Measuring UAM Social and Environmental Impact

Lessons learned from the MUSE project

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***Abstract*— Urban Air Mobility (UAM) offers new opportunities for parcel and emergency deliveries, but its integration into cities raises significant environmental and social concerns. The SESAR MUSE project develops a comprehensive Performance Framework to assess these impacts, introducing novel performance indicators for noise, visual pollution, privacy, access, and equity. The methodology combines trajectory generation, high-resolution noise and visual modelling, and dynamic population mapping derived from mobile network and satellite data. Case studies in Madrid on parcel and emergency deliveries illustrate the framework's application. Results show that noise and visual exposure along with privacy concerns vary significantly with altitude, routing, and traffic density, while access and equity effects depend on operational design and local urban structures. Emergency deliveries provide clear societal benefits through substantial time savings in congested areas, whereas parcel deliveries reveal trade-offs between efficiency and environmental impact. The paper concludes with lessons learned and recommendations for UAM stakeholders, emphasizing the importance of validated indicators, realistic thresholds, and participatory governance to ensure safe, sustainable, and socially acceptable drone operations.**

Keywords-Urban Air Mobility; Unmanned Aircraft, social acceptance; noise; visual pollution; privacy concerns; access and equity; performance assessment; policy recommendations; mobile network data

I. INTRODUCTION

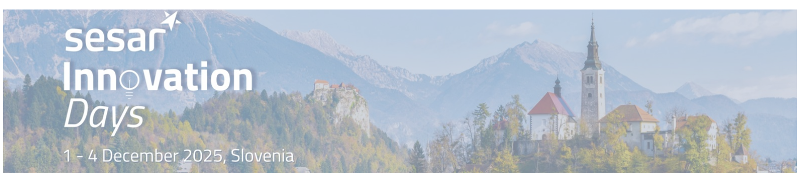
The rapid advancement of Innovative Air Mobility (IAM) is transforming urban transportation systems, with U-space in Europe emerging as a key enabler [1]. Its gradual implementation is expected to unlock the potential of the drone economy, supporting a wide range of use cases—from regional and urban air mobility to emergency medical services [2] Integrating these technologies into densely populated areas presents both opportunities and challenges. Urban Air Mobility (UAM) is seen by SESAR [1] to be one of the most demanding use cases for U-space.

While technological progress and pilot projects multiply, the societal implications of UAM remain only partially understood, with public acceptance proving decisive for successful deployment. Concerns such as noise pollution, visual intrusion, privacy, safety risks, equity of access, and environmental trade-offs pose significant barriers to adoption and may result in regulatory constraints. Among these, noise stands out as the most critical factor. Unlike conventional aircraft, whose impacts are concentrated around airports during take-off and landing, drones generate continuous disturbances at lower cruising altitudes. Research shows that drone noise, characterized by high-frequency tonal components, is generally perceived as more irritating than road traffic or civil aviation noise, especially in quieter urban contexts [3][4].

Comprehensive studies, such as those conducted by the European Union Aviation Safety Agency [5], emphasize that transparency, trust, and public perception will shape the trajectory of UAM implementation. Demonstrator projects with direct societal benefits, such as healthcare logistics, play an essential role in building acceptance by showcasing tangible value to citizens. Nevertheless, efforts to characterize UAM's broader impacts on urban environments remain limited. Existing assessments often rely on surveys or simplified assumptions, such as the use of census data that overlooks daily mobility patterns, leading to biases in estimating population exposure [6][7]. Current performance indicators developed under SESAR initiatives provide useful foundations but remain too general to capture the diverse effects of UAM across different urban contexts [8].

The MUSE SESAR project [9] addresses this gap by developing a performance framework, indicators, and tools to measure the social and environmental impacts of UAM. These include metrics for noise, visual pollution, privacy, and both economic and social benefits. The project proposes a U-space service concept aimed at quantifying the impact of urban drone operations with respect to sustainability and quality of life. By capturing the complex interactions between UAM activities, environmental impacts, and urban dynamics, this work enhances understanding of how UAM can be designed, governed, and accepted to prioritize public value.

This research contributes empirical evidence to support informed regulatory decision-making and the development of U-space services aligned with societal needs. It highlights the



pressing necessity for advanced indicators and robust measurement mechanisms to ensure UAM evolves as a sustainable and socially responsible component of urban mobility. Without evidence-based tools, policymakers and operators risk implementing solutions that could undermine social acceptance or environmental goals.

This paper presents findings from case studies conducted within the MUSE project, distils lessons learned, and provides recommendations for policymakers, U-space regulators, U-space service providers (USSPs), and drone operators. The rest of the paper is structured as follows: Section II details the methodology used to assess the environmental impact of UAM—including trajectory generation, noise and visual pollution modelling, dynamic population mapping, and exposure calculations. Section III presents the results of the case studies, while Section IV summarizes the lessons learned and offers policy recommendations.

II. METHODOLOGY

The methodology for simulating drone traffic and assessing its environmental impact is based on a framework previously described in our earlier work [10]. The process followed to obtain the social and environmental impact of drones' operations is as follows: i) generation of realistic 4D trajectories; ii) calculation of noise, visual pollution, privacy concerns and access and equity effects; iii) determination of dynamic population maps; and iv) fuse the drone effects with the population mapping to calculate the final indicators. For the current study, we use the same core components, focusing our analysis on a new set of data and scenarios. The key elements of the methodology are briefly summarized below.

A. Trajectory Generation

We use GEMMA, a trajectory generation engine from the Technical University of Catalonia, to create realistic drone flight paths. This software is highly configurable and incorporates various operational factors, including flight schemes, airspace restrictions, and aircraft performance data. A detailed description of GEMMA and its capabilities can be found in [10].

