**COLL**aborative network on unmanned **A**e**RI**al **S**ystems

# D4.1B – OVERVIEW OF CURRENTLY USED AND POSSIBLE TECHNICAL SOLUTIONS FOR DATA ANALYSIS AND DATA SHARING, INCLUDING COMMON PRACTICES: ASSESSMENT AND RECOMMENDATIONS FOR FUTURE USE.

## WP4 – Solutions for data analysis and data sharing and auxiliary support systems

**Deliverable type:** Report

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**Date:** 24 June 2024

**COLLARIS partner organizations:**

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# Executive Summary

This deliverable presents an assessment of currently used technical solutions for data analysis and data sharing, with a specific focus on Unmanned Aerial Systems (UAS) data. The aim of this document is to provide an overview of the state of the art in UAS data analysis and sharing, including key practices and recommendations for future implementation.

The first part of this deliverable focuses on UAS data analysis, highlighting its importance in various sectors. The key steps involved in the UAS data analysis process are outlined, emphasizing the need for accurate and efficient analysis techniques. An overview of the state-of-the-art solutions for UAS data analysis is then provided. These include image solutions such as image processing and computer vision, photogrammetry, LiDAR data analysis, data fusion, machine learning and artificial intelligence, real-time analytics, and Geographic Information Systems (GIS). Each solution is briefly explained, highlighting its potential applications and benefits in UAS data analysis. To ensure effective implementation, we also present an overview of common best practices in UAS data analysis. These practices encompass data quality assessment, standardization of processing workflows, validation techniques, and result interpretation. By adopting these best practices, organizations can optimize their UAS data analysis processes and achieve more reliable outcomes.

The next part addresses UAS data sharing, providing a general introduction and describing the associated process. The importance of data sharing for collaboration, research, and decision-making is emphasized. An overview of state-of-the-art technological solutions for UAS data sharing are then discussed. This includes cloud-based platforms, data repositories, and specialized data sharing tools. We highlight their key features, security considerations, and interoperability capabilities to facilitate efficient sharing of UAS data among stakeholders. In addition, we outline common best practices for UAS data sharing, such as data formatting standards, metadata inclusion, data access controls, and data privacy considerations. These practices help ensure the secure and effective exchange of UAS data while maintaining data integrity and confidentiality.

A short list of available software packages for UAS data analysis and sharing is provided, highlighting their key feature and functionalities. Finally, based on the assessment conducted, we offer future recommendations for UAS data analysis and sharing. These recommendations include exploring emerging technologies, enhancing automation capabilities, integrating real-time analytics, and promoting data standardization. The implementation of these recommendations will further advance the efficiency and effectiveness of UAS data analysis and sharing practices.

In summary, this deliverable provides a comprehensive overview of currently used technical solutions for UAS data analysis and sharing. By leveraging state-of-the-art techniques and adopting best practices, organizations can unlock the full potential of UAS data and derive valuable insights for their respective domains. The recommendations outlined herein aim to drive continuous improvement and innovation in UAS data analysis and sharing.

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# About COLLARIS

Scientific advances as well as fast-evolving drone technology and its applications have today become indispensable in all phases of the disaster risk management cycle. COLLARIS is a capacity-building initiative to develop a sustainable European network of scientific, engineering, and end-user expertise related to unmanned aerial systems (UAS) in civil protection and disaster response. COLLARIS covers the following thematic focus areas:

- Identification and sharing of operational procedures, lessons learnt, and best practices using UAS
- Elaboration of air traffic management challenges, solutions, and operational practices
- Acquisition of solutions for data analysis and data sharing, as well as auxiliary support systems (e.g. simulators)
- Development of methods for increasing end-user competences
- Foresight of new developments and future use case scenarios to identify tomorrow's needs and gaps, technological capabilities, and their potential applications

The general concept of COLLARIS is based on two assumptions: That the technical capabilities related to UAS will continue to develop rapidly, as will the scope of their application for civil protection and crisis management purposes; and that the gap between these recently created technical capabilities and the practical needs and operational practices of civil protection not utilising them yet will remain a permanent challenge. Therefore, there is a clear need for establishing a stable long-term mechanism to continuously support the civil protection community in gradual implementing innovations enabled by UAS developments. The COLLARIS-based community will make an important contribution to achieve that.

COLLARIS will offer a networking platform as part of the Union Civil Protection Knowledge Network for information exchange and experimentation with advanced concepts of UAS for disaster response and crisis management. These activities are accompanied by thematic workshops, webinars, and moderated discussions as well as trials and embedded first responder trainings, aimed at increasing the efficiency of UAS operations by bringing knowledge closer to operational use.

Representatives of civil protection authorities at all levels, first responders, crisis management practitioners, and researchers interested in issues related to further development and operational use of UAS in their activities are cordially invited to join the COLLARIS Network initiatives.

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# About this deliverable

This document is the first output for Task 4.1 which provides an overview of current and potential technical solutions for data analysis and sharing. The aim is to assess common practices and make recommendations for future use. This task is expected to generate discussions that will lead to 2-3 thematic workshops. Further research will focus on comparing available features. Specific solutions and practices will be identified and tested in future trial activities. Once the trials are complete, a summary workshop will be organized to finalize the report and prepare recommendations by the end of the project.

The current deliverable provides a comprehensive overview of currently used technical solutions for UAS data analysis and sharing, common best practices, available software packages, and future recommendations.

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# List of Abbreviations

| | |
|---|---|
| AI | Artificial Intelligence |
| APIs | Application Programming Interfaces |
| AR | Augmented Reality |
| CNNs | Convolutional Neural Networks |
| DEM | Digital Elevation Model |
| DLT | Distributed Ledger Technologies |
| GCPs | Ground Control Points |
| GDI | Geospatial Data Infrastructure |
| GEOINT | Geospatial Intelligence |
| GIS | Geographic Information Systems |
| GPS | Global Positioning System |
| IMU | Inertial Measurement Unit |
| JAUS | Joint Architecture for Unmanned Systems |
| LiDAR | Light Detection and Ranging |
| ML | Machine Learning |
| PM | Particulate Matter |
| RGB | Red, Green, Blue |
| SHE | Secure Homomorphic Encryption |
| STANAG | Standard and Agreement |
| TIN | Triangulated Irregular Network |
| UAS | Unmanned Aerial Systems |
| UAV | Unmanned Aerial Vehicles |

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# 1 INTRODUCTION

UAS, commonly known as drones or unmanned aerial vehicles (UAV), have become an incredibly useful tool in collecting data across a range of industries. They are versatile and powerful in fields such as environmental monitoring, infrastructure inspection, agriculture, disaster response, and more. UAS provide a cost-effective solution for gathering high-resolution aerial imagery and other sensor data, allowing researchers, professionals, and organizations to make informed decisions and gain valuable insights. They can be equipped with a range of sensors and payloads that capture data from the environment. These sensors can vary depending on the specific application and data requirements. A detailed overview of UAS payload sensors is depicted in Table 1.

| UAS Payload sensor | Description | Applications |
|---|---|---|
| RGB (Red, Green, Blue) Cameras | They capture visible light imagery, similar to conventional digital cameras with high-resolution images as output. | visual analysis<br>mapping |
| Thermal Cameras | They capture infrared radiation emitted by objects and can detect temperature variations. | thermographic inspections<br>search and rescue operations<br>monitoring heat signatures |
| Multispectral Cameras | They capture imagery in specific wavelength bands beyond the visible spectrum, such as near-infrared and ultraviolet. | vegetation analysis<br>crop health assessment<br>environmental monitoring |
| Hyperspectral Sensors | They capture many narrow spectral bands across the electromagnetic spectrum and provide detailed spectral information. | mineral exploration<br>precision agriculture<br>environmental monitoring |
| LiDAR (Light Detection and Ranging) Sensors | They emit laser beams and measure the time it takes for the beams to bounce back after hitting objects, capturing detailed 3D point cloud data. | terrain mapping<br>building reconstruction<br>vegetation analysis |
| Gas and Chemical Sensors | They measure atmospheric conditions, air quality, or detect specific gases. | environmental monitoring<br>pollution tracking<br>industrial inspections |
| GPS and IMU | UAS relies on GPS (Global Positioning System) and IMU (Inertial Measurement Unit) sensors for navigation, positioning, and attitude estimation. | flight control<br>accurate geolocation<br>data synchronization |
| Magnetometers | They measure magnetic fields. | geomagnetic surveys<br>metal detection<br>navigation in areas with magnetic anomalies |
| Laser Altimeters | They measure the distance between the UAS and the ground surface using laser pulses providing accurate terrain elevation data. | surveying<br>mapping |
| Air Quality Sensors | They measure parameters such as particulate matter (PM), gases, humidity, and temperature helping assess the environmental conditions during UAS flights and monitor air pollution levels. | environmental monitoring<br>pollution tracking |

**Table 1: Overview of UAS sensor payloads**

After gathering data using UAS, it's important to analyze it thoroughly in order to extract meaningful information and derive actionable insights. UAS data analysis involves a wide range of techniques, including image processing, photogrammetry, data fusion, machine learning, and others. These analytical methods aim to reveal patterns, trends, and relationships within the data, facilitating informed decision-making and improving operational efficiency. UAS data analysis isn't limited to just one field since it has applications in diverse areas such as agriculture, forestry, urban planning, environmental management, infrastructure assessment, and disaster response. Being able to quickly acquire and analyze data from UAS provides a powerful toolset for addressing complex challenges in these domains, allowing for more accurate assessments, timely interventions, and effective resource allocation.

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In addition to analysis, the sharing of UAS data plays a crucial role in promoting collaboration, transparency, and the advancement of research and applications. UAS data sharing involves making datasets, processed results, and associated metadata accessible to other stakeholders, researchers, or the general public. This sharing process promotes data-driven decision-making, reproducibility, innovation, and knowledge dissemination. However, sharing UAS data also raises concerns over privacy, data security, intellectual property, as well as legal and ethical considerations. Therefore, it is crucial to establish appropriate protocols, frameworks, and standards for UAS data sharing to ensure responsible and ethical use of the collected data.

