored using six drones over two days at each site. More specifically, the drones hovered the Embajadores area during the morning and afternoon peak hours on the 23 and 24 September 2024 and the Plaza de España area on the 1 and 2 October 2024. Almost 53 h of recording was collected in total.

With the drone flights in the city centre of the second largest city in the EU, crucial data were obtained about exposure to traffic-exhaust gases and traffic-related noise. With the extraction of trajectories and the use of microscopic emission models—MOVES [30,37] for traffic exhaust and CNOSSOS-EU [38,39] for noise-, vehicle-related emissions were estimated. In addition, safety-related metrics were also obtained using the location and speed of vehicles, following the methodology described in [32].

Figure 9 shows two aerial views of a monitored segment in the Ronda de Atocha street in central Madrid. In Figure 9a, the image is overlaid with the average spatial CO₂ emission rate of detected vehicles based on data collected between 08:00 and 09:00 on 23 September 2024. Elevated emission levels—highlighted in red—are predominantly observed near the traffic light on the main avenue, particularly for vehicles travelling from left to right. This direction corresponds to the dominant flow of morning traffic, with increased emissions primarily attributed to idling and stop-and-go conditions at the signalized intersection.

Using the same dataset, Figure 9b illustrates the frequency of unsafe rear-end vehicle interactions (red points indicate high frequency). These events are represented by low Time-To-Collision (TTC) values, which indicate the time remaining before a potential collision if both vehicles maintain their current speed and direction. A significant cluster of low TTC values is observed near the traffic light in the left-to-right traffic direction driven by high vehicle density and frequent stopping. Additionally, smaller clusters are also visible in the bus lane in the opposite direction, suggesting localized unsafe events with buses in that area.