B. Social and Environmental Impact Assessment

The social environmental analysis is split into four parts: noise and visual pollution, privacy concerns and access and equity.

Noise Modelling: The noise module consists of a sequential three-step process.

1. It uses DynaPyVTOL for calculating dynamic flight parameters to recreate realistically flown mission,
2. CARMEN for calculating noise emissions, and
3. the open-source software NoiseModelling for noise propagation by means of ray tracing [11]. The noise propagation takes into account the urban architecture (3D buildings and Digital Elevation Model). Based on the CNOSSOS-EU guidelines, the calculations include one order of reflection as well as horizontal and vertical diffractions.

The study only focuses on outdoor noise calculation. These tools are integrated to produce detailed noise maps.

Visual Pollution: We quantify visual pollution using a combination of GIS functionalities and geometric analysis of drone visibility. To this aim we use the Digital Surface Model (DSM) of the area to be studied, which includes not only terrain elevations but also buildings and other human constructions that affect visibility, and the drones' size. The visual pollution concentration (VPC) is calculated using two metrics: the formula derived by the project AirMOUR [12] and the Visual Area formula, which considers both the drone's dimensions (width and length) and its distance from the observer.

Privacy Concerns: Measuring of the number of people that can be annoyed by presence of a single drone operation or by Unmanned Aircraft (UAs) within an area (during observed time period) or observed from a drone, flying in a distance smaller than a threshold distance.

Access and Equity: Measuring time savings (drone flight time vs. road travel time) and distribution of negative effects of drone operations across the population. In this paper, we present only time savings.

C. Population Mapping

To accurately assess population exposure to UAM impacts, we utilize a dynamic population mapping approach, rather than relying on traditional methods such as surveys or using census data. This module leverages anonymized mobile network data (MND), which is processed using Nommon's Population Insights software [13]. This tool generates dynamic population maps and activity indicators. To overcome the geographical resolution limitations of MND, we combine it with historical GPS data from mobile apps [14]. This process allows us to allocate the population into a high-resolution grid (15-meter resolution), creating detailed probability heat maps of people's presence at different times of the day with the differentiation of outdoor and indoor activities.

The MND+GPS population presence has been calibrated and validated with pedestrian counts detected with Earth Observation satellite images [15] by comparison of the population detected with both sources [16].

TABLE I. PERFOMANCE INDICATORS

PIs	Unit	Measurement mechanism
NO-3: Trajectory-based people exposure to noise (SEL_A)	person	The amount of people exposed to a sound exposure level higher than a certain threshold in dBA, for a single drone operation, for a time period fixed by the drone trajectory, within an area.
NO-5: Area based people exposure duration to noise	D.person	A certain duration D of noise levels exceeding a certain threshold in dBA multiplied by the number of people exposed, over a fixed period of time (15 min), within an area.
VP-4: Trajectory based visual exposure	person.vp.h	Total visual pollution exposure perceived by the people exposed to a single drone operation.
PC-1: Trajectory-based people visually annoyed	person	Total amount of people annoyed by (presence of) a single drone operation.
PC-3: Area based people visually annoyed	person	Total amount of people annoyed by presence of UAs within an area, during observed time period.
AE-2: Reduced travel time for health care-related deliveries	seconds	The amount of time reduced for health care-related deliveries by UAs compared to the delivery by road transport.

D. Exposure and Indicator Calculation

The final stage of the methodology combines the calculated impact maps (noise, visual pollution, etc.) with detailed, high-resolution population maps, which are split by different sociodemographic groups. This integration is crucial for understanding the UAM operations impact on citizen's life.

MUSE project has established a comprehensive framework for assessing noise, visual, privacy and access and equity effects from multiple perspectives, including the metrics used and their scope (trajectory-based and traffic-based). The objective here is to present findings on those most relevant indicators for the analysis. Before discussing the results, the list of indicators included in [17] together with the corresponding definitions is provided in the Table I.

The use of trajectory-based indicators (NO-3 and VP-4) allows for a focused analysis of individual routes, helping to address the following questions:

- Examining the differences in the indicator for the same trajectory flown at different altitudes, where one corresponds to an inbound flight to a hub and the other to an outbound flight;
- Comparing similar trajectories at the same altitude, one inbound and the other outbound, to assess potential differences on the selected metric.

On the other hand, area-based indicators aims to describe the global impact of all the traffic as a whole.

VP-4 not only counts the number of affected individuals but also considers the severity of visual pollution and the duration of exposure. It measures both the extent of the impact and the intensity over time. Similarly, NO-5 is a composite metric that evaluates the duration of noise exceeding a predefined threshold and the number of affected individuals within a 15-minute period in the area of interest.

With PC-1 and PC-3, the framework provides objective measures to assess the number of people that can be annoyed (seeing a drone or being seen by a drone) by presence of a single drone operation or by UAs within an area (during observed time period). Applied annoyance sensitivity values for specific areas are taken from the DACUS project, as explained in [17].

Finally, AE-2 allows to evaluate drone-based emergency deliveries in Madrid and estimate the reduced travel time for health care-related deliveries compared to the delivery by road transport.

E. Case Studies

The goal of the following case studies is to evaluate the impact of UAM and determine their usefulness in creating policy recommendations. Two different case studies (CU) have been defined, parcel delivery and emergency delivery, based on consultations with stakeholders such as bilateral meetings with a drone manufacturer and operator, insights from experts at the U-Space Coordination Cell (UCC) meeting and members of the MUSE External Experts Advisory Board (EEAB), and comments and suggestions gathered during the EUROCONTROL Active Zone Learning webinar. Both cases considered are located in Madrid (Spain).

