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Tech Brief

DATA MANAGEMENT AND GOVERNANCE IN UNMANNED AIRCRAFT SYSTEMS

INTRODUCTION

State Departments of Transportation (State DOTs) across the Nation have seen a rapid increase in the use of unmanned aircraft systems (UAS) because of their ability to collect detailed data, especially in high risk areas when using traditional data collection methods can be difficult (Neubauer et al., 2021). The American Association of State Highway and Transportation Officials (AASHTO) has reported that nearly all State DOTs are using UAS in some capacity (AASHTO, 2019). As UAS data collection increases, the data needs for storing information may increase exponentially. Some of the goals of this tech brief are to:

- Help surface transportation organizations understand some potential ways they may use UAS data.
- Identify innovative solutions for what can be achieved with UAS data through processing.
- Considerations regarding data management and governance solutions.

A sample workflow of the key terms and data governance policies, processes, and tools discussed in this Tech Brief are illustrated in Figure 1.

KEY TAKEAWAYS

- Considerations for UAS data governance policies, processes, and tools.
- Identify innovative solutions for what can be achieved with UAS data through processing
- Understanding asset inventories using engineering asset data models.
- Roadmap considerations for data storage and provisioning with UAS.

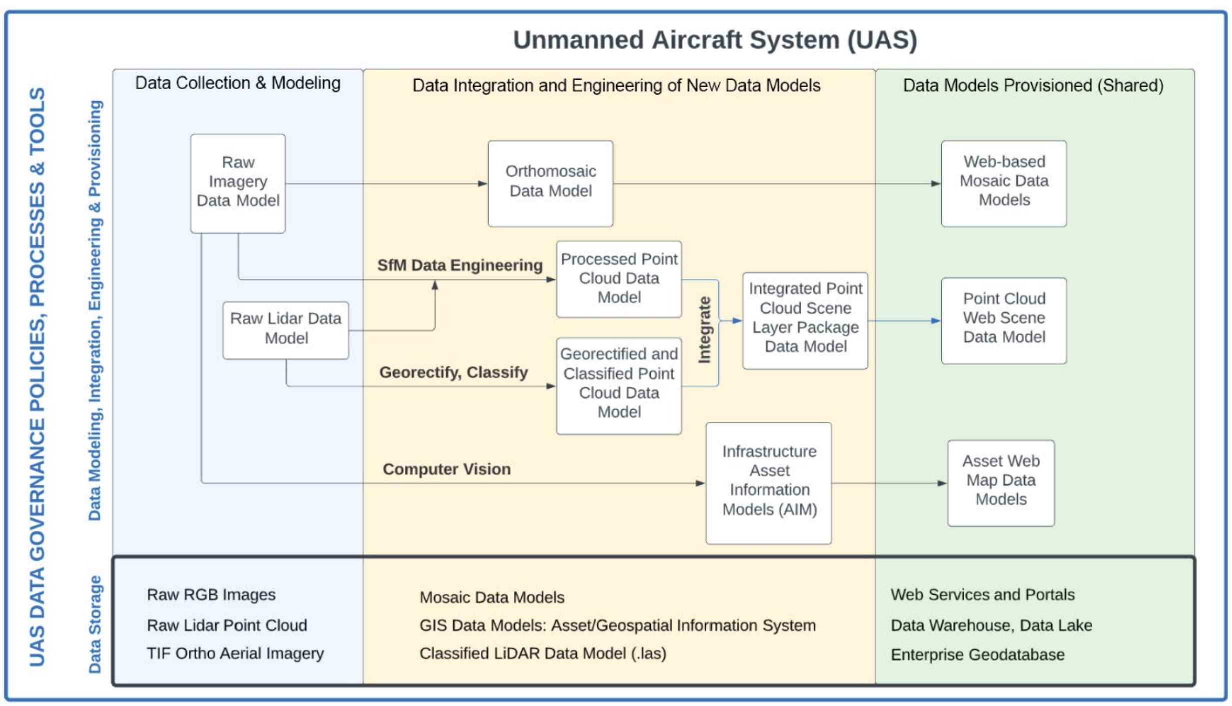

Figure 1. Sample UAS Data Governance Policies, Processes, and Tools. Image Source: FHWA