In the rest of this deliverable, we present an overview of UAS data analysis and sharing methods. We discuss the fundamental concepts, challenges, and best practices associated with analyzing UAS data, as well as methods for sharing the data in a secure and efficient manner. Moreover, we provide available software packages that utilize methods for UAS data analysis and sharing along with possible future recommendations for further utilization of UAS data while promoting innovation, collaboration, and responsible use of UAS technology.

# 2 UAS DATA ANALYSIS

UAS data analysis involves analyzing and interpreting data collected by UAS from a range of onboard sensors (as listed in Table 1). This process is used in many industries and applications where the data from UAS can provide valuable insights and benefits [1]. For instance, UAS data analysis is commonly used in aerial mapping and surveying to create precise digital elevation models, orthomosaic maps, and 3D terrain reconstructions that are useful in urban planning, infrastructure development, and land management. Disaster response and emergency management is another critical use case where UAS data analysis plays a crucial role in providing real-time situational awareness, damage assessment, and helps identify areas in need of assistance [2]. Furthermore, it assists in search and rescue operations, monitoring disaster-affected regions, and coordinating relief efforts. UAS data analysis is also valuable in environmental monitoring and conservation, as it can help to monitor environmental changes, assess biodiversity, track deforestation, and analyze ecosystem health. It can also provide insights into climate change, habitat monitoring, wildlife surveys, and natural resource management. Other use cases include infrastructure inspection, agriculture and crop monitoring, as well as surveillance and security [3]. Overall, data analysis is an important process that interprets raw data from UAS onboard sensors into valuable and meaningful information.


**Figure 1: Key steps for UAS data analysis.**

The UAS data analysis process typically involves key steps to extract meaningful insights from the collected data, as shown in Figure 1. The first step involves data collection (e.g., images, LiDAR point clouds, thermal data, etc.) from UAS through onboard sensors and payloads. This step requires proper flight planning, sensor settings, and data capture techniques to collect high-quality data. The second step is pre-processing the collected data to prepare it for analysis. This involves organizing and cleaning the data, removing any noise, outliers, or artifacts and may involve georeferencing the data and aligning it with a known coordinate system if necessary. Next, if data has been collected from multiple sensors or flights, the data integration step aligns the data and ensures compatibility across different sources. Data analysis follows, where appropriate techniques are applied, such as statistical analysis, machine learning algorithms, geospatial analysis, or other domain-specific methods, depending on objectives and data nature. Validation and quality control come next, where analysis results are compared with ground truth data, reference datasets, or expert knowledge to ensure output accuracy, reliability, and consistency. Lastly, interpretation and visualization occur, where data analysis results are interpreted and visualized through maps, charts, graphs, or interactive dashboards, enabling precise and meaningful presentation of findings for decision-making.

Generally, the use of UAS data analysis has several benefits. UAS data collection is more flexible, cost-effective, and secure than traditional methods such as field surveys, manned aircraft, or satellite imagery. Moreover, UAS can access remote, inaccessible, or hazardous areas that are challenging or dangerous to reach by other means [4]. Additionally, with the available variety of payloads, UAS can collect high spatial and temporal resolution data, capturing fine-scale details and changes in natural resources. This data through analysis can support decision-making and natural resource management by providing timely and accurate information. Nevertheless, UAS data analysis also presents some challenges [5]. For instance, UAS data can be affected by various technical, operational, and environmental factors that can introduce errors, uncertainties, and biases in the data. Sensor quality, flight altitude, speed, angle, lighting conditions, weather, and vegetation cover are some of these factors. Additionally, UAS data analysis requires specialized skills, equipment, and software to collect, process, and analyze the data. Proper training and certification are necessary for UAS pilots to operate UAS safely and legally. Data analysts need to have knowledge of photogrammetry, image processing, feature extraction, and validation methods. Furthermore, legal, ethical, and social issues can limit or restrict the use of UAS in certain areas or situations. For example, UAS operations need to comply with the regulations and policies of the relevant authorities regarding airspace, privacy, security, wildlife protection, etc. Finally, UAS data users must respect the rights and interests of the data owners and stakeholders.

UAS data analysis has proven to be an incredibly valuable tool across various industries, offering detailed insights and improving decision-making processes. Its potential for scientific research, infrastructure planning, environmental conservation, agriculture, and disaster management is immense, and continued development and integration are crucial for addressing complex challenges and driving innovation. Below, we provide a comprehensive list of state-of-the-art data analysis solutions, with descriptions for each.

## 2.1 State-of-the-art solutions

Advanced computational techniques and machine learning algorithms have spawned various UAS data analysis solutions to extract meaningful insights, identify patterns, and enable informed decisions [1]. These solutions offer unique capabilities and can be used for different types of UAS data analysis tasks. To choose the right solution, one must consider the specific requirements of the application, the nature of the data to be analyzed, and the desired outcomes. Integrating multiple solutions can provide a more comprehensive and powerful analysis framework, leveraging the strengths of each approach. The field is rapidly evolving with new techniques and advancements continually emerging, enabling more sophisticated analysis and insights from UAS-collected data. Figure 2 shows an overview of the main categories of UAS data analysis solutions and their available techniques which will be discussed in more detail in the following sections.

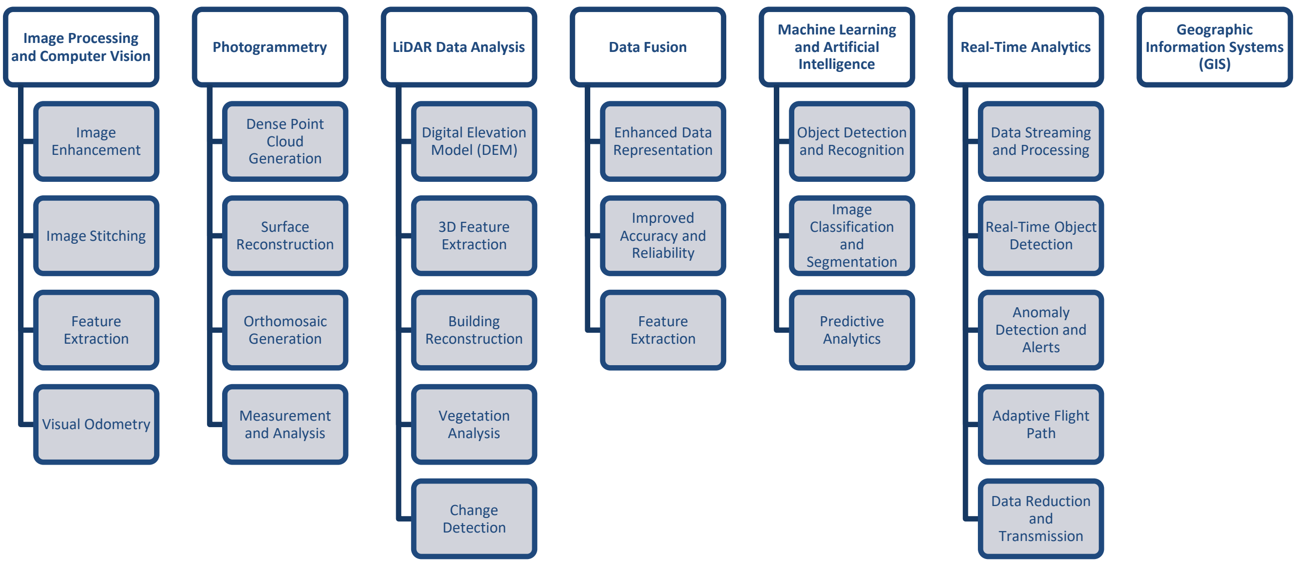


**Figure 2: UAS data analysis solutions.**

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## Image Processing and Computer Vision

Utilizing image processing and computer vision techniques, valuable information can be extracted from UAS imagery, making it useful for a wide range of applications such as surveillance, infrastructure inspection, and environmental monitoring [6]–[8]. These techniques improve the analysis capabilities and provide insights from visual data collected by UAS. Specifically, image processing enhances the quality of the imagery, corrects distortions, and facilitates accurate analysis. Computer vision algorithms are also utilized to process and analyze images and videos captured by UAS cameras. This includes tasks such as object detection, image classification, feature extraction, and image stitching. The techniques falling under this solution category are discussed below.

**Image Enhancement:** Image enhancement techniques are applied to improve the quality and clarity of UAS imagery [9]. This may involve adjusting brightness, contrast, or sharpness, reducing noise, or enhancing specific image features to make them more distinguishable. Additionally, any geometric distortions caused by factors such as lens distortion, camera tilt, or perspective effects are corrected to ensure accurate measurements and spatial analysis.

Figure 3: Example of image enhancement [9].

**Image Stitching:** Image stitching algorithms merge multiple UAS images that overlap, creating a seamless and continuous larger image or mosaic [10], [11]. These algorithms align the images, correct geometric distortions, and blend the overlapping areas to produce a visually coherent composite image. Image stitching is beneficial for constructing orthomosaic maps, panoramic views, or large-scale visual representations.

Figure 4: Example of UAS imagery stitching [10].

**Feature Extraction:** Feature extraction algorithms identify and extract meaningful features from UAS images [12], [13]. These features can include edges, corners, textures, or other distinct visual patterns. Feature extraction aids in tasks such as image matching, change detection, or object recognition.