CU 1: Parcel Delivery

Drones are becoming a popular solution for delivering small packages in cities [18]. Their key benefits include faster delivery times, higher accuracy, and being more environmentally friendly than traditional delivery methods. These drones can transport a wide variety of goods, from groceries and household products to medical samples. In this case study, we have considered the drone flights to choose a direct flight route between origin and destination. The airspace allowed for parcel delivery is between 45 and 90 m above ground level, where flights are randomly assigned to an altitude in this range. The trajectories are designed to follow the terrain, maintaining the assigned altitude with the ground. As it can be seen in Fig.1, the irregular profile of urban environments makes that these smooth trajectories have variations around the selected altitude of several meters (20 m) and discrepancies in the average altitude (63 m vs a selected altitude of 61 m).

Flights are performed by DJI Matrice 600, the specification of the drone have been retrieved from open sources to feed the trajectory generation engine (Table II). The distribution centers (DC) have a maximum capacity of 60 operations per hour.

For our analysis, we did not model the entire city of Madrid. Instead, our study focused on a specific, predefined urban zone (shown as the yellow rectangle in Fig. 2). This area was carefully chosen because it contains a mix of important locations, including residential neighborhoods, recreational spaces, restricted areas like the Royal Palace, and hospitals.

The decision to limit the study area to 5.9 km long and 1.7 km wide was made for a practical reason: a full-city simulation would have been too demanding on our computing resources, preventing us from focusing on the most valuable insights.

TABLE II. DRONES USED IN THE EMERGENCY DELIVERY SIMULATIONS

Characteristic	**DJI Matrice 600**	**RigiTech Eiger**
Maximum Take-Off Weight	15.5 kg	21 kg
Maximum Payload	2.7 kg	3 kg
Cruise velocity (min-max)	12 – 18 m/s	23 – 35 m/s

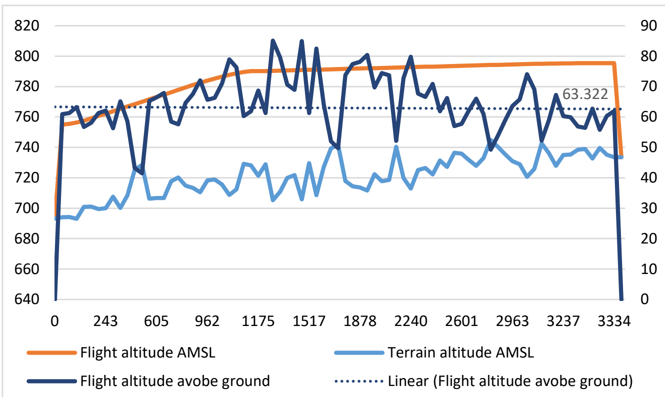


Figure 1. Flight altitudes for an example flight. Left axis: the orange line provides the altitude of the flight Above Mean Sea Level (AMSL); the light blue line provides the terrain altitude (including buildings) AMSL. Right axis: the dark blue line provides the real altitude of the flight with respect to the ground. Avg. altitude 63 m, min. altitude 41 m, max. altitude 85 m. Selected altitude of 61 m.

CU 2: Emergency Delivery

Medical parcel delivery, while sharing similarities with goods delivery, has unique characteristics due to the urgency required. This includes direct routes between hospitals and the use of reserved airspace: a layer at 105 m for South-North flights and another at 120 m for North South. The application of drones in the medical sector represents one of the most promising uses of this technology, likely to gain public confidence and acceptance.

Drones effectively transport various medical supplies, such as medications, blood samples, and organs, between hospitals. They also deliver essential medical goods to rural areas and those impacted by natural disasters.

In MUSE project we evaluate the time saved by using drones for healthcare deliveries compared to traditional road transport. Our methodology calculates this time difference by subtracting the drone's flight time (estimated using the GEMMA tool) from the road transport time, which we estimate using the Google Routes API. This service, provided by Google Maps Platform, calculates optimal routes between locations, considering real-time traffic conditions, tolls, and various travel modes. It uses historical data to predict traffic patterns, but specific past departure times cannot be used to retrieve historical travel time estimates. To account for varying road traffic, we analyzed one week of data from May 4 to 10, 2026, covering both weekdays and weekends. Ground-handling operations, such as preparation, loading, and unloading, were excluded from this analysis for both drone and ground-based transport modes due to the absence of consistent operational data. Nevertheless, these procedures are anticipated to be more automated and time-efficient in drone operations, with a lower reliance on human intervention compared to road transport. Therefore, incorporating such handling times in future research could further highlight the advantages of drone-based emergency delivery systems.

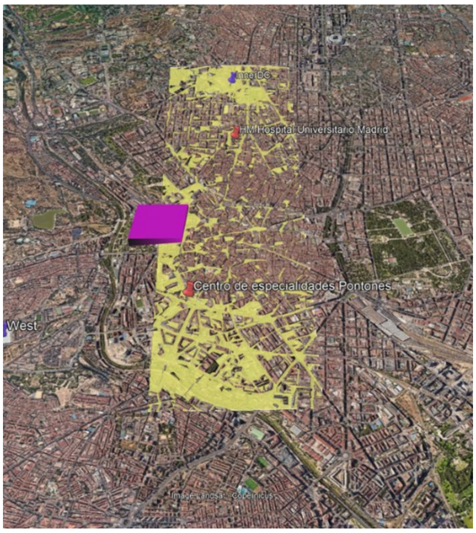


Figure 2. Study area for parcel delivery operations

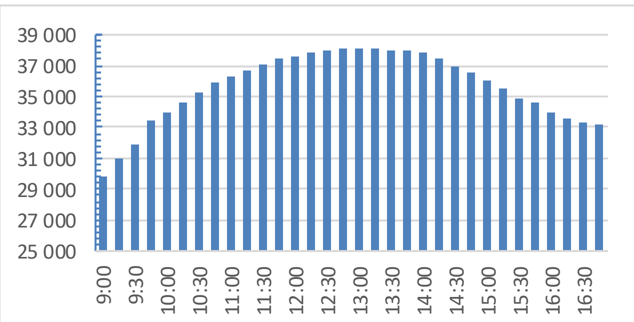


Figure 3. Population presence outside along the daytime in the study

For our simulation, we used two drone models: the DJI Matrice 600, and the Eiger, as detailed in Table II. To enhance realism, we randomly selected each flight's cruise speed within the specified minimum and maximum values for each drone in GEMMA. This approach simulates varied operational conditions and the effects of wind on flight dynamics.