U.S. Department of Transportation
Federal Highway Administration

FAA REGULATIONS

UAS operators in both the public and private sectors must also adhere to statutory and regulatory requirements. Public aircraft operations (including UAS operations) are governed under the statutory requirements for public aircraft established in 49 USC § 40102 and § 40125. Additionally, both public and civil UAS operators may operate under the regulations promulgated by the Federal Aviation Administration. The provisions of 14 CFR part 107 apply to most operations of UAS weighing less than 55 lbs. Operators of UAS weighing greater than 55 lbs may request exemptions to the airworthiness requirements of 14 CFR part 91 pursuant to 49 USC §44807. UAS operators should also be aware of the requirements of the airspace in which they wish to fly as well as the requirements for the remote identification of unmanned aircraft. The FAA provides extensive resources and information to help guide UAS operators in determining which laws, rules, and regulations apply to a particular UAS operation. For more information, please see https://www.faa.gov/uas/.

DATA MANAGEMENT

Transportation data systems, including UAS, comprise of multiple data models, applications, tools, and processes. The data processes are used by field data collectors, data processing engineers, and data modelers to work with the raw imagery and Light Detection and Ranging (LiDAR) data collected in the field and engineer new processed data models that can be used in downstream business processes. The data management processes in the UAS ecosystem can broadly be categorized as follows:

- **Data Collection and Modeling:** This process involves collecting raw imagery and LiDAR data in the field, using unmanned aircraft.
- **Data Integration and Engineering:** This process involves integrating and engineering new data models from the raw imagery and LiDAR data collected in the field.
- **Data Storage and Provisioning:** This process involves managing the storage of raw and engineered data models. It also involves provisioning raw and engineered data models through an enterprise data warehouse or cloud-based data lake.

Data Collection and Modeling

UAS has become a versatile geospatial data collection system that can transform how highway facilities are planned, designed, built, operated, and maintained (Mallela et al., 2018). UAS can be a versatile tool to build a virtual representation of transportation corridor systems that can be used for multiple use cases relevant to State DOTs (Choi, 2016). Multiple State DOTs have identified significant monetary savings of 40 percent or more and safety benefits when using UAS over conventional methods (Snyder et al., 2018). With the growth of UAS collection activities, the variety of data types has expanded, and organizations should select data collection tools based on their needs and budgets (Dalamagkidis et al., 2016). With so many options available, it can be beneficial to identify the end goals prior to data collection to assist with selecting a data solution that will be adequate for those goals. UAS are typically used for infrastructure mapping and inspections to collect two types of data—LiDAR point cloud and imagery. The LiDAR point cloud and imagery data collected come with metadata that are packaged with the raw data into a data model. Two types of raw data models are available at the end of the data collection in the field—a raw imagery data model or a raw LiDAR data model.

Data Integration and Engineering

State DOTs are primarily using four data transformation techniques to process the raw data models created using UAS. The raw data models are integrated and transformed through a series of algorithms to engineer new data models. The four data transformation techniques used most frequently by State DOTs for UAS data are described in this section: (a) structure for motion (SfM), (b) computer vision, (c) georectification and classification, and (d) point cloud data fusion (or integration).

Engineering Processed Point Cloud Data Model Using Structure for Motion

Significant developments in digital photogrammetry techniques over the last decade have revolutionized the collection of three-dimensional (3D) topographic data. Unlike traditional photogrammetry, the SfM workflow does not require prior knowledge associated with conventional photogrammetry (Cullen et al., 2018). SfM is a photogrammetric range imaging technique for estimating 3D structures of a scene from two-dimensional image (2D) sequences. (Figure 2) SfM can work with a wide range of cameras and is well-suited to UAS imagery. Multiple software packages incorporate SfM into their solutions at various price points, including open-source software. SfM and low-altitude platforms can produce point clouds with point densities comparable to airborne LiDAR, with horizontal and vertical precision in the centimeter range, low capital and labor costs, and low expertise levels (Fonstad et al., 2013).