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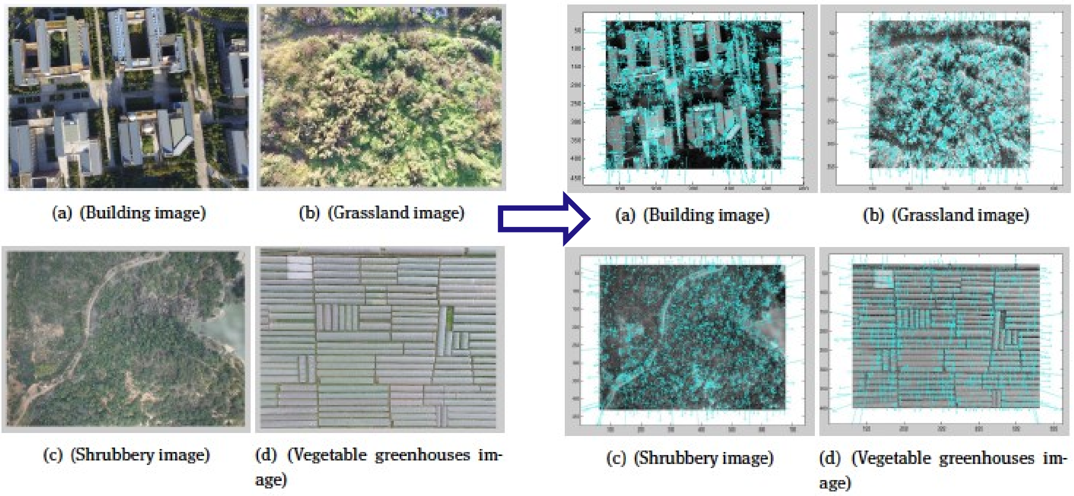


**Figure 5: Example of feature extraction from UAS imagery [12].**

**Visual Odometry:** Visual odometry algorithms estimate the UAS's position and orientation by analyzing sequential UAS images [14]. These algorithms track and match visual features across consecutive frames to compute the UAS's motion trajectory. Visual odometry assists in navigation, mapping, and autonomous flight control.

## Photogrammetry

Photogrammetry is a powerful technique for analyzing data collected by UAS. It can create detailed and precise 3D models, terrain reconstructions, and orthomosaic maps [15]. This technique uses the overlapping images captured by UAS cameras to gather accurate spatial information which can be applied to different industries and emergency response scenarios [16]. To achieve accuracy, photogrammetry requires a series of overlapping images taken from different angles during UAS flights. It is important to ensure that there is enough overlap between each image and that the entire area of interest is covered. These overlapping images help to identify common features that are necessary for accurate matching and reconstruction. These features include details like corners, edges, and textures from these images, which are then matched to establish corresponding points that allow for the determination of spatial relationships between images. Some of the most used applications of photogrammetry are discussed further below.

**Dense Point Cloud Generation:** Photogrammetry algorithms generate a dense point cloud by triangulating the matched feature points in the overlapping images [17]. The dense point cloud represents the 3D coordinates of the scene's surface providing detailed geometric information which have many applications in various fields. For instance, a dense point cloud can be used to create 3D models of objects and environments, survey large areas and create detailed maps, monitor construction sites tracking progress, and help agriculture in monitoring crop health and growth.

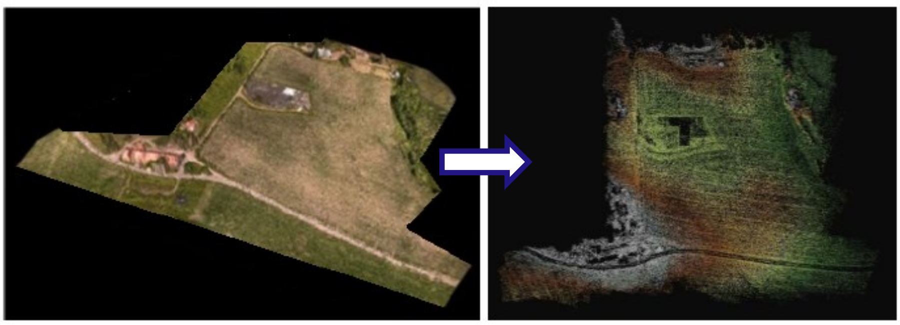

**Figure 6: Example of point cloud generation from UAS acquired RGB image [17].**

**Surface Reconstruction:** Based on the dense point cloud, photogrammetry algorithms reconstruct the scene's surface by generating a digital elevation model (DEM) or a triangulated irregular network (TIN) representing the terrain or object surfaces with accurate spatial information [18]. Specifically, DEM is a raster-based representation of the terrain where each pixel represents the elevation value of the corresponding location on the ground. DEMs are commonly used in topographic mapping, land surveying, and terrain analysis. They enable the visualization of terrain features, such as hills, valleys, and ridges, and support calculations of slope, aspect, and volume measurements. TINs, on the other hand, are vector-based and use triangular facets to represent complex surfaces with irregular geometry, such as buildings or objects. TINs offer a more accurate representation of surface morphology and can be used for 3D modeling, visualization, and analysis. Both DEMs and TINs provide valuable information for various applications, such as terrain analysis, hydrological modeling, flood mapping, land cover classification, and 3D scene visualization. They can also be integrated with other geospatial datasets, such as aerial imagery or GIS layers, to support further analysis and decision-making processes.

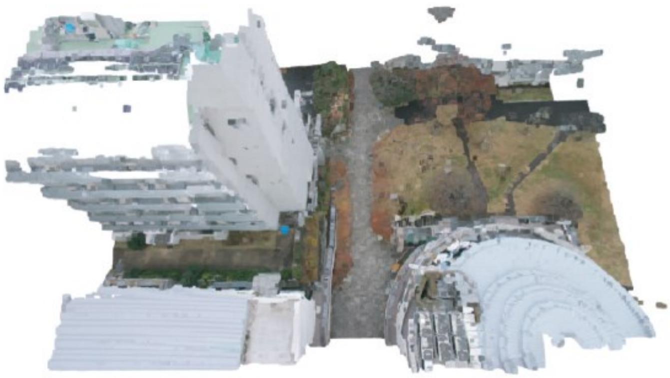

**Figure 7: Example of a digital elevation model (DEM) [18].**

**Orthomosaic Generation:** Orthomosaic maps are created by projecting the UAS images onto the surface model, correcting for perspective distortions and relief displacements. The orthomosaic provides a geometrically accurate representation of the area, allowing for precise measurements and planimetric analysis. Orthomosaics can be used for land mapping, asset inventory, and visualization purposes.

**Figure 8: Orthomosaic map generation through UAS images [19].**

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**Measurement and Analysis:** Photogrammetry enables various measurements and analyses, such as distance measurements, area calculations, volume estimations, and change detection. These measurements are performed on the reconstructed 3D models or orthomosaic maps, providing valuable information for applications like land surveying, construction planning, and environmental monitoring.

### LiDAR Data Analysis

UAS equipped with LiDAR (Light Detection and Ranging) sensors can capture point cloud data which can be processed using specialized algorithms to derive accurate 3D representations of the environment. [20]. LiDAR data analysis has many applications, including terrain modeling, elevation mapping, vegetation analysis, and building reconstruction. To generate this data, a LiDAR sensor on board a UAS emits laser pulses and measures the time it takes for the pulses to bounce back after hitting objects on the Earth's surface. This creates a dense point cloud dataset, with each point representing a 3D coordinate in space. However, the data often requires pre-processing steps to remove noise, outliers, and artifacts using filtering techniques such as statistical outlier removal, ground point classification, and vegetation filtering. By rendering the point cloud data, visually appealing and interactive 3D models can be created for virtual tours, simulations, and immersive visualizations. LiDAR data can be integrated with other data sources, such as aerial imagery or GPS data, to enhance the analysis capabilities and create colorized point clouds or textured 3D models, providing a more realistic representation of the environment. The main uses of UAS LiDAR data analysis are discussed below.

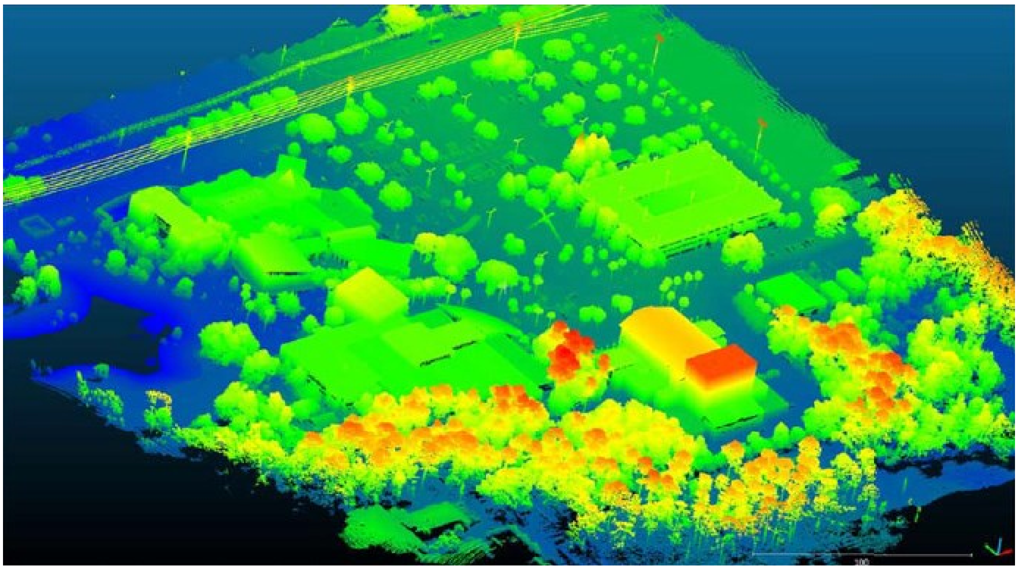

**Figure 9: Point cloud generated from UAS LiDAR data [20].**

**Digital Elevation Model (DEM) Generation:** LiDAR point cloud data can be processed to generate a Digital Elevation Model (DEM) which represents the bare Earth surface without any above-ground objects. DEMs offer valuable information for a variety of applications, such as terrain modeling, landform analysis, slope determination, and land cover classification. They also serve as a foundation for accurate elevation mappingwhich can be used to create contour lines, hillshades, and 3D representations of landscapes. Moreover, DEMs can aid in floodplain mapping and analysis as well as hydrological modeling, by providing information on flow direction, flow accumulation, and watershed delineation. Lastly, DEMs can help with environmental planning by providing insights into landforms, land cover changes, and suitability analysis for various purposes, such as infrastructure development or habitat assessment.

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**3D Feature Extraction:** LiDAR data analysis enables the extraction of 3D features from the point cloud, such as buildings, trees, power lines, or other objects of interest. The process involves utilizing techniques like point cloud segmentation, classification, and object recognition to identify and extract these features.