The most relevant indicators for this case study are Access and Equity indicators. The indicators values for other focus areas such as noise, visual pollution and privacy concerns were negligible and not presented here due to small number of drone operation and high flight levels compared to parcel delivery case study.

III. RESULTS

A. Parcel delivery

Before discussing the results, it is important to consider the temporal variation in population within the study area. Fig. 3 shows the population curve every 15 minutes, providing essential context for interpreting the exposure results. The population shows a peak between 12:30 and 14:30 of 38 000 persons outside.

1) Results for noise pollution

a) NO-3: Trajectory-based people exposure to noise

To demonstrate how the time of day affects the results of the NO-3 indicator, we compared two flight paths with similar altitudes that flew over the same city area but at different times (see Fig. 4). The intensity of the purple color indicates the number of people in the affected areas, as shown at the top of the figure. The findings revealed that the number of people exposed to noise levels above a 40-dBA threshold was roughly the same in both scenarios. Specifically, the morning flight affected 1,034 individuals, while the afternoon flight had a slightly smaller impact, affecting 951 people. Given the fact that the drone type is the same, any difference in this case is due to the population presence variation.

Analyzing the NO-3 indicator for the same flight path flown at different altitudes, it is expected that a higher altitude will affect fewer people than a lower one. We can see this when comparing an inbound flight to a DC with an outbound flight, as they operate at different altitudes. The results confirm this: the flight at 58 meters (SO6388-B) exposed approximately 44% fewer people to noise (1,193 individuals) than the lower flight at 49 meters (SO6388-F), which affected 2,127 individuals (see Fig. 5).

The relationship between a drone's altitude and the number of people exposed to noise isn't always straightforward, and it's important to be cautious when interpreting it. Contrary to what was previously shown, a higher-altitude flight path can sometimes affect more people. In the following example, the higher flight path (IN8351-B) at 73 meters impacted about 70% more individuals than the lower one (IN9596-B) at 38 meters. Specifically, the higher-altitude flight affected approximately

2,244 people, while the lower one affected around 1,317 (see Fig. 6).

A detailed analysis of the noise maps associated with both trajectories reveals the underlying reason for this discrepancy (see Fig. 7). The main reason of the observed differences in ground noise levels appears to be small variations in the flight trajectories. Introducing even a modest vertical component to the trajectory can result in substantial changes in noise generation, despite the overall trajectory remaining nearly identical to a perfectly horizontal flight. This finding is particularly relevant, as it suggests that minor adjustments in planned flight paths may yield significant reductions in noise pollution.

b) NO-5: Area based people exposure duration to noise

While NO-3 measures the number of people exposed to a specific noise level, NO-5 is a compound metric. It combines the duration of noise exposure above a certain threshold with the number of people affected within a 15-minute period. Results are expressed in D.person, where D denotes duration (in seconds) and "person" the number of people exposed. We will show the results for two different thresholds: 40 dBA and the daily averaged background noise level (L_{day}) produced by road traffic [19]. As it can be seen in Fig.8, road traffic noise exceeds the 40 dBA threshold in most places, except for some urban squares restricted to traffic, inner courtyards and green areas.

The choice of threshold greatly impacts the NO-5 results. For example, during a morning period with low traffic, the NO-5 value for the 40 dBA threshold is 14 D.person. However, when using the background noise level as the threshold, the value drops to 0 D.person. This difference is expected because in most cities, the ambient noise is already above 40 dBA. Therefore, setting the threshold to the existing background noise makes the drone's impact on noise exposure seem much less significant.

Similarly, the results for the afternoon period (5:00 p.m. - 5:15 p.m.) align with previous findings. Due to a high volume of drone traffic, the values are significantly higher for both thresholds. Specifically, the NO-5 value for the 40-dBA threshold reaches 13,728 D.person, while for the background noise threshold, it is 461 D.person. In this case, given that the variation in population density between the morning and the afternoon period is small (11%), the most relevant explanatory variable is the drone traffic volume.

To wrap up, Fig. 9 show the distribution of NO-5 indicator throughout the day using the two different thresholds. With the 40 dBA threshold, the NO-5 value peaks at about 50,000 D.person around 3 p.m. This suggests that noise exposure, as measured by NO-5, is strongly influenced by both the density of drone traffic and operational schedules. On the other hand, the distribution of the values with the average daily background noise has its peak of around 3,500 D.person around 11 a.m.

