Framework for Multi-Asset Comparison and Rapid Down-selection for Earth Observation Missions

Jerome Gilleron *, Marc Muehlberg †, Alexia Payan ‡, Youngjun Choi §, Simon Briceno ¶, Dimitri Mavris ‖.
Aerospace Systems Design Laboratory, School of Aerospace Engineering
Georgia Institute of Technology, Atlanta, GA, 30332, USA

Observing the Earth, whether it be from space or from the air, has become easier in recent years with the advent of new space-borne and airborne technologies. First, satellites constantly provide data about almost any point on the globe with varying resolutions and in various spectral bands. Second, Unmanned Aerial Vehicles (UAV) are becoming more readily accessible to the public and may be rapidly deployed to take high resolution images of ground features or areas of interest. Third, manned aircraft may be used to image large areas of land at a higher resolution than satellites and have been used regularly in disaster monitoring and surveillance missions. However, when multiple heterogeneous assets compete to perform a given aerial imaging mission, deciding which asset is better suited and/or less costly to operate in a timely manner is challenging. Every acquisition mode is different, resolution values are computed differently and there currently does not exist a common framework to compare UAV, manned aircraft and satellites. To address this challenge, this paper describes a methodology to rapidly compare various types of aerial assets (such as UAVs and manned aircraft) and space assets (such as satellites) to decide which one would be better able to perform an Earth observation mission depending on a set of requirements. To demonstrate the proposed methodology, this paper executes numerical simulations with three different representative scenarii in California.

***Keywords*—** Earth observation, Heterogeneous asset comparison, multi-attribute decision making process, trajectory generation, UAV imagery, satellite imagery, manned aircraft imagery

I. Introduction

The objective of Earth observation missions has long been to provide the public and the private sectors, as well as scientists with the necessary data to better understand and protect our planet or to respond to catastrophic events in a timely manner. Among the many potential applications of Earth observing systems are vegetation monitoring, urban planning, disaster monitoring, land and sea temperatures monitoring, and weather reporting. The resulting datasets are plentiful, and their costs vary depending on the resolution and the age of the acquired pictures or videos. The assets used to take such images or videos are also quite different: a UAV, a manned aircraft, and a satellite can compete to perform the mission. This provides the customer with various options to choose from, but this usually means that it is challenging to compare assets between each other and select the most appropriate one. Therefore, there is a need in the imagery service industry for harmonizing the way different assets are represented to be able to compare them and select the most appropriate for the mission under consideration. This paper focuses on the development of a framework to address that need. The work expands the framework developed by Choi et al. [1] to down-select UAV assets for aerial imaging missions, by including manned fixed-wing aircraft and satellites in the selection and ranking process.

This paper deals with the comparison of different aerial and space assets. The reason why comparing heterogeneous assets is complicated is threefold. First, the UAV industry has been expanding rapidly over the past three years. In 2015, the Federal Aviation Administration (FAA) authorized the use of UAVs for recreational and commercial purposes. This led to the development of a legal environment for both UAV manufacturers and operators[2]. UAVs can have different shapes and forms such as fixed-wing, including

*Graduate Research Assistant, Aerospace Systems Design Laboratory, School of Aerospace Engineering, Georgia Institute of Technology.
†Graduate Research Assistant, Aerospace Systems Design Laboratory, School of Aerospace Engineering, Georgia Institute of Technology, AIAA Student Member.
‡Research Engineer II, Aerospace Systems Design Laboratory, School of Aerospace Engineering, Georgia Institute of Technology, AIAA Member.
§Research Engineer II, Aerospace Systems Design Laboratory, School of Aerospace Engineering, Georgia Institute of Technology, AIAA Member.
¶Senior Research Engineer, Aerospace Systems Design Laboratory, School of Aerospace Engineering, Georgia Institute of Technology, AIAA Senior Member.
‖S.P. Langley NIA Distinguished Regents Professor, Boeing Regents Professor of Advanced Aerospace Systems Analysis, School of Aerospace Engineering, Director Aerospace Systems Design Laboratory, School of Aerospace Engineering, Georgia Institute of Technology, AIAA Associate Fellow.