**Building Reconstruction:** LiDAR data can be utilized to generate detailed 3D models of buildings and structures [21]. By analyzing the point cloud, algorithms can identify building boundaries, roof structures, and other architectural elements. This information is useful for urban planning, infrastructure management, and construction applications.

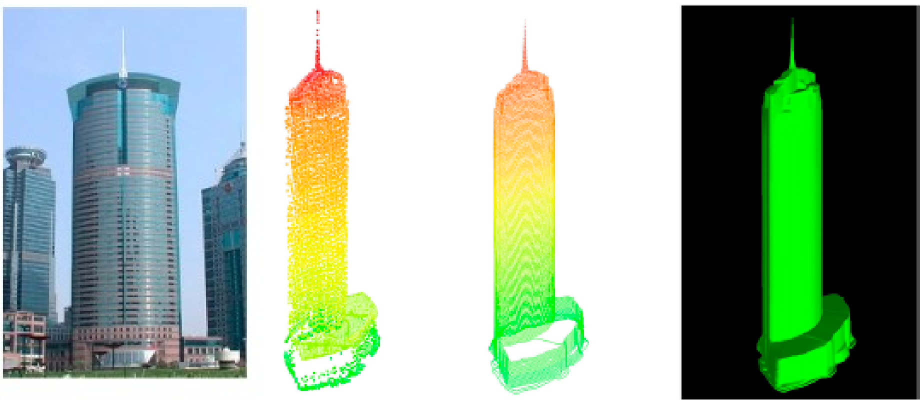

**Figure 10: Example of building reconstruction after UAS LiDAR data analysis [21].**

**Vegetation Analysis:** Analysing LiDAR data can provide valuable insights into vegetation characteristics and structure. Algorithms can extract useful vegetation metrics like canopy height, tree density, biomass estimation, and vegetation classification from the point cloud. Such information is crucial for forestry management, ecological studies, and environmental monitoring.

**Change Detection:** LiDAR data analysis allows for the comparison of multiple LiDAR datasets acquired at different times to detect changes in the environment. Algorithms can recognize changes in vegetation growth, land coverage, or structural modifications by assessing LiDAR point clouds. Detecting changes is effective in overseeing land use, tracking forest disruptions, and assessing the impact of natural disasters.

## Data Fusion

UAS can be equipped with multiple sensor payloads simultaneously, such as RGB cameras, thermal cameras, multispectral sensors, LiDAR scanners, or hyperspectral imagers (see Table 1). Each sensor captures different types of data and provides unique insights about the environment. Data fusion techniques combine and integrate these different data sources to create comprehensive and enriched datasets for analysis [22]. For optimal results, it is important to align the data acquired from different sensors to a common coordinate system or reference frame, ensuring that the data from different sources are spatially consistent. Additionally, it's essential to register the data from different sensors to establish correspondences between the acquired data points or pixels, enabling coherent fusion and analysis. Data fusion algorithms, such as rule-based, statistical, or machine learning-based approaches, can then be employed to integrate the data from multiple sensors and sources, exploit the complementary nature of the data, and provide a unified representation for analysis. Overall, data fusion enhances the accuracy, reliability, and insights derived from UAS data, supporting various applications across industries such as agriculture, infrastructure management, environmental monitoring, and more. Below the main benefits of UAS data fusion are presented.

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Figure 11: 3D building model generation from fused UAS data [22].

**Enhanced Data Representation:** Data fusion creates comprehensive and enriched datasets that go beyond the capabilities of individual sensors. For example, combining RGB imagery with LiDAR point clouds can result in colorized point clouds or textured 3D models, providing a more realistic and detailed representation of the environment. Moreover, it can enable precise object detection and classification, accurate vegetation mapping, or detailed infrastructure modeling. Overall, data fusion enhances data representation, facilitating more accurate analysis and interpretation.

**Improved Accuracy and Reliability:** Data fusion improves the accuracy and reliability of the derived insights by integrating multiple data sources. The fusion of complementary information helps to fill gaps, reduce uncertainties, and mitigate limitations inherent in individual sensor data. It enhances the robustness of analysis outcomes and supports more informed decision-making.

**Feature Extraction:** Data fusion enables the extraction of complementary features from different sensor data. For example, RGB imagery provides visual information about surface appearance, while LiDAR point clouds provide detailed 3D structural information. By fusing these data sources, it becomes possible to extract both visual and geometric features, enhancing the analysis capabilities.

## Machine Learning and Artificial Intelligence

UAS data analysis often involves Machine Learning (ML) and Artificial Intelligence (AI) techniques [23]–[26]. These techniques can automatically detect patterns, classify objects, identify anomalies, and make predictions based on the data collected. With ML models, it's possible to train the system to recognize specific objects or features in the imagery, enabling automated analysis and decision-making. Supervised learning is the most common ML approach, where models are trained on labeled data, such as annotated images or classified point clouds. With labeled data, ML models can be trained for certain tasks such as recognising specific objects, classifying land cover types, identifying anomalies, etc. Unsupervised learning techniques are applied when labeled training data is unavailable. Unlabeled images or unclassified point clouds collected from UAS sensors can be used with unsupervised learning algorithms to discover patterns, clusters, or anomalies in the data. This can assist in tasks like data exploration, anomaly detection, or unsupervised segmentation. Deep learning is a subfield of ML that utilizes artificial neural networks with multiple layers to extract complex features and learn hierarchical representations from data. Convolutional Neural Networks

(CNNs) are commonly used in UAS data analysis for tasks like image classification, object detection, or semantic segmentation. Leveraging ML and AI techniques for UAS data analysis can allow tasks automation, extract meaningful insights, and enable predictive capabilities. These technologies enhance the efficiency, accuracy, and scalability of UAS data analysis workflows, supporting a wide range of applications such as surveillance, infrastructure inspection, precision agriculture, environmental monitoring, and more. Below are some of the main uses of ML and AI.

**Object Detection and Recognition:** ML and AI techniques enable the detection and recognition of objects of interest in UAS imagery [27], [28]. Object detection algorithms can locate and identify specific objects, such as people, buildings, vehicles, vegetation, infrastructure elements, and other pre-determined targets within the images. Object recognition algorithms can then classify these objects into predefined categories, which allows for automated analysis and decision-making. These techniques are particularly useful in emergency response applications as they enable real-time or near-real-time identification and analysis of objects or targets that are of interest [29]. By automatically detecting and analyzing objects of interest, they can assist in search and rescue operations, damage assessment, fire detection, hazardous material identification, crowd management, and traffic monitoring, enhancing the effectiveness and efficiency of emergency response efforts.

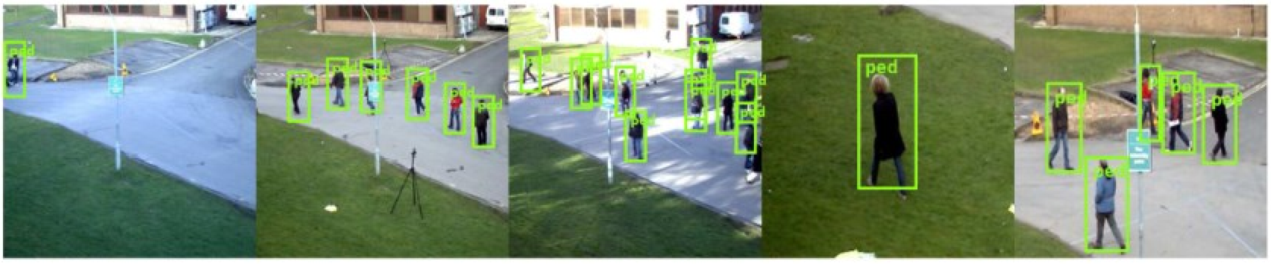

Figure 12: Object detection example using pedestrians [30].

**Image Classification and Segmentation:** Image classification algorithms assign predefined labels or classes to UAS images based on their visual characteristics. These algorithms can automatically categorize images into different classes, such as land cover types, vegetation species, or object categories. Similarly, ML algorithms can perform image segmentation to delineate different regions or objects within UAS images, aiding in detailed analysis and understanding. Image classification and segmentation help in land monitoring, environmental assessments, and agricultural applications.

Figure 13: Image segmentation example with vehicle segmentation [31].

**Predictive Analytics:** ML models can be trained to make predictions based on UAS data. For example, models can forecast changes in vegetation health, predict crop yields, estimate pollutant levels, or identify areas prone to erosion or flooding. These predictive capabilities assist in proactive decision-making and planning.

## Real-Time Analytics

UAS often have onboard processing units that perform real-time data analysis for quick decision-making during flights [32], [33]. This is especially helpful in applications like surveillance, search and rescue, and disaster response. Real-time analytics includes onboard data processing, analysis, and decision-making, enabling UAS platforms to make informed decisions or provide feedback to human operators. This feature is especially valuable in urgent situations like emergencies or disasters. Real-time analytics can also be combined with Augmented Reality (AR) to provide live overlays or visualizations of analyzed data during the flight, enhancing situational awareness and decision-making. By leveraging onboard processing units and deploying real-time algorithms, UAS platforms support immediate data processing, analysis, and decision-making during flights. Some examples of real-time analytics applications are presented below.

**Data Streaming and Processing:** UAS equipped with onboard processing units have the capability to process data in real-time while it's being collected. This allows instant data stream analysis, providing immediate insights and feedback during the flight. The data can be received from sensors like cameras or LiDAR and streamed to the onboard processing unit for analysis.

**Real-Time Object Detection:** During UAS flights, real-time analytics enables onboard object detection. Onboard processing units can deploy ML and AI algorithms to detect and track objects of interest, including vehicles, people, or specific targets, in real-time. This is especially useful in applications like surveillance, security, or search and rescue operations.

**Anomaly Detection and Alerts:** Real-time analytics enables the detection of anomalies or abnormal events during UAS flights. ML models can be trained to recognize patterns and identify deviations from normal conditions from the collected data. Upon detection of an anomaly, alerts or notifications can be generated in real-time, allowing for immediate action or further investigation.

**Adaptive Flight Path:** By utilizing real-time analytics, UAS can adjust their flight path and behavior based on analyzed data. For instance, the UAS can modify its route, altitude, or imaging parameters in response to real-time analysis results, ultimately enhancing data collection and targeting particular areas of interest.