2) Results for visual pollution

a) VP-4: Trajectory based visual exposure

Fig. 10 shows the same flight path at two different altitudes, one for outbound flights and one for inbound flights. The results for the VP-4 indicator highlight a clear difference: the inbound flight, which is at a lower altitude, has a value of 2,079 person.vp.h (where vp denotes the chosen visual pollution metric— in this case "Visible Area") In contrast, the outbound

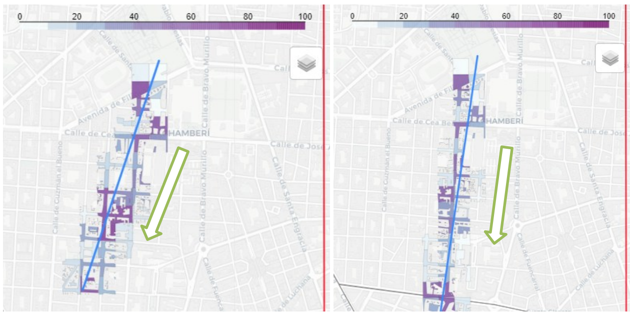


Figure 4. Trajectories of similar altitude at different time periods. Left: Trajectory IN10744-B, 65m at 8:07 a.m.. Right: Trajectory IN11162-B, 60m at 4.31 p.m.

Figure 5. Similar trajectories at different altitudes (case 1). Left: Trajectory SO6388-F, altitude: 49 m. Right: Trajectory SO6388-B, altitude 58m.

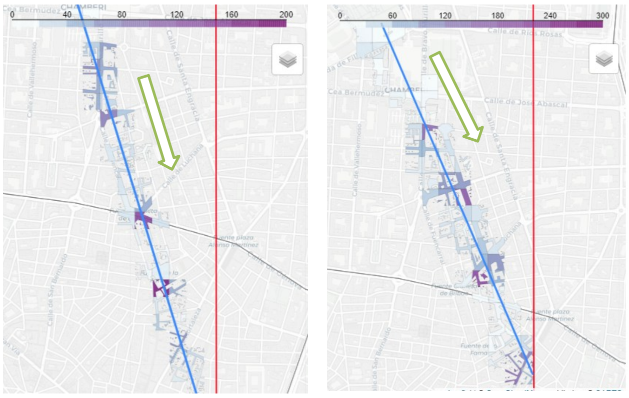


Figure 6. Similar trajectories at different altitudes (case 2). Left: Trajectory IN9596-B at 9.03 a.m., altitude 38m. Right: Trajectory IN8351-B at 8.32 a.m., altitude 73m.

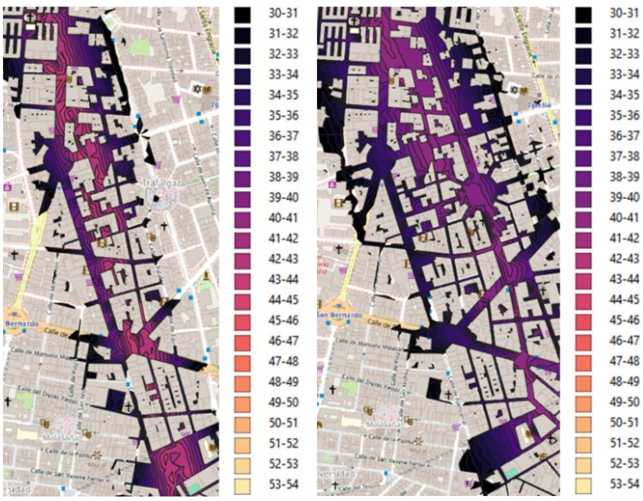


Figure 7. Noise map of NO-3 indicator (SELA, [dBA]) for similar trajectories at different altitudes (case 2).

flight, which is at a higher altitude, has a significantly lower value of 1,277 person.vp.h.

To see how a flight's direction affects its visual pollution score, we analyzed two similar flight paths at the same altitude. As Fig. 11 shows, the inbound flight had a VP-4 value of 1,281 person.vp.h, which is almost 60% higher than the outbound flight at 808 person.vp.h. It appears that the direction of the flight is dominant influential factor, not the altitude variation. This difference likely stems from the inbound flight's landing phase, which is typically slower than takeoff and happens within the area of interest, causing a longer period of visual exposure for people below.

In order to evaluate the impact of metric selection on the results, the same experiment was repeated using the AiRMOUR formula (see Fig. 12). Similar to the visual area metric, the results are higher in absolute terms for the inbound trajectory, with a value of 156,153 person.vp.h, compared to 151,328 person.vp.h for the outbound trajectory. The findings suggest that the AiRMOUR metric does not penalize distance in the same manner as the visible area metric, leading to significant exposure even at longer distances from the observer.

The results for indicator VP-4 Trajectory based visual exposure, for low-altitude and high-altitude trajectory, provide a good approximation how the people are visually affected by trajectories at different levels. The results for two different metrics demonstrate how the number of people varies depending on different thresholds.

3) Results for privacy concerns indicators

a) PC-1: Trajectory-based people visually annoyed

The analysis of PC-1 aims to assess the influence of flight altitude on its final outcome. To achieve this, two trajectories were selected at approximately the same time period (4:00 p.m. and 4:22 p.m.) but with a difference in altitude of 49 meters—the first trajectory was flown at 35 meters, while the second was conducted at 84 meters (see Fig. 13).

The results indicate that the low-altitude trajectory affected 5,496 persons, whereas the high-altitude trajectory impacted 9,026 persons, representing a relative difference of 64.2%. This significant discrepancy arises from the fact that higher altitudes increase the visibility of the drone over longer distances, thereby exposing a larger population to potential visual disturbance.

b) PC-3: Area based people visually annoyed

It is defined as the total amount of people annoyed by presence of UAs within an area, during observed time period. The PC-3 indicator aims to assess the potential impact of different traffic levels at different times of the day on privacy concerns. As shown in Fig. 14, the afternoon period, characterized by higher traffic density, results in a PC-3 value of 23,163. In contrast, during the morning period, when traffic is less dense, the PC-3 value is significantly lower at 11,428, representing a reduction of approximately 50%.