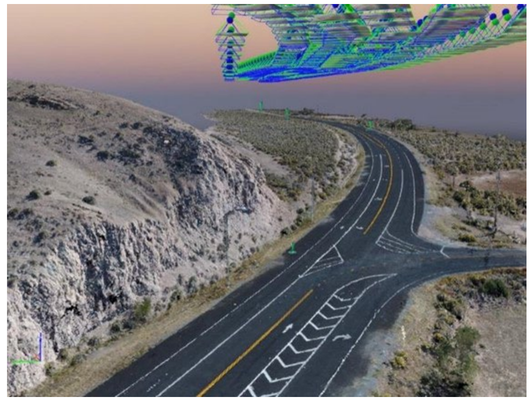

Figure 2. Example of 3D model from photogrammetry. Image Source: Utah DOT

The high-resolution 3D point cloud provides a digital representation of the physical world that engineers, inspectors, asset managers, and others can repeatedly explore, query, and analyze to mine important information (Mallela et al., 2018). The quality of the point cloud depends on the quality of the source data, including having clear images and proper overlap between images on both the front and sides. (Figure 3). Furthermore, using ground control points may also be beneficial to improve the accuracy and precision of the final deliverables.

Point clouds from SfM and LiDAR collection can look similar in many ways because both can incorporate colorized point clouds. Yet, LiDAR will have additional information in the point cloud, such as intensity and return values. SfM is a passive technique that uses images collected from a camera. A camera is considered a passive remote sensing instrument that relies on the scene having proper illumination and appropriate lighting conditions. A camera does not actively send pulses of light but instead captures what is visible on the scene. (Figure 4) Without adequate light, the sensor cannot capture an adequate image for SfM. Once a point cloud is created using SfM, various point cloud tools may be used to analyze the data further (e.g., quantities of a site, as-built models, or advanced analytics).

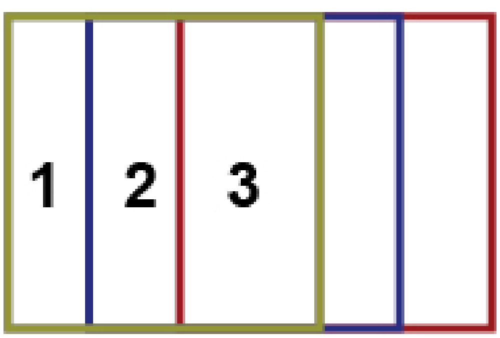

Figure 3. Image Overlap for SfM. Image Source: FHWA

Engineering Asset Data Models Using Computer Vision

Transportation agencies maintain an inventory of highways assets in the right-of-way to support various design, construction, operations, and maintenance business processes. Per the ISO-19650 information management standard, asset information models (AIMs) should be created and maintained to meet all the asset information requirements (AIRs) that are typically established by asset managers.[1] Location is one of the most important AIRs for infrastructure assets such as culverts, bridges, drainage structures, guardrails, medians, shoulders, ground-mounted and overhead signs, pavement markings, rumble strips, sidewalks, and crosswalks. The location of these assets can be engineered (extracted) from imagery data that are collected via UAS using an artificial intelligence (AI) technique known as computer vision.

Computer vision uses known methods (algorithms) to detect each asset in the imagery. The process of detecting each asset is referred to as object detection, wherein the term “object” refers to the asset that is being detected. Once the asset location information is determined, it can be added to the geospatial AIMs that are managed in geospatial asset management systems (AMS).

UAS imagery operations may have advantages over traditional "boots in the field" inspections in performing asset inspections, particularly in situations where data collection on the ground may be dangerous or where an aerial perspective may provide a more holistic understanding of a project. However, an unintended consequence of UAS operations is the volume of data, specifically imagery, that still needs to be reviewed by an inspector. This may result in inspections where many images need to be reviewed, cropped, and pasted into reports.

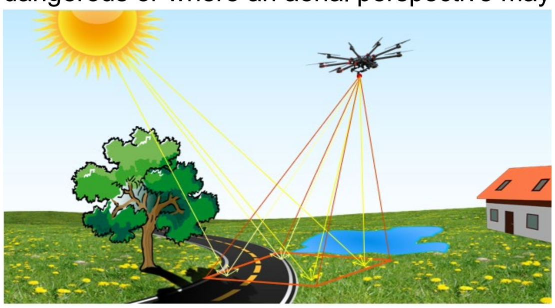

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Figure 4. UAS Image Collection (e.g., Passive Sensor).