**Data Reduction and Transmission:** Real-time analytics can include onboard data reduction techniques to minimize the amount of data that needs to be transmitted from the UAS platform to the ground station. This can involve compressing, summarizing, or selecting the most relevant data for transmission, optimizing bandwidth usage, and reducing latency.

## Geographic Information Systems (GIS)

GIS software is widely used in UAS data analysis [34]–[36]. GIS software allows for the seamless integration of UAS data with other geospatial datasets, such as aerial imagery, satellite imagery, topographic maps, or existing GIS layers. By combining these datasets, analysts can leverage the spatial relationships and attributes of different data sources, gaining a more comprehensive view of the study area. Additionally, GIS platforms enable the visualization, analysis, and modeling of UAS data in a spatial context in the form of maps, images, or three-dimensional representations. This visual representation aids in the interpretation and communication of UAS data, enabling stakeholders to easily understand and analyze the information captured by UAS. In general, GIS software is widely utilized in UAS data analysis due to its ability to integrate spatial data, visualize UAS data in a spatial context, perform spatial analysis, develop models and simulations, optimize routes, and facilitate data sharing and collaboration. These capabilities enhance the value and utility of UAS data, enabling tasks such as land cover classification, change detection, route planning, and various spatial analyses in diverse domains.

## 2.2 Common Best Practices

The rapid proliferation of UAS and the increasing utilization of their data across various industries have highlighted the importance of establishing common best practices for UAS data analysis [37]–[39]. These practices aim to ensure that the process of UAS data analysis is accurate, consistent, and reliable, while also promoting quality assurance, reproducibility, data interoperability, efficiency, safety, regulatory compliance, and ethical considerations. Ultimately, the goal of establishing these common best practices is to improve the credibility and reliability of UAS data analysis, encourage collaboration, and support the responsible and effective use of UAS technology in various scenarios. Figure 14 provides an overview of key common best practices when contacting data analysis utilizing UAS data which are described in the following paragraphs.


**Figure 14: Overview of UAS data analysis common best practices.**

**Define Clear Objectives:** It is important to establish clear objectives for your UAS data analysis project. This involves identifying the specific questions you want to answer or insights you want to gain. These objectives will serve as a guide for your data collection, processing, and analysis efforts.

**Plan Data Collection:** When planning your UAS data collection strategy, it is important to consider various factors such as flight paths, altitude, sensor settings, and weather conditions. Doing so will help optimize the quality and coverage of the data collected. It is also crucial to ensure that your flight plan aligns with the objectives of your analysis project.

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**Use Quality Sensors:** When selecting sensors and payloads for your application, it's important to choose high-quality ones suitable for your specific needs. To ensure accurate and reliable data, make sure the sensors are well-maintained and calibrated. Regularly checking and calibrating sensor measurements to reduce errors is also a good practice.

**Collect Sufficient Ground Control Points (GCPs):** When utilizing photogrammetry or LiDAR, it's crucial to gather a sufficient amount of GCPs to ensure precise georeferencing and data alignment. GCPs are specific points on the ground with accurate coordinates which ultimately enhances the accuracy of your analysis results.

**Ensure Sufficient Overlap:** Maintaining sufficient overlap between consecutive flight lines or adjacent images is important when capturing images or point clouds. This helps with accurate stitching, 3D reconstruction, and subsequent analysis by ensuring better feature matching.

**Maintain Data Integrity:** To preserve the accuracy of your UAS data, it's important to handle it with care. Make sure to securely store and transfer the data and have backup measures in place. Additionally, keeping detailed metadata and documentation will help with tracking and referencing the data in the future.

**Preprocess and Clean Data:** To ensure accurate and high-quality analysis, it's important to preprocess and clean your UAS data. This may include removing outliers, correcting sensor biases, applying noise filters, and getting rid of artifacts. By doing so, you can improve the accuracy and quality of your subsequent analysis.

**Employ Robust Data Analysis Techniques:** When analyzing data, it's important to use the appropriate techniques based on your objectives. This could entail utilizing statistical methods, machine learning algorithms, or specialized algorithms for image processing, point cloud analysis, or GIS analysis (see Section 2.2 for available techniques). Be sure to choose techniques that are suitable for your data type and research questions.

**Validate and Cross-Check Results:** To ensure the reliability of your findings, it's crucial to validate your analysis results with ground truth data or reference datasets, if possible. It's also recommended to cross-check your results with other sources of information or alternative analysis methods to verify their accuracy. Verification and validation are essential steps in the analysis process.

**Document and Communicate Results:** It's important to document your data analysis process, methodologies, and assumptions. Make sure to clearly communicate the results with visualizations, reports, and interpretations. Don't forget to provide context and caveats to help with understanding and decision-making.

**Regularly Update Skills and Knowledge:** Keep up-to-date with the latest developments in UAS technology and data analysis techniques. Enhance your skills and knowledge by participating in training sessions, workshops, and engaging with the research community.

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# 3 UAS DATA SHARING

UAS can carry various sensors, cameras, and data collection devices that capture a diverse range of information during flight operations. This includes aerial imagery, videos, LiDAR scans, thermal imaging, and other sensor readings. Sharing UAS data involves transferring, distributing, or granting access to this collected data to people, organizations, or systems that can benefit from it [40]–[43]. The goal of sharing UAS data is to encourage collaboration, analysis, decision-making, and generate more value from the gathered information.

UAS data sharing can take various forms depending on the specific use case and requirements. It may involve sharing raw data files, processed datasets, or derived products like maps, 3D models, or analytical reports. The data can be shared through cloud-based platforms, APIs, data exchanges, collaborative software tools, or other means of data transfer. Recipients of UAS data include stakeholders such as researchers, analysts, emergency responders, infrastructure managers, agricultural experts, environmentalists, and other professionals who can leverage the data for their specific purposes. UAS data sharing allows these stakeholders to access accurate, valuable, and timely information captured by UAS, facilitating informed decision-making, insights, and improved operational efficiency in their respective fields.

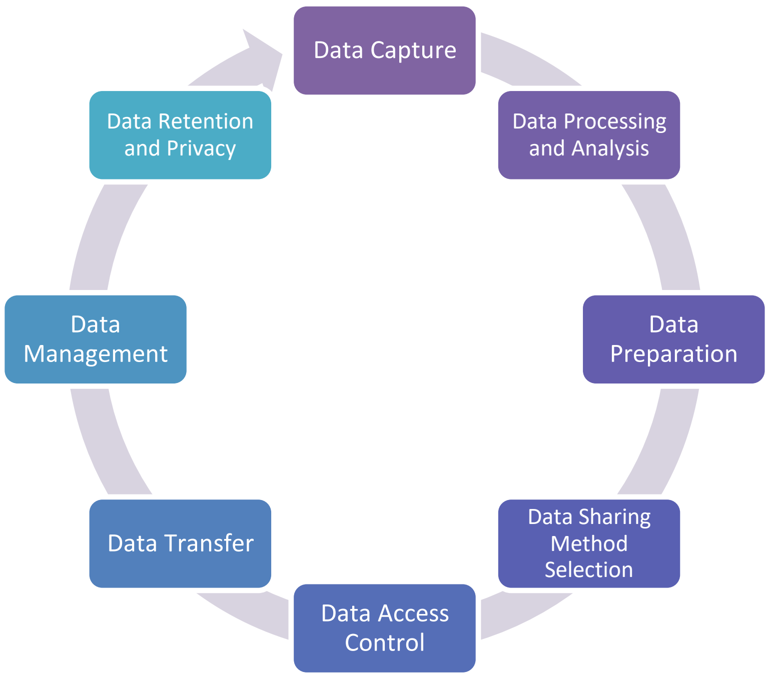


**Figure 15: UAS data sharing process.**

To ensure the secure and effective transfer of UAS data to intended recipients, data sharing generally involves some typical steps as depicted in Figure 15. First, the UAS is/are deployed to collect data using sensors, cameras, or other devices. After collecting the data, it may need to be processed or analyzed to extract useful information. This step can involve techniques such as calibration, stitching, georeferencing, image enhancement, or 3D modeling. The processed data is then prepared for sharing by organizing it into relevant datasets, creating metadata to describe its characteristics, and ensuring proper data formatting and compatibility with the chosen sharing method. Next, the most appropriate sharing method is selected based on factors such as data size, sensitivity, and recipient requirements. Data access control is set to ensure that only authorized individuals or organizations can access and use the data. The data is then transferred to

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recipients using the selected sharing method. This can involve uploading the data to a cloud-based platform, sending files via secure channels, granting access permissions to specific users, or using APIs to transfer data to integrated systems. Data management practices are implemented to track and monitor the shared data, including version control, usage tracking, and auditing for compliance with legal and regulatory requirements. Finally, retention policies and privacy considerations are taken into account, such as determining how long the data should be retained and whether it needs to be anonymized or aggregated. The UAS data-sharing process should be regularly reviewed and evaluated to identify areas for improvement, seek feedback from recipients, and adapt the process as needed to enhance efficiency, security, and value.

Sharing data effectively is essential to maximize the advantages of UAS operations and promote cooperation among involved parties. In the upcoming section, we will explore some of the most used methods of UAS data sharing.

## 3.1 State-of-the-art solutions

Effective data sharing is crucial for optimizing the benefits of UAS operations and enabling collaboration among stakeholders in various industries, such as agriculture, infrastructure inspection, aerial photography, and emergency response. Below is an overview of state-of-the-art technological solutions for UAS data sharing, which provides a snapshot of the current landscape and highlights key areas of focus in this domain. It's worth noting that the state of the art is constantly evolving, with new technological solutions being developed to enhance UAS data sharing capabilities.

### Cloud-based Platforms

Cloud-based platforms provide secure and scalable environments for storing, processing, and sharing of UAS data. With these platforms, UAS operators can upload, manage, and share their data with authorized users in centralized repositories. Examples of such platforms are Amazon Web Services, Microsoft Azure, and Google Cloud.

### Application Programming Interfaces (APIs)

APIs enable seamless integration between UAS platforms and third-party applications. UAS operators can use APIs to share data with external systems, including mapping software, data analytics tools, and GIS. APIs make real-time data exchange possible and help to streamline workflow processes.