hybrid Vertical Take-Off and Landing (VTOl), or rotary-wing, including single-rotor and multi-rotor helicopters, and new types and shapes emerge every year. Second, delivery and military UAVs are engines for new developments. In the United States of America only, more than one million personal UAVs were sold in 2016 regardless of the type of UAV. Moreover, this number is only considering UAVs and the wide variety of model on the market. Now, this study aims at comparing various types of UAVs to manned aircraft or satellites. Finally, the way those assets operate and are deployed are intrinsically different: UAVs fly and hover, manned aircraft fly but do not hover and satellites orbit. To prove the increasing use of UAVs, Berni and al., Tang and al. and Anderson and al. bring up relevant examples where UAVs are performing efficiently during diverse missions [3] [4] [5]. This ever-growing market, especially interesting for Earth Observation, complicates the comparison and ranking due to the lack or absence of information on UAV performance. Even when the information is available, the format in which the information is presented differs across manufacturers. Choi and al. [1] develop a way to compare the performance of different UAVs and to obtain a ranking after having filtered out options that are not able to perform the mission (resolution too low or required altitude too low).

This study expands the aforementioned framework to manned aerial assets and space assets where the main imagery drivers can be different. Concerning manned airborne imagery, there is also a wide variety of applications such as coral reef inspections and coastal inspection and CO2 quantification missions [6] [7]. Manned airborne solutions are chosen instead of UAVs when distances are greater than ten kilometers, when the area to inspect is difficult to reach (ex: coastal environment) and when the resolution is above ten centimeters. In that case, no UAV or even combinations of UAVs can be used due to the complexity of UAV deployment along a 500 km coastline. In his paper, Ayanu et al. compare airborne and space-based solutions to monitor ecosystems [8]. In this study, we focus on two small twin-engine aircraft: the CESSNA 172 and the Zenith STOL CH 750. However, again, many different aircraft with various flight performance may be used. It is important to take the time to gather information to compare them properly.

The satellite Earth observation (EO) industry has been mainly dominated by a few actors during the era of large and heavy satellites like the Pleaides and the SPOT constellations. They have been able to map the entire planet. While they are still operating and highly solicited, there is a new wave of opportunities for smaller actors in the imagery business, launching smaller satellites or constellation of satellites, or sometimes both.

The European Space Agency (ESA) which has launched multiple Earth Observation satellites, recognizes this trend of having fewer larger satellites and more smaller and cheaper satellites [9]. They also identify manned aircraft and UAVs as Earth Observation contributors but in a different category compared to satellites. The National Aeronautics and Space Administration (NASA) recognizes the same trend and expects satellites to weigh from 200kg to 500kg instead of two to five metric tons today. Earth observation applications are, again, numerous for satellites and several studies have used data acquired over the previous decades to make significant scientific discoveries as described by Boyd and al. [10]. Denis and al. explore scenarii for the future of satellite-based Earth Observation [11]. In their last scenario, they confront satellites and UAVs where there would be "huge competition between data and satellite owners" . In the case where data were flooding and where UAVs were deployable anywhere, there is a high risk of having satellite data become the extra layer of data that no customer or end-user wants because they would come too late and produce lower quality images than UAVs would.