Automated imagery analytics using AI techniques such as computer vision are expected to greatly reduce the burden of human effort involved in asset data collection and may assist with the processing of the imagery captured by UAS operations while improving accuracy (Chen et al., 2023). AI experiments by State DOTs resulted in favorable results, including Utah DOT automated detection of missing rivets in overhead signs and North Carolina DOT automated detection of airport runway cracks.

For State DOTs to evaluate the benefit from an investment in automated imagery analytics, it may be beneficial to understand the general method used to achieve the desired results. Computer vision relies on training data sets, usually annotated boxes of the object of interest, to produce the object detection model. Key terms are clarified here to avoid any confusion:

- Algorithms - An algorithm is a sequence of instructions used to solve a problem or carry out a computation. In computer vision, the term algorithm refers to functions that learn feature extraction from labeled and unlabeled training data resulting in an inference "model." For example, convolutional neural networks is an algorithm.
- Inference "Models" - In computer vision applications, the inference model is trained to "infer" the class and location of objects with a statistical probability. This is what is operationalized to automate object detection.
- Training Data - In computer vision, the training data used are "annotated imagery." (Figure 5) Annotations (usually square boxes, but they can be polygons) mark the area representing the object to be detected. There can be multiple annotations on a single image; the more quality training annotations, the better the quality of the inference model.

Typically, an AI developer will annotate training data, run the data through training models, annotate more training data, retrain the model, and combine the resulting AI models with deterministic vision algorithms

[1] The use of ISO specifications is not a Federal requirement.

until satisfactory results are obtained. (Figure 6) The resulting system is then integrated into the production system pipeline.

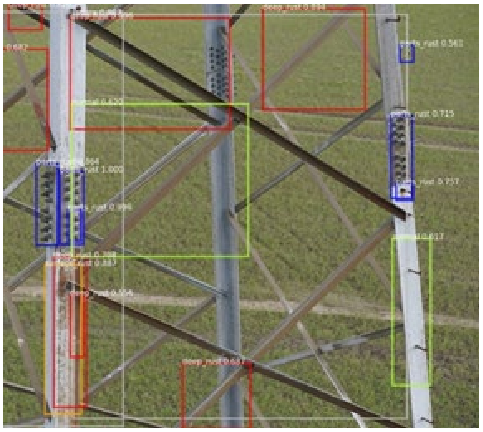

Figure 5. Bounding Box Rust Detection. Image Source: Sanjay Mishra 2020

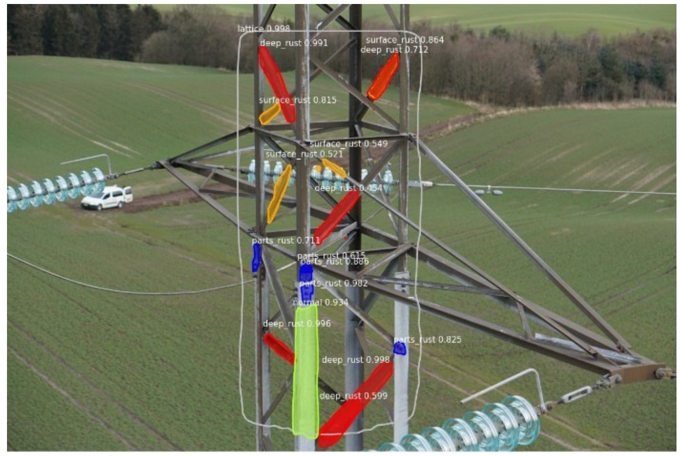

Figure 6. Pixel Based Classification – Mask Rust Detection. Image Source: Sanjay Mishra 2020

The approach to automated imagery analytics using computer vision may benefit from further research. Training data can be unique to each environment and use case, including the camera angle or the perspective from which the data were captured. With AI, the more information that is provided, the better the analysis becomes, and the results progressively improve as the AI learns over time (Krizhevsky et al., 2012). Opportunities for collaboration between State DOTs may exist to gather similar data to improve algorithms that could benefit multiple State DOTs in the future for AI and machine learning.