### Geospatial Data Infrastructure (GDI)

GDI are platforms that facilitate the management of geospatial data, including data from UAS [44]. They provide centralized data catalogs, metadata management, and spatial data services, which allow UAS operators to publish and share their data with other users, agencies, or organizations.

### Distributed Ledger Technologies (DLT)

DLT, commonly known as blockchain, offers decentralized and tamper-proof data sharing capabilities [40]–[42], [45]. When UAS data is recorded on a blockchain, it can be securely shared among multiple parties while maintaining data integrity and auditability. Solutions based on blockchain technology improve trust, transparency, and accountability in UAS data sharing.

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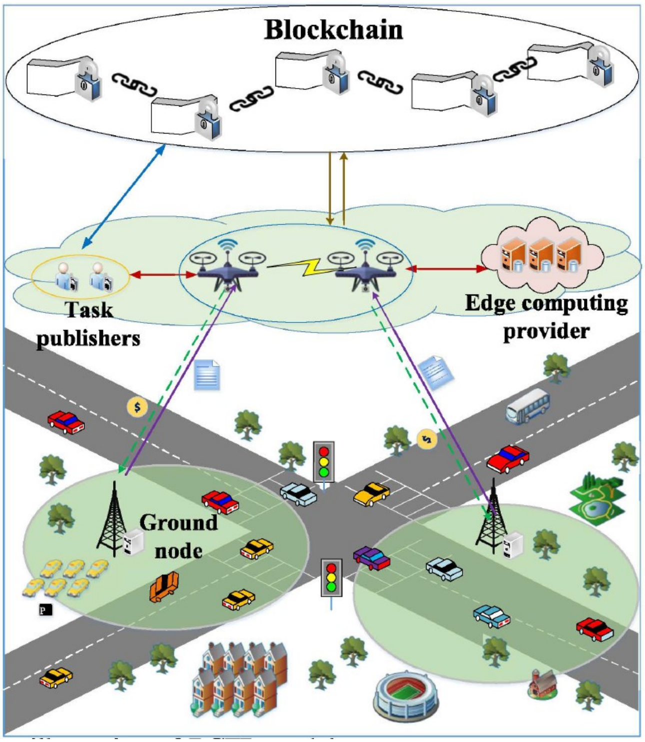


Figure 16: Example of blockchain-based data sharing architecture [40].

### Collaborative Platforms

Collaborative platforms allow multiple UAS operators and stakeholders to share data cooperatively. These platforms enable pooling of data, collaborative analysis, and joint decision-making. They improve coordination and exchange of information in scenarios involving multiple organizations or multi-UAS missions.

### Real-time Streaming and Telemetry

UAS platforms equipped with real-time streaming and telemetry capabilities allow for immediate sharing of data during flight operations. This means that live video feeds, sensor data, and telemetry information can be sent to ground stations or remote operators in real-time, which enables quick analysis and decision-making.

### Edge Computing

Edge computing entails the processing and analysis of UAS data at the network's edge, which is closer to the data source [46]. This approach utilizes edge computing capabilities to reduce latency, improve real-time data sharing, and reduce dependence on centralized cloud infrastructure for UAS operators.

### Geospatial Intelligence (GEOINT) Frameworks

GEOINT frameworks offer a structured approach for handling, examining, and sharing geospatial data, including UAS data [47]. These frameworks combine geospatial data from various sources and make it easier for intelligence agencies, defense organizations, and civilians to share UAS data.

### Open Data Initiatives

Various entities, such as governments, research organizations, and industry groups, frequently endorse open data initiatives encouraging UAS operators to share non-sensitive information with the public. Open data platforms and portals facilitate the sharing of UAS data for research, innovation, and public benefit, promoting cooperation and knowledge dissemination.

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### Interoperability Standards
Interoperability standards define common protocols and data formats to ensure seamless data sharing and integration between different UAS platforms and software applications [48]. Standards such as the STANAG (Standard and Agreement) 4586 and the Joint Architecture for Unmanned Systems (JAUS) promote interoperability and facilitate UAS data sharing [49]–[52].

### Privacy-Preserving Techniques
As privacy concerns surrounding UAS data increase, various privacy-preserving techniques have been developed. Cryptographic methods, such as differential privacy, secure multi-party computation, and secure homomorphic encryption (SHE), allow for data sharing and analysis while safeguarding sensitive information [53]–[55].

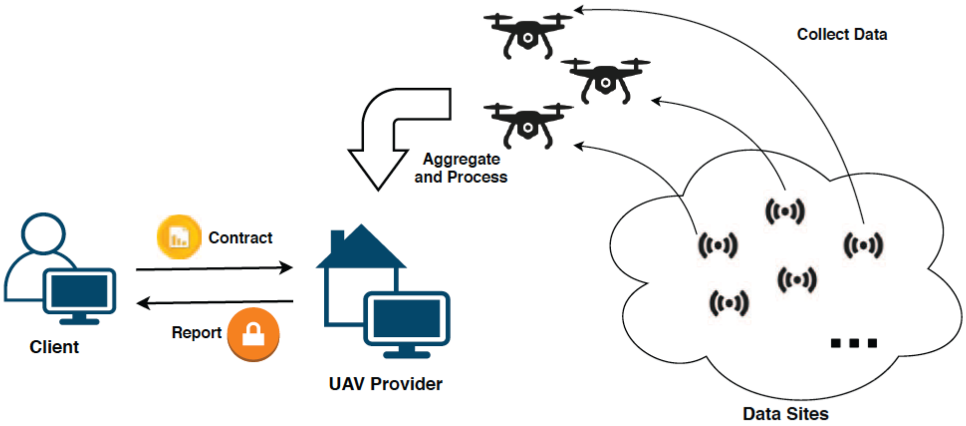


**Figure 17: Example of high-level concepts of secure homomorphic encryption (SHE) framework [53].**

## 3.2 Common Best Practices

UAS data sharing best practices are guidelines and standards that ensure the effective and responsible sharing of UAS data among researchers, organizations, and stakeholders [56]–[58]. UAS data sharing best practices are essential for ensuring consistency, quality, security, interoperability, and ethical considerations while sharing datasets. They promote collaboration, reproducibility, expanded data utility, trust, and efficiency. By implementing best practices, researchers and organizations can effectively share UAS data, unlocking its full potential for advancing knowledge, addressing societal challenges, and driving innovation. Figure 18 provides an overview of common best practices for UAS data sharing, which are described in the following paragraphs.

**Data Privacy and Security:** It's crucial to prioritize data privacy and implement strong security measures to safeguard sensitive UAS data from unauthorized access and cyber threats. This involves using encryption, access controls, and authentication mechanisms. It's important to have granular access controls and permissions to make sure that only authorized individuals or organizations can access and share UAS data. This is done by assigning different user roles and levels of access based on the specific needs and responsibilities of stakeholders.

**Consent and Legal Compliance**: Before collecting, storing, or sharing UAS data, it is crucial to obtain the necessary permissions, consent, and comply with legal requirements. It is important to adhere to data protection regulations and respect the privacy rights of individuals or property owners captured in the data.

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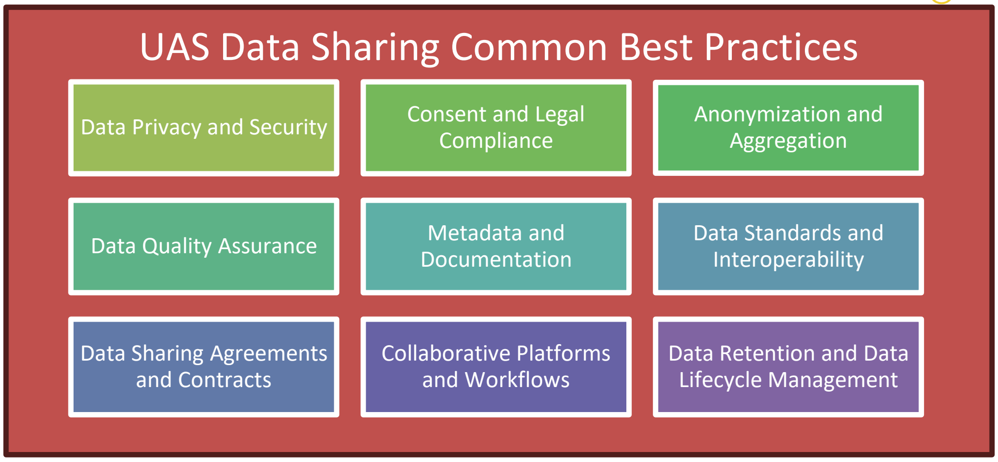


**Figure 18: Overview of UAS data sharing common best practices.**

**Consent and Legal Compliance**: Before collecting, storing, or sharing UAS data, it is crucial to obtain the necessary permissions, consent, and comply with legal requirements. It is important to adhere to data protection regulations and respect the privacy rights of individuals or property owners captured in the data.

**Anonymization and Aggregation:** It's important to protect people's privacy when dealing with UAS data. Anonymizing or aggregating the data is a good way to remove any personal information and minimize the risk of privacy breaches. Also, make sure that any shared data cannot be easily linked back to any individual or location.

**Data Quality Assurance:** Before sharing UAS data with others, it is important to validate and ensure its accuracy, reliability, and quality. This can be achieved through performing data validation checks, calibration, and verification processes to maintain data integrity and improve its usability.

**Metadata and Documentation:** When sharing UAS data, it is crucial to provide comprehensive metadata and documentation. Metadata offers valuable insights into the data's source, collection procedures, accuracy, constraints, and any relevant contextual information. This helps users to better understand and interpret the data.

**Data Standards and Interoperability:** To improve compatibility and allow for easier data sharing between various UAS platforms, software applications, and users, it is important to follow established data standards and interoperability protocols. Adhering to common standards facilitates seamless integration and collaboration.

**Data Sharing Agreements and Contracts:** It is important to establish clear agreements or contracts with all parties involved in data sharing. These agreements should clearly outline the terms, conditions, and limitations of the data being shared. It is important to address ownership rights, usage rights, intellectual property rights, and any restrictions on data redistribution.