B. Emergency delivery

1) Results for access & equity (time savings)

Fig. 15 shows the time saved on healthcare deliveries for different hospital pairs and drone models, including the average, minimum, and maximum savings across 24 h of the day. The smallest time saving was 1.6 minutes, which occurred on Pair 6-F (from La Paz to HU Carlos III) with the DJI Matrice 600.

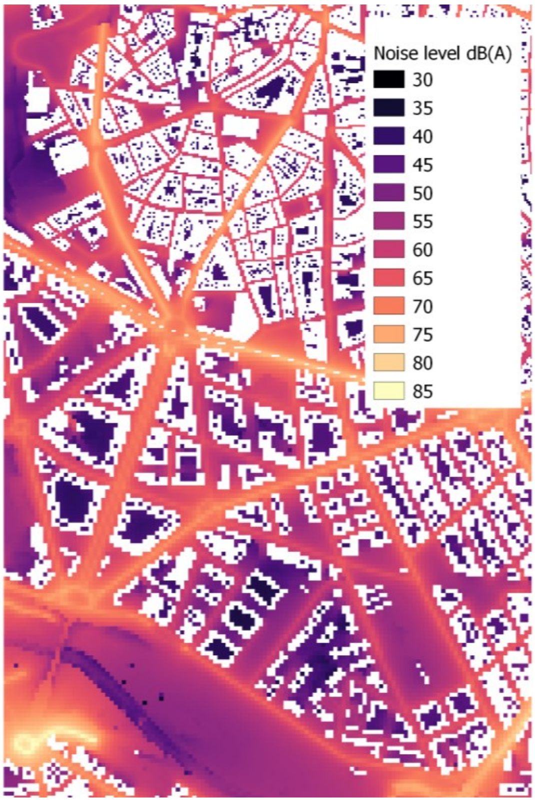


Figure 8. Road traffic background noise daily average (Lday) provided by the Madrid City Council for 2021.

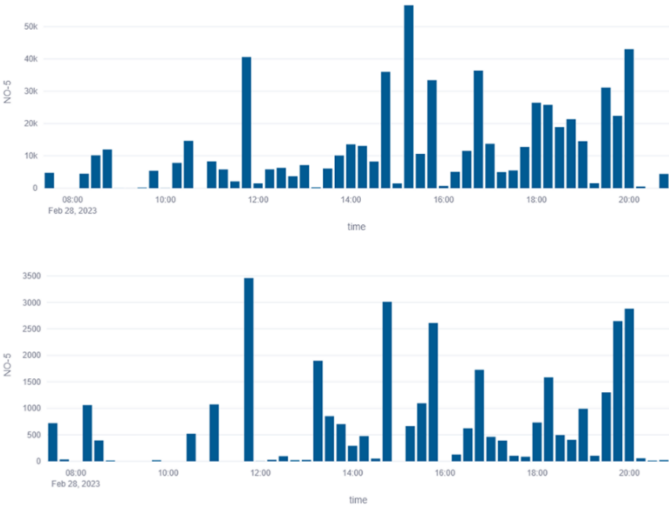


Figure 9. NO-5 indicator time distribution along the day. Top: 40 dBA threshold. Bottom: threshold corresponding to the background noise (Lday).

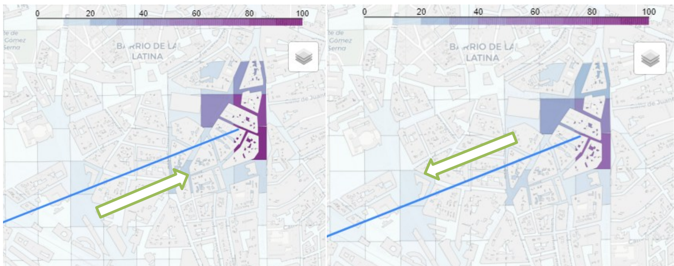


Figure 10. Results for VP-4 indicators for low-altitude and high-altitude trajectory at different altitude (visible area metric). Left: inbound flight, altitude 56m. Right: outbound flight, altitude 72m.

Conversely, the largest saving was 25.7 minutes, achieved on Pair 3-F (from Hospital 12 de Octubre to HU Carlos III) with the RigiTech Eiger drone. A total of 180 flights per day were analyzed in this scenario.

Fig. 16 illustrates the average time savings over a 24-hour period. The blue line shows the absolute time reduction, which ranges from about 4.4 to 11.7 minutes. The red line represents the relative reduction, varying between 35% and 58%. The data shows the most significant savings happen in the evening, peaking at 11.7 minutes around 6:00 p.m., a 53.2% reduction. The highest relative reduction 57.9%, occurs around 7:00 p.m., with a saving of 10.2 minutes.

Overall, time savings are moderate in the early morning, increase slightly toward midday, and become most significant in the evening. This indicates that drone deliveries are most efficient during peak road traffic hours, when traffic congestion is at its highest point.

To illustrate how traffic and the day of the week affect the efficiency of drone deliveries for healthcare, we analyzed one full week of traffic data and presented the findings in Fig. 17. The figure shows the average travel time savings for each drone model, broken down by hospital pair and day of the week.

For all six hospital pairs, the average time savings stay fairly consistent from Monday to Friday. As expected, there is a moderate drop on Saturday and Sunday due to less road traffic.

The data confirms that the effectiveness of drone delivery for emergency medical supplies is most pronounced when road traffic is at its peak. Fig. 18 explores the connection between the road distance between hospitals and the time saved by using a drone, which highlights how traffic conditions impact flights. For instance, for a distance of 16,947 meters (Hospital pair 4), the time savings varied significantly, from 5 to 22 minutes, showing the effect of traffic variability. The overall data shows a positive correlation—as the distance between hospitals increases, so does the time saved.