Engineering Geo-rectified and Classified Point Cloud Data Model

LiDAR is becoming increasingly popular across the United States, and State DOTs are adopting this technology for practical uses in transportation-related applications (Chang et al., 2014). Mississippi DOT recently acquired UAS LiDAR to perform tasks in the field much faster than using traditional measuring tools (Mississippi DOT, 2022). Washington State DOT found LiDAR could modernize some of its operations efficiently and improved desirable outcomes such as employee safety and data accuracy (Yen et al., 2011).

LiDAR is an active sensor that sends pulses of light (Figure 7), whereas SfM is a passive sensor based on imagery processing. The point clouds associated with LiDAR do not depend on scene illumination and can provide additional information such as intensity or return values.

- Intensity refers to the surface reflectance of an object, which may help identify different characteristics in a scene.
- Return refers to multiple pulses or emissions that are intercepted and reflected with the ability to better penetrate through vegetation.

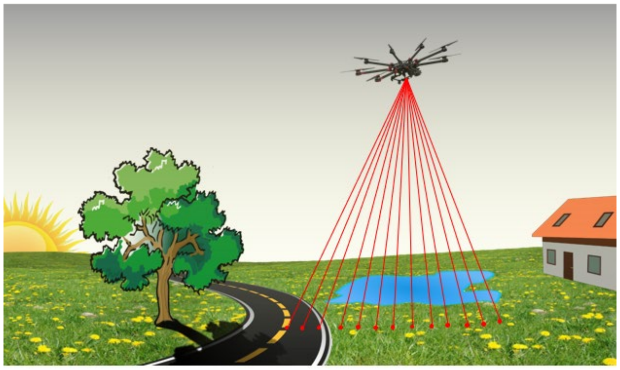

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Figure 7. UAS LiDAR Collection (e.g., Active Sensor).

LiDAR point clouds generally take less time to process than SfM point clouds because they are created in real-time from the active sensors. LiDAR with multiple returns also increase the chance of penetration through vegetation because it actively sends pulses of light rather than relying on passive processing methods. Aerial LiDAR has been found to be more accurate for characterizing bare earth in dense vegetative areas than SfM or terrestrial LiDAR (Swetnam et al., 2018). Furthermore, LiDAR does not depend on light and is not affected by areas in shadow.

Although the processing time for LiDAR can be less than for SfM point clouds, a raw LiDAR point cloud may still need additional processing to provide the most accuracy and precision. UAS LiDAR, when raw, is typically accurate relative to itself; however, it may not be aligned to other flight lines within the data set or have georeferencing information for absolute spatial accuracy. A processing workflow may increase the accuracy of the data by aligning each flight line and adding spatial information to reference the point cloud to known coordinate systems to align the data with other geospatial data. A generalized workflow of UAS LiDAR data processing is illustrated in Figure 8.