In order to satisfy different kinds of requirements faced by imaging service providers, it is necessary to consider various types of assets (such as small UAVs, larger manned fixed-wing aircraft, and even satellites) capable of performing a mission of interest. For example, Barnes and al. discuss the competitive or complementary face of the imagery market shared by UAVs and satellites[12]. Tobias and al. explain the differences between those three types of imagery services (unmanned aerial, manned aerial and space) and why they are used today [13] . UAVs can operate at very low altitudes and can provide high-quality and detailed pictures with comparatively small and light equipment and at lower costs. However, their range (and thereby the area of interest which can be scanned) is limited due to their size, and especially their power source, as well as the communication range with the on-ground operator. Furthermore, the operation of UAVs requires ground transportation from/to the mission area. Compared to UAVs, manned aircraft fly directly to the area of interest, thereby reaching places faster, and can cover larger distances. They can also operate in isolated regions not reachable by a UAV and its ground crew. Although manned aircraft have the disadvantage to be required to operate at higher altitudes compared to UAVs, they are able to carry larger and higher resolution imaging equipment. Satellites do not require this preparation time due to their constant orbit and permanent operation. They can deliver images of large areas in a very short amount of time and at a global scale. However, the demand for satellite images is high and it is possible that another customer has already requested a picture of a different place at the time when the satellite will be above the area of interest. In that case, the pictures or video would need to be taken the next time the satellite is free of duty and above the area of interest. Also, due to their distances to the ground, satellites can only take images at a relatively rougher resolution. In this paper, we detail the process used to allocate an Earth Observation mission to the best possible asset available - UAV, aircraft or satellite. In section II, we describe the background of this study and the baseline which was used to shape this advanced framework. In Section III, we detail the filtering approach, the manned aircraft trajectory computation, the satellite imagery analysis, the parameters of the multi-asset comparison method and the Multi-Attribute Decision Making (MADM) process. In section IV, some results are presented on a variety of test cases. In section V, we conclude and present some future directions to upgrade and improve the proposed framework.

II. Background

The proposed framework is an extension of the automated UAV mission planning framework developed by Choi et al. [1] which was divided into two separate steps: a filtering process and a multi-attribute decision making process. Only focusing on UAVs, the purpose of the filtering process was to determine the appropriate combinations of UAV platforms, sensors, pilots and operating altitudes to satisfy mission requirements such as image quality, area coverage (endurance capabilities), and deadline (asset availabilities). The resulting candidate combinations were then ranked using a multi-attribute decision-making process based on the user preference with respect to four criteria: image resolution (or Ground Sampling Distance), cost (associated with taking and post-processing the pictures), mission flight time and both pilot experience and performance.

In this paper, the aforementioned framework is extended to include manned aircraft and satellite assets to address larger mission areas and collect more diverse candidate combinations. This requires the development and query of a database of manned aircraft and satellites able and available to fulfill the mission of interest according to a set of requirements (a certain mission type over a user-defined area of interest with a specific resolution before the mission deadline). The resulting filtering process, including satellites and manned aircraft, is shown in Figure 1. Although there are similarities between UAVs, manned aircraft, and satellites, some differences need to be taken into account in the filtering process. First, the endurance filtering process described in Choi et al. [1] only accounts for the UAV trajectory over the area of interest. However, for manned aircraft, the trajectory from the base airport to the area of interest and vice versa needs to be taken into account as part of the calculation of the flight distance and time required to perform the mission. Therefore, a database of potential airport locations as well as a modified trajectory computation are necessary for manned aircraft.
Second, for satellites, the filtering process is different as it requires the computation of the satellite orbit to determine when the satellite will go over the area of interest and the consideration of the incidence angle at which the picture will be taken as the satellite does so. Finally, this study uses a similar multi-attribute decision making process as that described in Choi et al. [1]. Information about UAV and manned aircraft service providers (called vendors) will be added to the model to account for the variety of service providers in terms of location, pricing, and reputation. In the case of satellites, the concepts of vendors and pilots do not apply and the decision-making process is adjusted accordingly.