This case study demonstrates how factors like traffic, distance, time of day, and day of the week influence the effectiveness of drones for emergency deliveries. By comparing flights with the same origin and destination, we found that the time saved varies based on urban traffic patterns and the specific drone model used.

- Smallest time saving reduction: The lowest time saving was 1.6 minutes, recorded at 3 a.m. on a Wednesday. This occurred with the DJI Matrice 600 drone on Hospital Pair 6-F (from La Paz to HU Carlos III), which aligns with expectations for early morning hours when road traffic is minimal.
- Largest time saving reduction: In contrast, the largest reduction was 25.7 minutes, recorded at 8 a.m. on a Tuesday—during the morning rush hour—with the Eiger drone on Hospital Pair 3-F (from Hospital 12 de Octubre to HU Carlos III). This highlights the significant advantage drones offer when urban roads are most congested.

On average, each flight saved 8.3 minutes, showing a consistent benefit from using drones even with varying traffic conditions. The total time saved for all flights conducted in a single day was 1502 minutes (or 25 hours). Based on these savings and the average flight duration between the selected hospitals, we estimate that the number of additional drone delivery flights that could be performed within the same operational window is 75 for the DJI Matrice 600 and 119 for the RigiTech Eiger. Additional analyses on estimating time savings and predictability of drone emergency deliveries are presented in a companion paper [20].

Figure 11. Results for VP-4 indicators for inbound and outbound trajectory at the same altitude (visible area metric). Left: inbound flight. Right: outbound flight. Altitude 66 m.

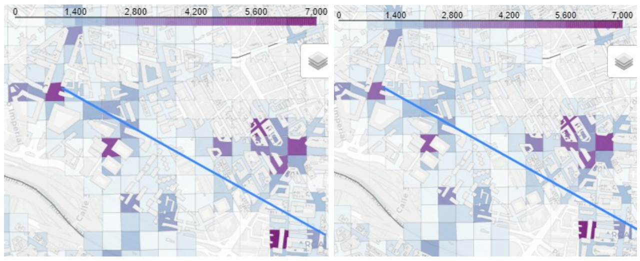


Figure 12. Results for VP-4 indicators for low-altitude and high-altitude trajectory at the same altitude (AiRMOUR metric). Left: inbound flight. Right: outbound flight. Altitude 66 m.

Figure 13. Results for PC-1 indicator. Left: Low-altitude trajectory (IN10226-B at 35m). Right: High-altitude trajectory (IN10481-F at 84m).

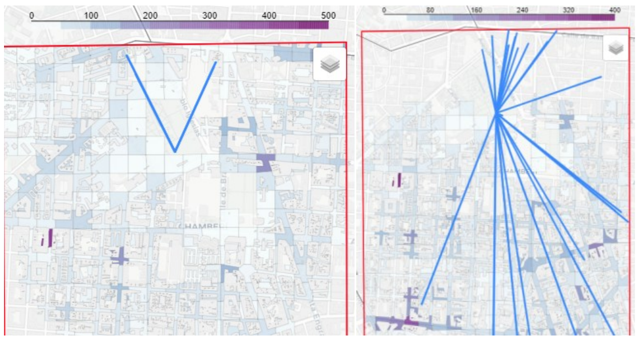


Figure 14. Results for PC-3 indicator. Left: morning period. Right: afternoon period.

IV. RECOMMENDATIONS AND LESSONS LEARNT

A. *Technical insights*

The MUSE project explored the innovative and uncertain domain of drone delivery, where technical, environmental, and social dimensions remain only partially defined. Developing and testing a performance framework for assessing impacts required addressing trajectory generation, noise and visual pollution, population exposure, and integration of UAM into urban environments, with expert contributions essential for validating indicators and assessing realistic impacts.

The MUSE Performance Framework is among the first to consolidate environmental and social impact indicators for UAM, including novel proposals, though further validation is needed via surveys, interviews, and iterative testing under various scenarios with preliminary thresholds for noise and visual pollution to strengthen the framework and ensure applicability.

Lessons were also drawn regarding traffic generation. A direct route is not necessarily the most efficient, since terrain elevation, altitude changes, and wind resistance may increase energy consumption and costs. Future routing algorithms should therefore evaluate multiple alternatives, balancing efficiency with environmental impacts. Integrating noise considerations at an early stage of trajectory planning will help to optimize routes in a socially responsible way.

Noise emission assessment proved particularly complex. Detailed noise source models are needed for absolute comparisons, while simplified or empirical models may suffice for scenario-level trends. Reliable background noise data is indispensable, and in some cases indoor exposure must also be considered. Results indicate that comprehensive evaluation requires a combination of metrics (e.g., LAeq, SEL and LAmax) rather than reliance on a single value. Population-weighted indicators also need further methodological development, including ways to visualize exposure ranges. An open question remains regarding the most appropriate time interval for assessment, since shorter periods provide greater detail while longer periods are standard in environmental acoustics.

Visual pollution caused by UAs represents a psychological impact and due to its subjective and complex nature, it is difficult to quantify. The perception of visual pollution significantly depends on the geographical location, type of area (urban, rural, city center, etc.), and demographic and socio-economic profiles of the affected population. Key contributing factors include the number of drones in the field of view, their size and flight altitude, and the duration of their presence overhead. However, public perception of visual pollution is not linear: a small number of drones may attract more attention than a large fleet, and noise can amplify visual disturbance. Establishing a baseline for acceptable visual impact is therefore essential, even if this threshold evolves as the novelty effect diminishes. Virtual reality simulations, supported by surveys and interviews, are promising tools for this purpose [6][21]. More systematic data collection across geographic regions and demographics will be required to inform predictive models and policymaking.