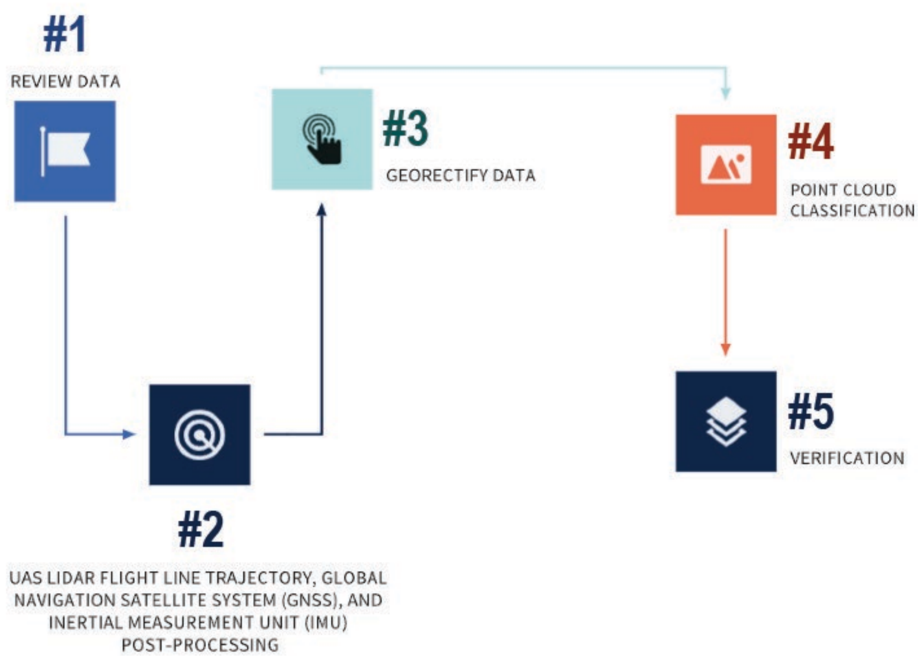

Figure 8. General LiDAR Post Processing Workflow.General LiDAR Processing Workflow. Image Source: FHWA

Review Data

In a LiDAR processing workflow, it is often beneficial to review the data to ensure the collection meets the goals of the operation. Reviewing the data directly after its collection may help identify sufficient density or errors in the information while on-site. The process may include checking each flight line, reviewing the density of the point cloud to monitor that it sufficiently defines the area of interest, and analyzing for errors. (Figure 9)

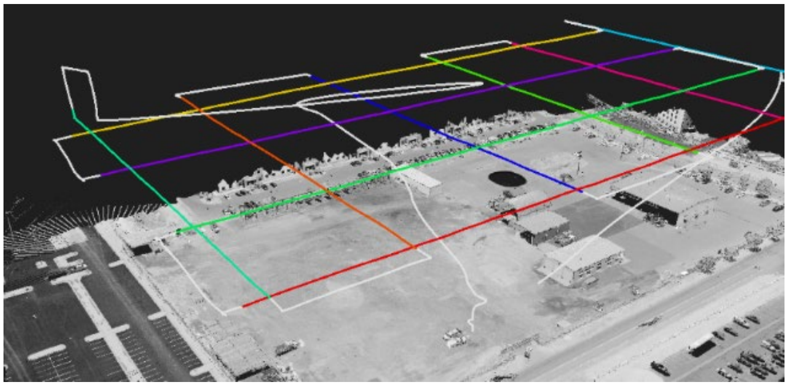

Figure 9. UAS Raw LiDAR Flight Lines and Associated Point Cloud Data.
Image Source: Utah DOT

Flight Line Trajectory, Global Navigation Satellite Systems, and Inertial Measurement Unit Post-Processing

Due to variations between satellite observations during the data collection process, additional processing tools can assist in further aligning each section's trajectories to reduce noise, improve accuracy and precision, and reduce discrepancies on overlapping point clouds. Trajectory reconstruction quality can be a significant factor affecting the accuracy of the final data set (Jozkow et al., 2017). The raw observations may be compared against a Global Positioning System base station or Continuously Operating Reference Station network and use software to improve the absolute accuracy of the solutions.There may be discrepancies in the two flight lines that may be improved through processing. Additionally, this process may also assist in identifying anomalies in the data.

Georectify Data

LiDAR data may need to be translated from a relative coordinate system into a spatial reference to align with other data used on a project. Data in multiple datums or projections may be a source for translation errors on a project. Software solutions are increasing to assist with real-time translation from disparate spatial reference; however, it is often beneficial to re-project the data to align with the coordinate system that will be used on a project (Fonstad et al., 2013).

Point Cloud Classification

Classification of the point cloud can assist in organizing each element into its independent class. (e.g., bare earth, buildings, low vegetation, high vegetation). Point cloud classification can prove beneficial for extracting or isolating separate elements or geoinformation. In conventional LiDAR workflows, classification was completed manually by selecting and grouping points, which could be time consuming and cumbersome. Advances in tools and technology have improved classification using automated algorithms to expedite the process and substantially reduce the processing time (Zhao et al., 2020).

Verification

LiDAR applications have increased significantly in the past few years, but the user community still lacks standard and efficient procedures for evaluating the quality of provided point clouds (Habib et al., 2009). A variety of variables can affect the overall accuracy of data collection; therefore, it can often be beneficial to have a system of checks and balances to assist with quality control (QC) and quality assurance (QA) of the point cloud (Habib and Van Rens, 2012).