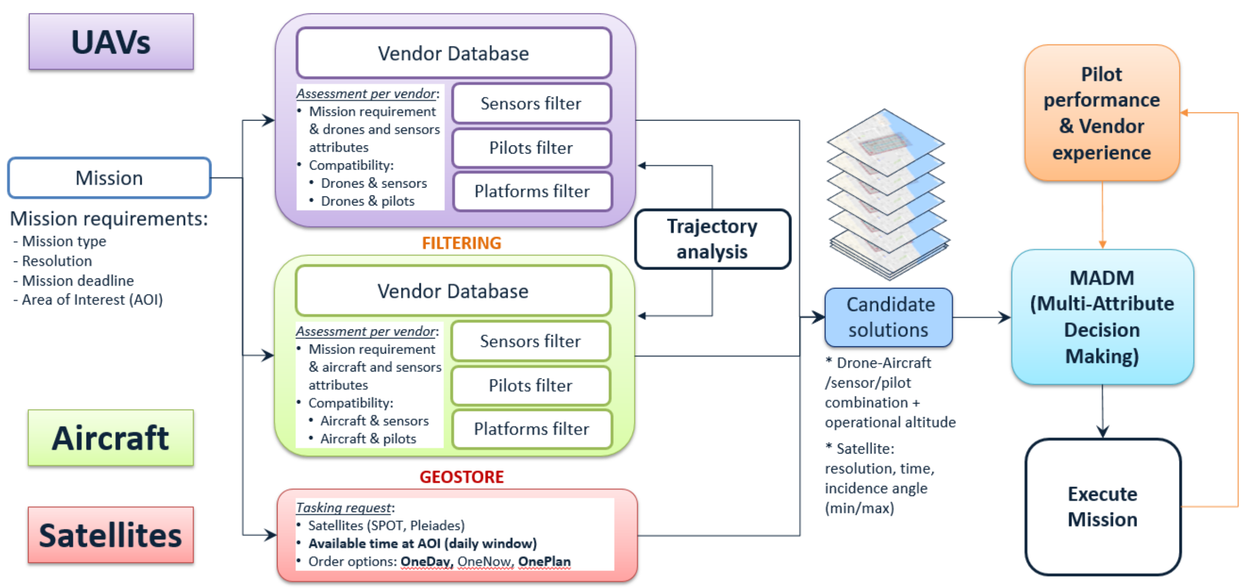

Fig. 1 Decision-making process encompassing UAVs, manned aircraft, and satellites.

III. Methodology

A. Asset Filtering Process

The filtering process for manned aircraft works similarly as the process established for UAVs by Choi and al [1]. Databases of pilots and sensors availabilities and compatibilities are used to identify combinations of platforms, sensors, and pilots based on mission scheduling and asset compatibility constraints. The maximum operating altitude that satisfies the mission resolution requirement is determined and the altitude range between the minimum (given by airspace restrictions and FAA regulations) and the maximum operating altitudes is divided into a set of possible operating altitudes.

Manned Aircraft Filtering Process

For the case of manned aircraft, FAA rules and regulations need to be taken into account [14]. Specifically, the FAA specifies the minimum altitude at which an aircraft may fly as 500 feet above the surface in non-congested areas - except over water or sparsely populated areas and 1,000 feet above the highest obstacle within a horizontal radius of 2,000 feet around the aircraft in congested areas. In this paper, we take 500 feet as the minimum operating altitude of manned aircraft. When needed, the user can manually discard solutions which are not appropriate for the mission (e.g. over cities where a minimum of 1,000 feet above the highest point is required). We take the service ceiling of the aircraft as the maximum operating altitude. As a reminder, the service ceiling is defined as the maximum altitude that may be reached by the aircraft under standard conditions of temperature and pressure (29.92" Hg and 15° C at Mean Sea Level) and at which the aircraft is still able to climb at a rate of at least 100 ft/min (e.g. for the Cessna 172, this is between 13,000-15,000 feet above sea level - an average value of 14,000 feet will be used in this study). Furthermore, aircraft trajectories are generated to optimize the flight path to cover the area of interest effectively and to account for the portion of flight required to go from the airport to the area of interest and back. This trajectory generation will be detailed in the next section.

Satellite Filtering Process

The satellite filtering process is conducted through the Airbus Geostore application, an on-line user interface provided by Airbus Intelligence Defense and Space [15]. The interface requires, as top-level inputs, the requested area of interest (AOI) and the desired resolution. Based on the those inputs, different numbers of satellites are available for tasking. The tasking itself can be done through four different modes: *OneDay*, *OneNow*, *OnePlan* and *OneSeries*.