**Collaborative Platforms and Workflows:** To improve communication and coordination among stakeholders involved in data sharing and analysis, it is recommended to use collaborative platforms and workflows that allow for seamless sharing, collaboration, and version control of UAS data. This will ensure efficiency and ease of use for all parties involved.

**Data Retention and Data Lifecycle Management:** It is important to establish and follow data retention policies. It is also essential to periodically review and modify data sharing practices to comply with changing regulations. Proper data lifecycle management, which includes securely deleting or archiving data that is no longer necessary, should also be prioritized.

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# 4 SOFTWARE PACKAGES

In the previous sections, we've discussed several ways to analyze and share data that are available in software packages. These solutions allow researchers, organizations, and stakeholders to extract insights from UAS data, combine them with other geospatial datasets, and share them securely for collaboration and decision-making purposes. This section explores some available software packages for UAS data analysis and sharing. The list is not exhaustive since the field is constantly evolving with new software and updates.

### DroneDeploy

DroneDeploy offers a cloud-based platform for UAS data management, analysis, and sharing. It provides features like aerial mapping, 3D modeling, and plant health analysis. The platform allows users to upload, process, and share UAS data with stakeholders through collaborative project management tools.

### Pix4D

Pix4D provides a suite of software solutions for UAS data processing, mapping, and sharing. The various software tools allow users to generate high-resolution maps, 3D models, and orthomosaics from UAS imagery. The data can be easily shared with clients and collaborators through Pix4D's cloud-based platform.

### PrecisionHawk

PrecisionHawk has an advanced UAS data management platform named PrecisionAnalytics that allows users to seamlessly process and analyze UAS data for diverse applications including agriculture, infrastructure, and insurance. The platform also offers collaboration features that enable users to share data, insights, and reports with their team members and clients.

### Kespry

Kespry offers a UAS data analytics platform specifically designed for industries like construction, mining, and aggregates. Their platform allows users to capture UAS data, analyze it for volumetric measurements, inventory management, and site monitoring, and share the insights with project stakeholders.

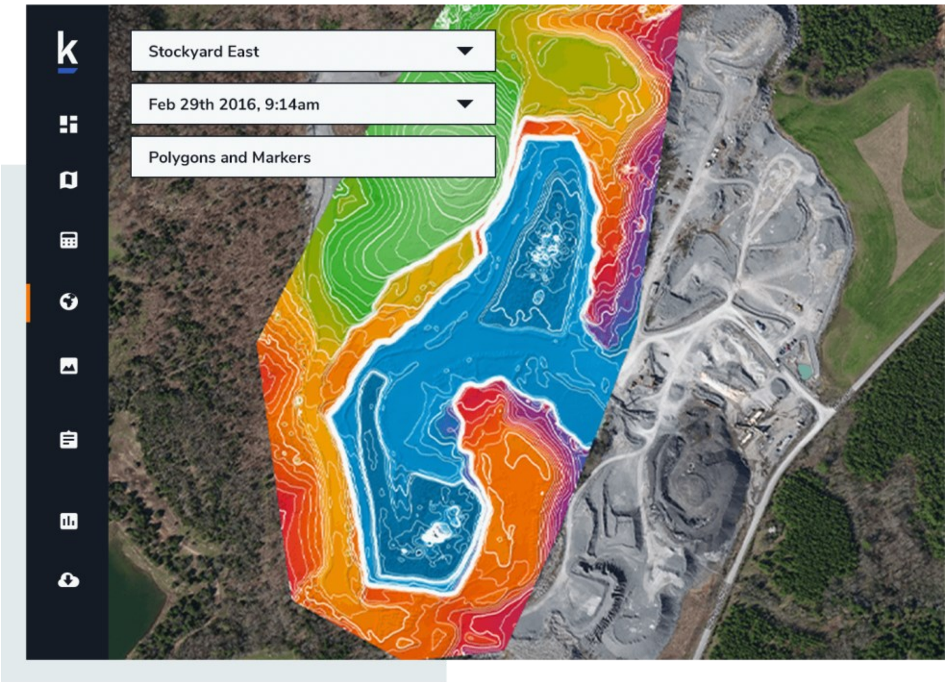


**Figure 19: Kespry UAS data analytics platform (https://kespry.com).**

### Agremo

Agremo specializes in agricultural applications and offers a platform for analyzing and sharing UAS data in the precision agriculture sector. With their software, users can process UAS data to count plants, assess crop health, and estimate yields. These results can be easily shared with farmers, agronomists, and consultants.

### Datumate

Datumate offers a software suite for surveying, construction, and infrastructure inspection applications. Their platform enables UAS data processing, 3D modeling, and survey-grade measurements. Users can share the results, including CAD drawings and reports, with project stakeholders.

### AIDERS

The AIDERS research project has created an open-source AI toolkit that provides tools for collecting and analyzing data about emergency responses from UAVs. This allows commanders to extract knowledge about the operational conditions on the ground and assist them in designing evidence-based response strategies.

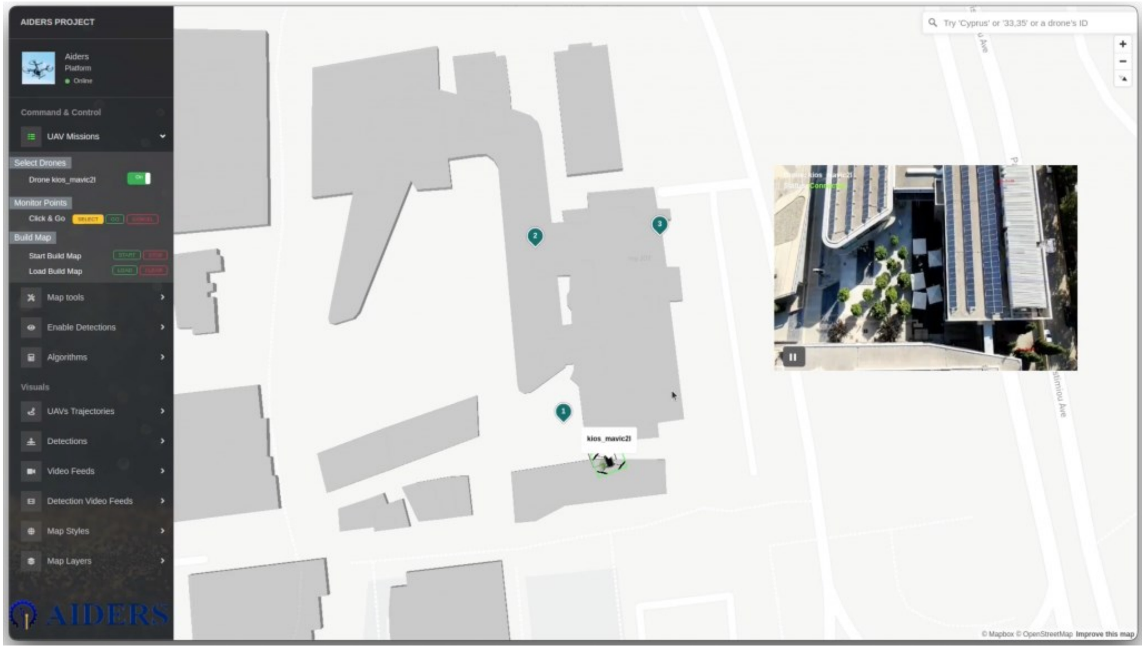


**Figure 20: AIDERS AI toolkit (https://www.kios.ucy.ac.cy/aiders).**

# 5 ACTIVE UAS REMOTE IDENTIFICATION (ID)

The scope of this effort is to investigate how remote identification for active UAS monitoring can be achieved. As part of this investigate we have used off-the-shelf trackers (that include GPS, and other telemetry sensors) and commercial UAS already being deployed in various security and safety missions by first responder authorities. Specifically, the T-Beam devices by Lilygo (as shown in Fig. 21) were used for trackers and a fleet of DJI M300 drones. The specific trackers are equipped with LoRA transceivers for long range communication and were programmed to broadcast telemetry data (location, speed, direction of travel) as part of a minimum data set for remote identification. We create a star topology with the sink being a LoRA receiver attached to the aforementioned AIDERS platform developed by KIOS CoE. Using the AIDERS platform, the telemetry coming from the LoRa nodes (which were attached on the drones) was collected, processed and visualized on the map in real-time. In this way, in addition to the real-time telemetry information, historic data about the previous drone trajectory can be displayed and time-series data extracted for better monitoring of drone

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operations. Figure 22 depicts the drone real-time position as indicated by the tracker devices using the LoRA transceivers while Fig. 23 enable both the real-time telementry visualisation and the drone trajectories over time.