Verifying the data and providing the root mean square error (RMSE) in documentation may provide users with a better understanding of the overall quality of the data, which can build confidence and help with planning. Furthermore, QA/QC procedures provide a means to discover errors early to help minimize costly change orders or other problems in future data use phases. Effective QA exercises may be more complex to apply to remote sensing data but can be seen as essential for a ground-based survey to ensure the accuracy of the solutions (Henrys and Jarvis, 2019).

Engineering Integrated Point Cloud Data Models

Remote sensing has been widely adopted for collecting dense and accurate topographic data for multiple applications (Habib et al., 2009). Like many tools, remote sensing platforms, whether SfM or LiDAR, have strengths and weaknesses associated with each technology. Research by Swetnam et al. (2018) discovered the following:

- Aerial LiDAR was found to be more accurate for characterizing bare earth in dense herbaceous vegetation than terrestrial LiDAR.
- Terrestrial LiDAR and high-resolution near-distance UAS were better and more accurate at detecting grass and fine woody vegetation.
- UAS SfM photogrammetry at lower spatial resolution under-estimated maximum heights in grass and shrubs.
- UAS and handheld SfM photogrammetry in near-distance high-resolution collections had similar accuracy to terrestrial LiDAR for vegetation but difficulty measuring bare earth elevation beneath the dense herbaceous cover.

A combination of platforms and techniques (e.g., UAS, mobile, terrestrial LiDAR, SfM) may provide complementary solutions to overcome the weaknesses of a single platform (Swetnam et al., 2018). Combining tools, whether conventional or newer, remote sensing technologies may provide a more accurate overall solution in varying terrain. Furthermore, the fusion of data from two or more sensors may create more complete models and be easier to interpret (Forkuo and King, 2005). Providing complete data for a scene, rather than a traditional breakline survey, may also make additional field collection visits unnecessary. With advances in automation, computer vision, and AI, future solutions may hold more significant opportunities for the automation of data interpretation.

Data Storage and Provisioning

As data volumes and computing power increase, and as AI, machine learning, and big data capabilities rise, established leaders will need to adapt and grow to stay competitive (Bean and Gupta, 2021).

UAS Data Can Grow Exponentially

20 UAS, mapping four times a week, could create 15.1 terabytes (TB) of data in one year.

UAS data management may quickly grow cumbersome if a good roadmap and plan are not followed as UAS operations expand. Having multiple UAS missions collecting gigabytes of data can quickly fill data storage drives.

For example, a Utah DOT mapping project on the Moki Dugway area for a landslide project using a platform with a 12-megapixel sensor generated 634 images with a combined file size of 3.04 gigabytes (GB). When processed to create a 3D point cloud and aerial imagery and associated processing files, the output was 1.82 GB, with the point cloud file of 1.39 GB and the associated TIF file of 432 megabytes (MB). The images and associated deliverables would equate to a combined total size of 4.86 GB. (Table 1) Assuming only four operations a week over 52 weeks, a single UAS could theoretically create more than 758 GB over the course of a year. An organization with 20 other aircraft with similar data collection efforts could produce 15.1TB in a year. With larger mapping sizes, the data storage needs could be even greater.

Table 1. Utah DOT, Moki Dugway Mapping Project Data Size Comparison.

UAS with 12 Megapixel Camera	Data Set Size
634 Raw Red, Green, Blue Images	3.04 GB
LAS Point Cloud	1.39 GB
TIF Ortho Aerial Imagery	432 GB
Combined Deliverable	1.82 GB
Raw Images and Deliverables Total	4.86 GB

UAS mission goals may dictate the data format, but there may be opportunities to share data across organizations to increase the return on investment. If managed correctly, data can become an organization's most valuable asset (Panian, 2010). Data analysis and asset management solutions have become more advanced and easier to use in recent years as a result of advances in computer speed, cost, and processing power (Brutus and Tauber, 2009). As the amount of available data increases, storage solutions become more important. Including UAS data early in future data management roadmaps may help agencies proactively prepare for the exponential growth in data across organizations.