OneDay creates options that allow the purchase of a picture at a time known a priori with the corresponding incidence angle. Options are available from the following day and then every day at similar times. Although this option provides a simple and, in comparison to the other modes, cheap approach, the customer needs to be mindful of the sensitivity of the area of interest to weather phenomena. Since the picture will be taken at a specified time, cloud coverage might make the image unusable. *OneNow* expands the *OneDay* options and tackles the usability problem by offering an "up-to-three-picture" option to the customer. It is a more expensive option, but it includes a set of possible times and a threshold for cloud coverage. If the threshold is exceeded, another picture is taken at a later time within this set of possible times. Thereby, the customer can triple the chance of getting a usable image. Both options further include maximum values for acceptable incidence angles of either 30° or 50°. *OnePlan* allows the customizable implementation of the mission requirements and the passing on of requirements fulfillment. After the initial definition, the option allows to specify in details which incidence angles (in increments of 1° between 0° and 50°) are acceptable, what cloud coverage is acceptable (either 5 %, 10% or 20%), i.e. what picture completeness factor is required, as well as which acquisition mode (either mono, stereo or tri-stereo) is desired. For the stereo and tri-stereo acquisition modes, the user can further specify which minimum and maximum breadth-to-height ratio (in increments of 0.01 between 0.2 and 0.8) of the picture is acceptable. *OneSeries* expands the *OnePlan* options and allows the placement of recurring imaging requests. In comparison to the established UAV process, this option is not included in this study. The different tasking modes offered through the Geostore are summarized in Figure 2.

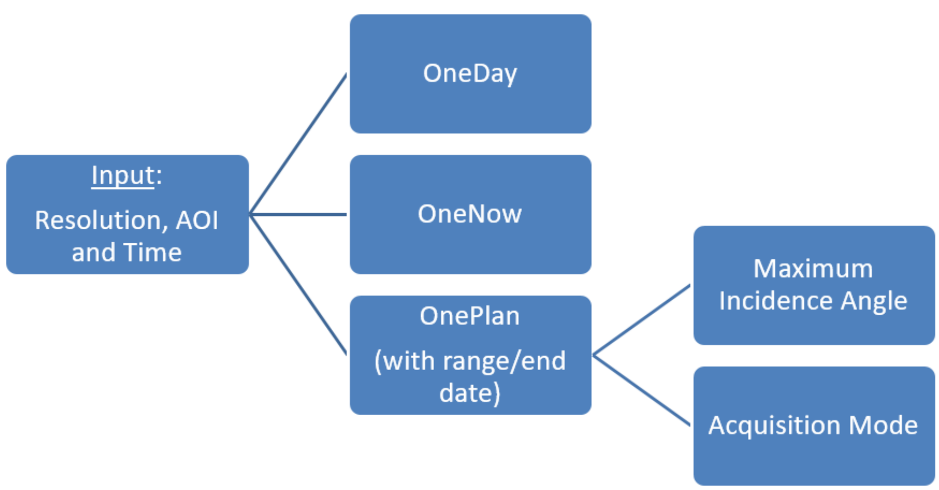

Fig. 2 Satellite filtering process conducted through Geostore

B. Manned Aircraft Trajectory

To efficiently compute the trajectory of manned aircraft assets, a few modifications need to be made compared to the UAV trajectory computation presented in Choi and al. [1].

Trajectory Generation

For UAVs, using high bank angle values to perform a turn is not a problem. Plus, time of flight - or endurance - is the key factor for the filtering process. For manned aircraft, maneuvers are usually not recommended at bank angles higher than thirty degrees for a standard flight. This limitation is due to both aircraft structural limitations as well as flight crew safety. We also need to be aware that the intent of the flight is to take pictures. Thus, even with a rotating photographic platform, higher bank angles can compromise the quality of the pictures or even the possibility of taking the pictures itself.

To address the issue of the bank angle for manned aircraft, a Dubins trajectory is implemented [16] as it takes into account the position and direction of the system as well as the maximum bank angle.