**Specifications**

| | |
|---|---|
| MCU | ESP32-S3FN8 Dual-core LX7 microprocessor |
| Wireless Connectivity | 2.4 GHz Wi-Fi & Bluetooth5 (LE) |
| Development | Arduino, PlatformIO-IDE, Micropython |
| Onboard functions | Boot (IO00) + Reset + Power Button |
| Flash | 8MB |
| PSRAM | 8MB |
| Six-axis IMU QMI8658 | |

**Figure 21: Lilygo T-Beam device employed as a tracker for UAS remote ID**

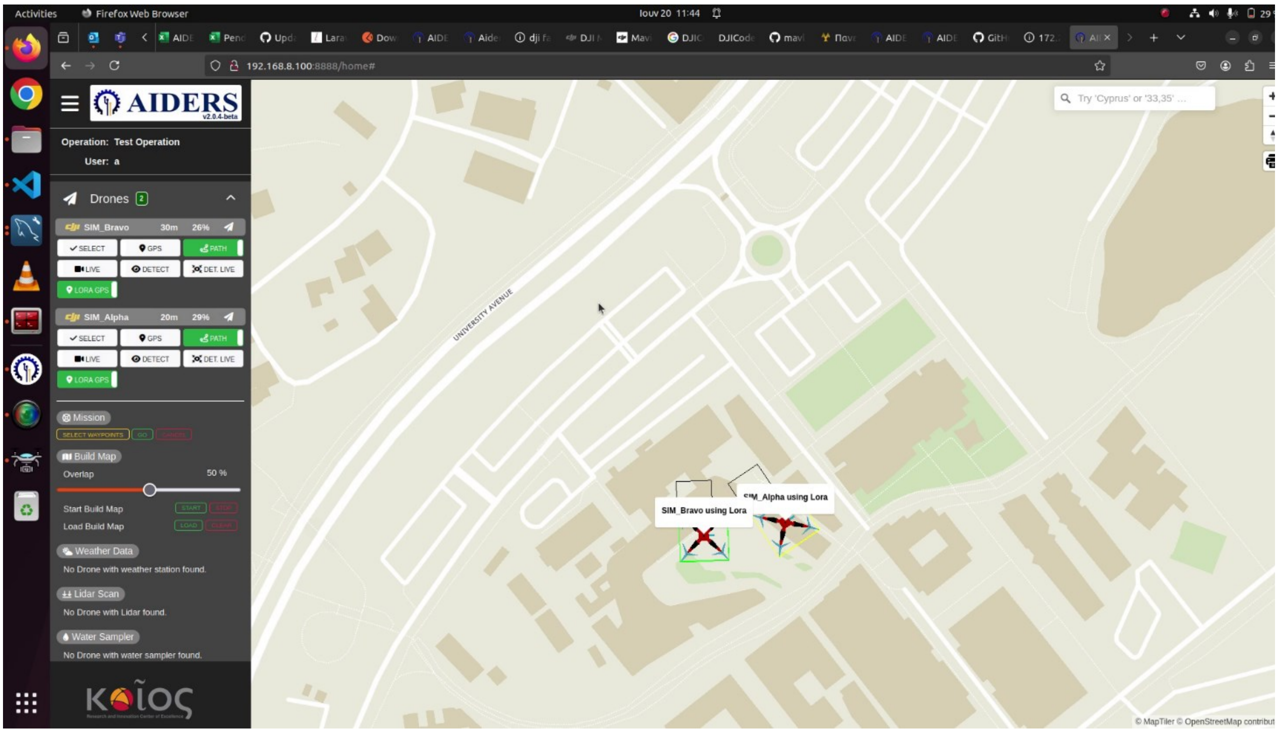


**Figure 22: AIDERS platform displaying telemetry data from T-Beam trackers.**

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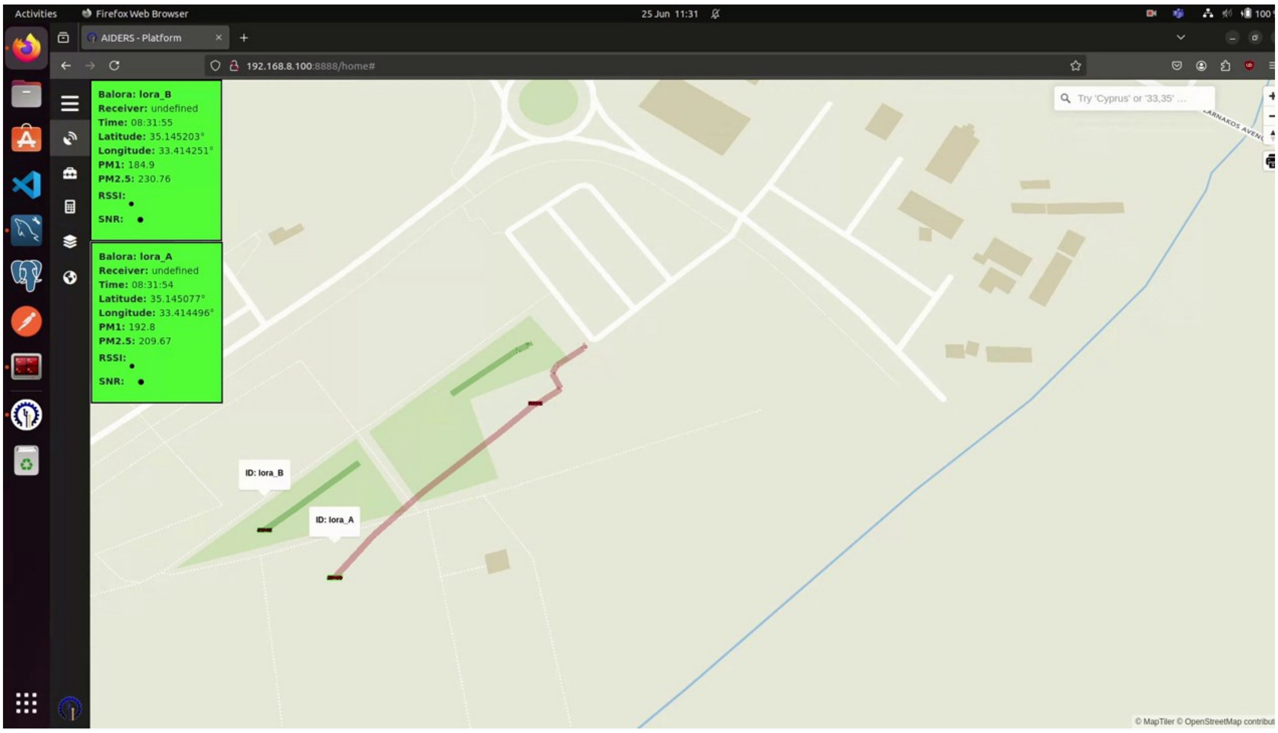


**Figure 23: AIDERS platform displaying real-time and history data from trackers.**

# 6 FUTURE RECOMMENDATIONS

UAS have witnessed widespread adoption and utilization across various industries and domains. Their versatility, efficiency, and technological advancements have opened numerous applications and possibilities. They are at the forefront of research and development, with several research groups and organizations working continuously on new methods to enhance their use and applicability. When it comes to UAS data analysis and sharing, there is a need for further improvement in several domains. Establishing standardized data formats and metadata for UAS data would facilitate data sharing and interoperability. Commonly agreed-upon formats and metadata standards would ensure that UAS data can be easily exchanged, integrated, and analyzed across different platforms, software, and organizations. Additionally, the further development of collaborative platforms and data sharing platforms specifically tailored for UAS data would promote the seamless sharing and exchange of data among researchers, organizations, and stakeholders. Collaborative platforms can provide secure and user-friendly interfaces for uploading, accessing, and analyzing UAS data, fostering collaboration and enabling broader utilization of UAS.

Encouraging the adoption of open data initiatives for UAS data would facilitate wider access to UAS datasets and promote innovation in UAS data analysis. Open data policies and platforms can allow researchers, developers, and organizations to freely access and utilize UAS data for research, development of new applications, and addressing societal challenges. Another crucial area for further improvement is the establishment of clear ethical and legal guidelines for UAS data analysis and sharing. These guidelines should address privacy concerns, data security, informed consent, and responsible data usage. It is important to ensure that UAS data analysis and sharing are conducted in a transparent, responsible, and respectful manner, and that compliance with regulations and ethical considerations is emphasized.

Further research and development of advanced data analysis techniques specifically tailored for UAS data would enable more sophisticated analysis and interpretation. This could involve further integration of machine learning, artificial intelligence, and computer vision algorithms to automate data processing, object detection, change detection, and classification tasks, thus accelerating the analysis process and extracting deeper insights from UAS data. Moreover, the improvement of algorithms to process and analyze UAS data even faster would greatly enhance its utility in emergency response, monitoring, and time-critical applications. Developing efficient algorithms and frameworks for real-time data processing, combined with high-speed data transmission capabilities, would enable timely decision-making and response to dynamic situations. Additionally, user-friendly data visualization tools and intuitive user interfaces for UAS data analysis would facilitate the understanding and interpretation of complex UAS datasets. Developing even more interactive visualization techniques, 3D modeling capabilities, and intuitive interfaces would enable users to explore and analyze UAS data more effectively, even for those without extensive technical expertise.

Improving training and education for data analysis and sharing is another crucial area that needs attention. Continuous training and education programs on UAS data analysis techniques, best practices, and regulatory compliance would enhance the knowledge and skills of professionals working with UAS data. These programs should cover data collection, processing, analysis, and interpretation, as well as addressing ethical considerations and regulatory requirements. By promoting a well-informed and skilled workforce, the potential of UAS data analysis can be maximized.

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# 7 CONCLUSION

UAS have revolutionized data collection, offering a wide range of applications and insights across various industries. In this deliverable, we have explored the methods and best practices associated with UAS data analysis and sharing, highlighting their significance in harnessing the full potential of UAS technology.

UAS data analysis involves leveraging advanced analytical techniques to extract valuable information from collected data. Through using data analysis methods, UAS data can unveil patterns, trends, and relationships which can help in making informed decisions and gaining deeper insights. This, in turn, can lead to improved operational efficiency and better outcomes. Sharing UAS data is important in promoting collaboration, transparency, and innovation. Proper sharing strategies and best practices can help stakeholders make data-driven decisions, facilitate reproducibility, and contribute to collective knowledge in their respective fields. However, it is crucial to address concerns related to privacy, data security, intellectual property, and legal and ethical considerations when sharing UAS data. Establishing robust protocols, frameworks, and standards ensures responsible and ethical use of the shared data.

To facilitate UAS data analysis and sharing, several software packages available specifically for UAS data processing and analysis are available. These tools offer a wide array of functionalities, ranging from image stitching and enhancement to advanced machine-learning algorithms for automated feature extraction and classification. Leveraging these software packages empowers users to effectively handle UAS data and unlock its full potential.

Looking toward the future, several opportunities and recommendations emerge for the field of UAS data analysis and sharing. Further integration of AI and ML techniques holds immense potential for automated data analysis and decision support. Besides that, collaboration and standardization across stakeholders and organizations are crucial for effective UAS data analysis and sharing.

UAS data analysis and sharing methods offer a powerful toolkit for extracting insights from aerial data. By leveraging advanced analytical techniques, adopting best practices, utilizing software packages, and embracing future advancements, stakeholders can unlock the full potential of UAS technology. Embracing responsible data sharing practices and fostering collaborations will pave the way for transformative applications, ultimately leading to improved decision-making, enhanced efficiency, and positive impacts across various sectors.

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