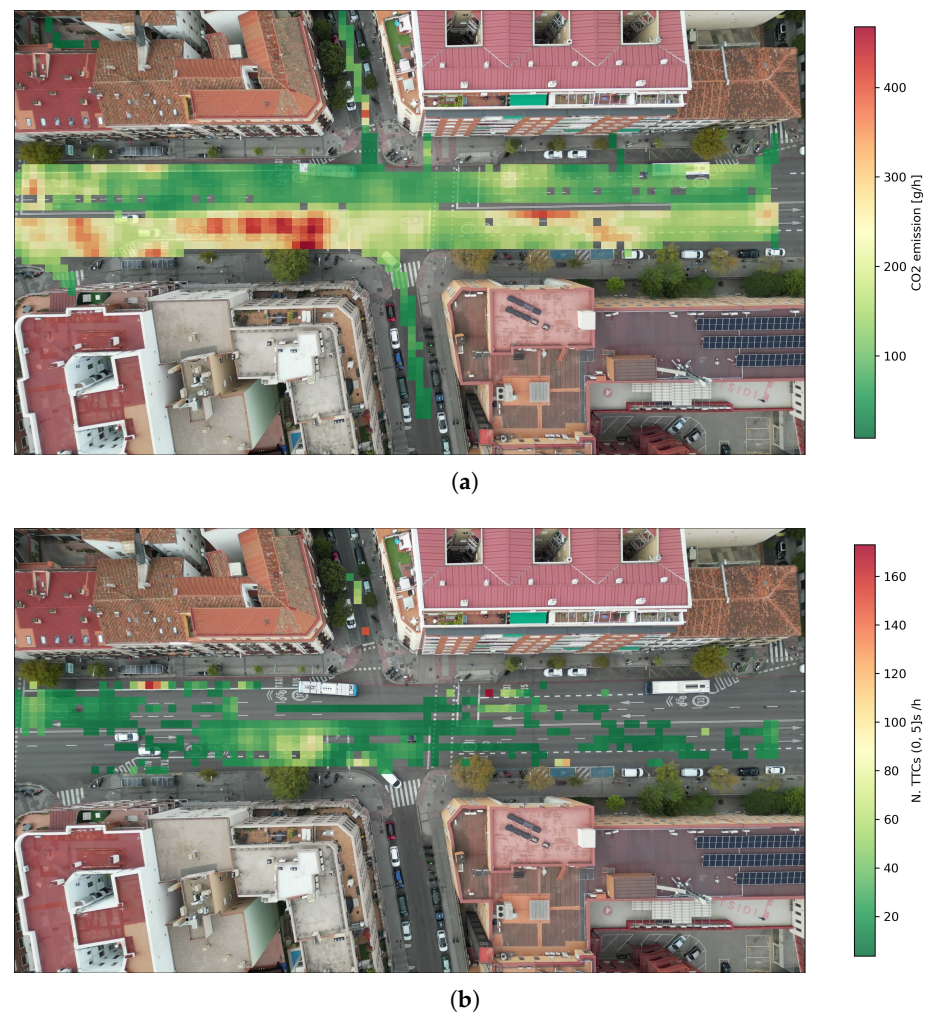


Figure 9. Spatial distributions in a segment from Ronda de Atocha, Madrid. **(a)** Average CO₂ emission rate in grams of CO₂ per hour for each 2 m × 2 m bin—red for higher polluting bins and green for less polluting bins. **(b)** Frequency of low TTC values below 5 s per hour for each 2 m × 2 m bin—red for bins with high frequency and green for bins with low frequency of dangerous events.

4.5. Limassol

Limassol is the second-largest city in Cyprus and an important transportation hub in the island. Drivers and commuters experience extensive traffic congestion in the city, leading to longer travelling times and increased emissions. In this context, five drones were deployed to monitor six congested intersections during the morning and afternoon peak hours of three consecutive days (26–28 March 2025). Over 50 h of recording was collected.

Figure 10 presents the average vehicle speed at the intersection of Archiepiskopou Makariou III Avenue and Agias Zonis in Limassol. The spatial distribution reveals distinct low-speed zones—highlighted in red—immediately upstream of the traffic light stop lines, corresponding to areas where vehicles queue while waiting for the signal to change. Notably, a concentrated red cluster appears at the centre of the intersection. This pattern is attributed to right-turning vehicles (as Cyprus follows left-hand traffic) that temporarily stop in the middle of the junction while waiting for oncoming traffic to clear before completing their turn.

Allowing right turns in all directions without dedicated signal phases can lead to potentially hazardous vehicle conflicts. In order to assess these risks, a traffic safety analysis was conducted using the well-established surrogate safety metric known as Post-Encroachment Time (PET). PET quantifies the time elapsed between the departure of one

vehicle and the arrival of another at a common conflict point, with lower PET values indicating a higher likelihood of near-collision events. Figure 11 highlights the spatial distribution of low PET occurrences, specifically those under 4 s. The results indicate a higher concentration of critical interactions in the southern part of the intersection, suggesting that this area poses an elevated safety risk due to vehicle crossing conflicts.

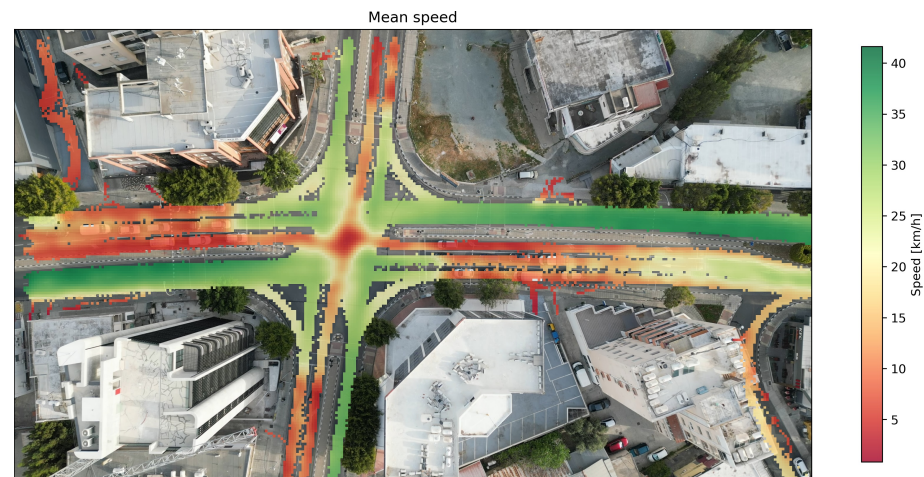


Figure 10. Spatial speed distribution in the Archiepiskopou Makariou III Avenue-Agias Zonis junction in Limassol.



Figure 11. Frequency of low PET events in the Archiepiskopou Makariou III Avenue-Agias Zonis junction in Limassol.