Accurate population mapping also plays a decisive role, as errors in estimating outdoor presence directly affect many indicators. Advances are needed in combining satellite imagery,

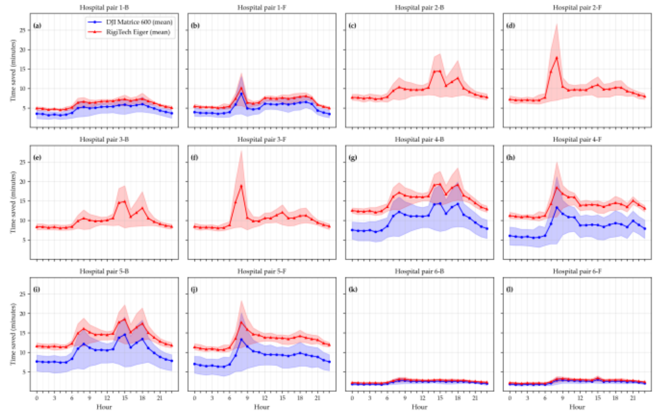


Figure 15. Average time saved by drone operations compared to road transport across 24 h of the day for six hospital pairs in both directions

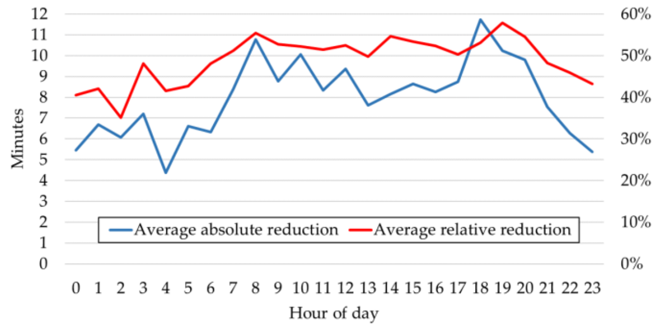


Figure 16. Absolute vs. relative average reduced travel time

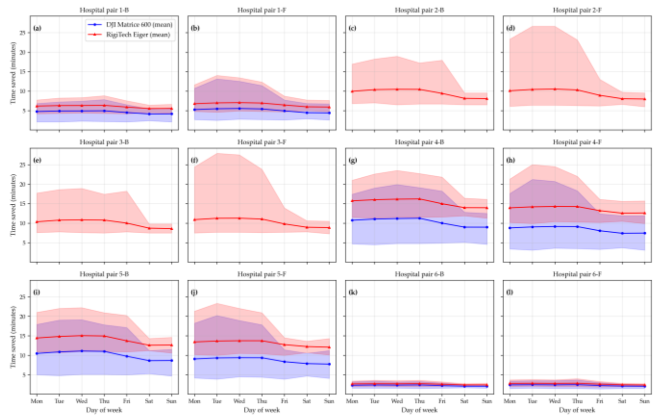


Figure 17. Average reduced travel time per day of the week for six hospital pairs in both directions (B-backward, F-forward)

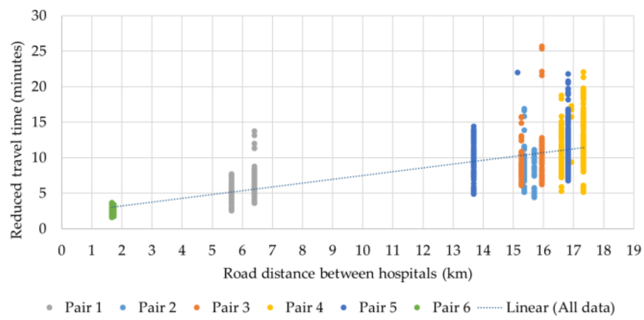


Figure 18. Correlation between hospital road distance and reduced travel time

Figure 19.

GPS traces, and statistical methods, as well as addressing biases caused by underground transport systems. Broader and more granular datasets will ultimately enable fairer and more reliable exposure estimates.

B. *Policy implications*

The findings of the MUSE project highlight several implications for policy and governance. UAM operations in a city directly affect residents, making it essential to integrate environmental and social assessments into the Concept of Operations (ConOps) and involve municipalities, authorities, operators, planners, and citizens.

Privacy concerns in UAM should not be treated as a regulatory issue separately but as interconnected with visual pollution and noise exposure, especially during low-altitude operations. People often assume drones carry cameras, which, combined with a lack of information about their purpose, creates discomfort and distrust. Sensitivity to drone presence varies across locations and populations, with factors like gender, age, and cultural context playing a role, and should therefore be part of holistic UAM impact assessments.

Access and equity are essential for the fair development of UAM systems. Policy frameworks should not only focus on the equitable distribution of services but also on the equity in exposure to negative environmental and social impacts.

The project's case studies reinforced these lessons. Parcel delivery operations provided a solid baseline, though results represent theoretical boundaries rather than predictions due to threshold uncertainties. Expanding to semi-urban and rural settings, considering different meteorological conditions, and analyzing the coexistence of parcel and emergency deliveries will strengthen future studies. Results also suggest trade-offs: free-route concepts appear to reduce visual impact, while grid-based networks help to mitigate noise. Emergency delivery scenarios, already operational in parts of Europe, require further analysis under traffic congestion, potential collaboration with medical vehicles, and variations in drone speed.

In summary, the MUSE project demonstrates that advancing UAM requires an integrated approach, combining robust performance frameworks, carefully designed operational concepts, validated indicators, and participatory governance. Balancing efficiency and service benefits with environmental protection and social acceptance will be essential for drone operations to evolve into a safe, sustainable, and equitable component of the urban environment.

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