State DOTs are managing big data by adopting big data management offices and data-governance boards to assist with data management (Mallela and Bhargava, 2021). However, UAS data may not always be considered in the data management equation. When creating a roadmap, it may be beneficial to address the following key questions presented by Mallela and Bhargava for a successful data management roadmap:

- What data is critical for an organization?
- What benefits does data management provide?
- What data models and data-exchange standards offer the most value?
- What needs to be done?

Including UAS data management in the organizational data management roadmap plan may prevent data integration issues associated with inadequate storage or insufficient dissemination solutions to share the data across the organization. The influx of data from UAS could be a means to create a rich database of information that may improve the understanding of each asset and the system as a whole. Using a phased approach for UAS data to achieve a completely integrated process can help achieve the full range of benefits that comes from integrating all departmental data and assets into a full data management lifecycle (Mallela and Bhargava, 2021).

DATA GOVERNANCE

As methods for digital information collection, modeling, and exchange increase for UAS, data governance can become more important.

An AASHTO survey showed that nearly all DOTs have incorporated UAS into their operations (AASHTO, 2019), and with this influx of use, data storage and data governance requirements increase. As State DOTs incorporate enterprise-level data management systems and assist with streamlining processes for digital delivery, including UAS data management and governance may help streamline multiple data sources.

Although organizations may strive in theory to achieve data governance goals, they may not be able to justify the effort without identifying a practical, concrete impact on the organization (Panian, 2010). Documenting the use of UAS data and their return on investment may justify their use further and provide a better understanding of the organizational impacts. Moreover, as data governance systems are developed, the use of open standard formats may assist with information sharing, which could reduce the limitations of proprietary software formats.

It is becoming clearer that enterprise data needs to be shared across multiple applications and business processes and not tied to one specific application (Panian, 2010) For example, Utah DOT has reported using a central image server database to store all aerial imagery collected from UAS. The image server facilitates information sharing and reduces redundant collection efforts. Utah DOT has also incorporated its UAS data into the entire project life cycle from conception to post-construction to assist with the creation of digital twins for each asset throughout its life. Setting organizational and enterprise-wide policies and goals for data management could be an effective means to help streamline data governance for UAS data. Panian describes the goals of data governance as:

- Ensure data meet the needs of the business.
- Protect and manage data as a valued enterprise asset.
- Lower the costs of managing data.

Panian also identified six attributes for creating a data governance roadmap:

- Accessibility: Ensure that all enterprise data can be accessed, regardless of their source or structure.
- Availability: Ensure that the data are available to users and applications, when, where, and how they are needed.
- Quality: Ensure data completeness, accuracy, and integrity.
- Consistency: Ensure data meaning is consistent and reconciled across all systems, processes, and organizational units.
- Auditability: Ensure there are controls and an audit trail for all data.
- Security: Ensure secure access to the data.

Replacing data solos to integrate data efficiently in an organization may create challenges that may require careful planning, phasing, and selection of an appropriate implementation path (Mallela and Bhargava, 2021). It may be helpful to review existing data governance standards to formulate a data governance framework. Resources include Control Objectives for Information and Related Technologies (COBIT) and ISO/IEC 38500.[2]

CONCLUSION

Multiple solutions are emerging for processing UAS data and incorporating them into a larger data management and governance workflow. State DOTs could benefit from an understanding of the variety of UAS sensors, platforms, and processing methods to select a solution that best meets their goals. Opportunities to use AI and gather more data may continue to improve the final deliverables, saving time

[2] The use of these resources is not a Federal requirement.

and increasing the return on investment as the AI learns from additional training data over time (Krizhevsky et al., 2012).

Opportunities also may arise for State DOTs to collaborate and research similar data to improve algorithms that benefit multiple States using AI and machine learning. As UAS use expands further, it may be helpful for organizations to understand the potential solutions that big data may provide, and address barriers that may limit their ability to take advantage of this new strategic resource (Alharthi et al., 2017). Setting organizational and enterprise-wide policies and goals for data management may help organizations streamline their data governance for UAS data and prevent potential issues arising from large data-gathering efforts.

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