Since the collected data includes timestamps, the traffic analysis can be extended with a dynamic component. For example, Figure 12 illustrates the evolution of the average delay across the four entry legs of the same intersection (Archiepiskopou Makariou III Avenue and Agias Zonis). The results are aggregated into 5 min intervals during the recording time, providing a clear visualization of delay patterns through the colour scheme (with red cells indicating delays close to 1 min and green cells representing free flow conditions). Delays are computed as the difference between actual and theoretical travel times, assuming vehicles travel at the speed limit. The Figure highlights that Makariou III Avenue experiences more congestion, particularly in the afternoon.

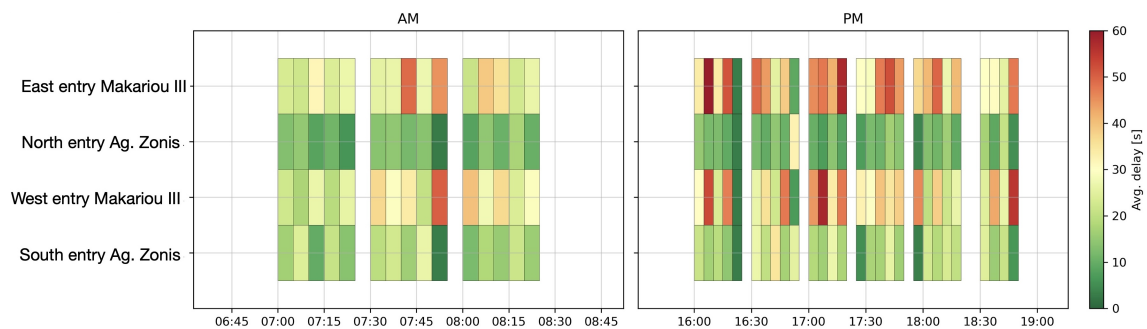


Figure 12. Average delay during a working day at 5 min intervals in the entry legs of the Archiepiskopou Makariou III Avenue-Agias Zonis junction in Limassol.

5. Cross-City Lessons: Ethical, Operational, and Strategic Insights

Through these five city deployments, we observed that drone-based monitoring offers a flexible and powerful means of collecting traffic and mobility data, adaptable to a wide range of geographies, infrastructure setups, and policy environments. Whether in dense cities with various sensors installed like Athens and Helsinki or in highly dynamic contexts without any monitoring infrastructure like Mykonos or Limassol, drone operations proved remarkably versatile. Flight paths and data collection protocols could be fine-tuned to local topography and traffic patterns, underlining the adaptability of this method across various contexts, and in cities with varying levels of existing sensor infrastructure.

A key enabler of this versatility was early and sustained engagement with local stakeholders. From city authorities and transport departments to on-site security personnel, drone pilots and port operators, proactive communication and co-design ensured that operations were not only logistically smooth but also aligned with local mobility goals. Notably, establishing connections with local drone pilots—who possess knowledge of relevant local regulations and maintain relationships with the appropriate authorities—was key in ensuring the feasibility of the drone operations. Moreover, cities were far more willing to support experimentation when they actively participated in the process in a transparent way and understood the specific benefits to their own policy or planning agendas. This co-design ethos also helped contextualize findings, leading to results that could be more readily interpreted and acted upon by local decision-makers.

Privacy and ethics, crucial to any aerial monitoring project, were not seen as obstacles but as design constraints to be innovatively addressed. By applying privacy-by-design principles—such as avoiding facial recognition or seeing vehicle plates—we were able to reassure city partners and the public alike. When privacy considerations were explained transparently, and when cities saw the trade-offs between resolution and anonymity clearly explained, the response was not resistance but support. This could suggest a growing maturity and pragmatism in how public institutions approach ethical concerns in urban data collection.

Furthermore, all collected videos were stored on private, password-protected hard drives, and their analysis was carried out offline using the MobiLysis' office equipment. The videos were never shared with third parties, and only fully anonymized trajectories were shared with local stakeholders and project partners. Also, areas such as private roads and parking lots were excluded from analysis. As aforementioned, GDPR compliance was ensured by the bird's-eye view perspective and the flight altitude, which prevented the identification of vehicle plates and facial features, and thus no information that can relate to personal data was collected. Finally, all raw videos were retained only for the minimum period necessary to complete the analysis and for audit purposes, in accordance with GDPR and the project's data management principles.

Most notably, across all contexts there was a strong demand for high-resolution, multimodal data, especially relating to road users who are typically under-monitored. Pedestrians, cyclists, and micromobility users have systematically been ignored by the existing digital infrastructure, such as inductive loops or fixed cameras. Drones bridged this gap by providing detailed data on movement flows, interactions, and safety-critical situations involving these vulnerable groups. In this way, drone-based monitoring served not just as a supplement to existing infrastructure, but as a critical enabler towards equality among all road users, providing quantifiable data on mobility patterns that would otherwise be invisible in cities' traffic analytics.

Additionally, our findings reaffirm the value of drones as a complementary data collection method, not a replacement for ground-based sensors [23]. Compared to loop detectors, LiDARs, Bluetooth scanners, and static CCTV cameras, drones offer a unique overhead, wide area perspective that captures full trajectories and crowd dynamics across different modes. However, when these data sources are fused with each other, validation and filling gaps can be ensured [20]. For example, drone-collected trajectories enhanced the calibration of simulation models in Helsinki and Athens, while validating pedestrian activity levels around ferry terminals in Mykonos that lacked any fixed infrastructure. Going forward, the emphasis should be on hybrid sensing strategies that blend fixed and temporary deployments and static and mobile platforms.

One further insight from our cross-context work is that drone deployments can catalyse organizational learning within cities. Several local authorities we collaborated with had never previously worked with drones nor were even aware of drone-based analytics. The projects became an opportunity not just for data collection, but for capacity building—encouraging cities to think differently about data governance, sensor networks, and privacy trade-offs. This may be as important as the technical insights generated, especially in fostering a culture of experimentation and data-informed policy.

Finally, ethical considerations extend beyond privacy into public trust and social license. Even when technically compliant, drone deployments must be perceived as legitimate. In future efforts, integrating visible public messaging, citizen feedback loops, or even participatory sensing components could further reinforce the social acceptance of such technologies—especially as they scale from research pilots to operational tools.

6. From Insights to Impact: Applications and Future Outlook

While this study demonstrates the significant potential of drones for urban mobility analysis, some limitations are worth noting. Current regulatory constraints limit certain types of flight operations, though the drone industry is actively working to relax these restrictions for safety, efficiency, and broader urban applications that could increase the efficiency of the drone as a monitoring tool. Additionally, battery life remains a limiting factor, requiring careful operational planning, yet rapid advances in energy density and drone design are expected to extend flight durations substantially in the near future.

This cross-city initiative underscores the transformative potential of scalable, drone-based mobility monitoring to address critical challenges in urban sustainability, equity, and governance. By demonstrating successful deployments across diverse urban contexts, we validated the adaptability and relevance of drones as both a diagnostic and planning tool. The richness of multimodal, high-resolution trajectory data not only enables localized improvements but also lays the foundation for system-level innovation. When integrated into digital twins that simulate full traffic networks and multi-modal interactions, enabling predictive scenario testing, infrastructure optimization, and long-term planning, edge computing platforms that allow real-time processing and decision-making at the network edge and AI modelling frameworks capable of dynamic traffic flow estimation, conges-

tion prediction, and incident detection, these data can transform how urban mobility is monitored, understood, and managed. In the near future, drones could feed AI models that dynamically control traffic lights, communicate rerouting alternatives to automated vehicles during congestion, optimize public transit schedules, and coordinate multi-modal flows in real time, effectively turning cities into adaptive, self-regulating mobility systems.

Furthermore, as cities face increasing pressure to ensure that digital innovations do not exacerbate existing inequalities, drone-collected data offer a critical lens for AI fairness, ethical model development, and privacy-preserving urban sensing. By embedding drones into broader urban analytics ecosystems, these platforms could support predictive interventions that improve accessibility and equity, for example by identifying underserved areas in need of better transit or safer pedestrian infrastructure. These studies demonstrate that with careful stakeholder co-design, transparent communication, and rigorous privacy regulations, drone-based monitoring integrated with advanced computational and predictive platforms can gain public acceptance and deliver actionable insights without compromising civil rights.

In the end, the success of this work points toward a future where drones become an integral part of urban intelligence infrastructures, supporting real-time monitoring, adaptive traffic management, predictive simulations, and long-term mobility system optimization, not only in managing current challenges but also in anticipating and shaping the sustainable, equitable, and resilient mobility systems of tomorrow.

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