When the aircraft bank angle is unknown, it can be computed using the true air speed (TAS) and the turn radius. It is sometimes called the constraint in curvature. This means that abrupt changes in direction are prohibited. The Dubins path is based on the principle that there are only six possible scenarii to join any two points: Right-Left-Right turns, Left-Right-Left turns, Right-Straight-Left turns, Left-Straight-Left turns, Right-Straight-Right turns, and Left-Straight-Right turns. Although directions of flight do not really matter for UAVs, they do matter for manned aircraft. They are implemented in such a way that the Dubins path is only computed when there is a change in the path greater than a few degrees. This means that, if the aircraft is going straight, there is no need for a Dubins path scenario between these points. A theoretical example of a Dubins path is shown in Figure 3. Figures 4 and 5 show the difference between trajectories obtained using a Dubins path (for manned aircraft) and a cubic spline interpolation (for UAVs).

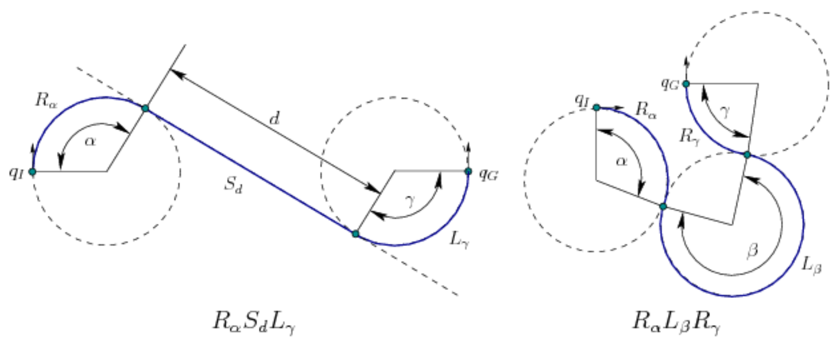

Fig. 3 Dubins curves - example of a Right-Straight-Left trajectory (left) and a Right-Left-Right trajectory (right) [17]

The endurance filtering process for the manned aircraft starts with the sensor characteristics computation and is followed by the minimum and maximum altitudes determination. Those altitudes come from either regulations (detailed previously) or GSD characteristics. The process continues with the computation of the complete trajectory using Dubins path, airport runway information, and aircraft performance.

In this paper, we consider two types of manned fixed-wing aircraft: a CESSNA 172 and a Zenith STOL CH 750. Their performance were extracted from their Pilot Operating Handbook to compute the time of flight during each flight segment. A margin

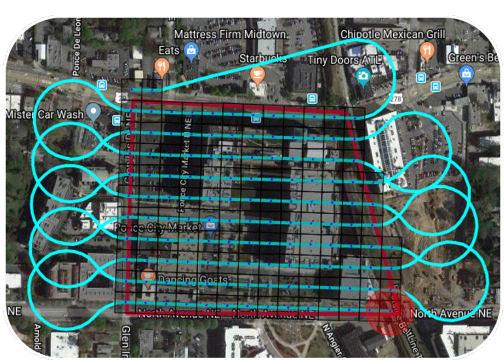

Fig. 4 Dubins path - used for manned aircraft

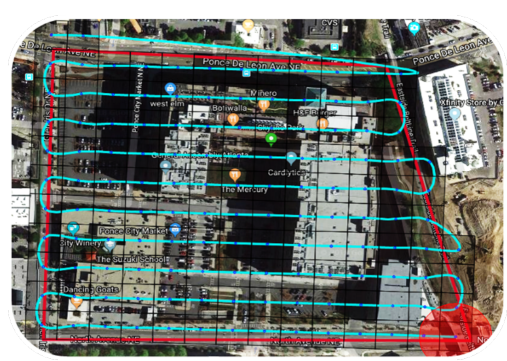

Fig. 5 Cubic spline interpolation - used for UAVs

Fig. 6 Complete trajectory computed for manned aircraft solutions: to and over the area of interest and back to the airport

of 20% was then added to the resulting time of flight to account for procedures around the departure/arrival airport and near the area of interest required to prepare for the imaging mission. Figure 6 shows an example manned aircraft trajectory from the home airport and back and the zigzag trajectory taking into account turn rate limitations and the Dubins path characteristics.

An immediate implication of this modified trajectory is that a manned aircraft solution is a combination of 5 elements (aircraft asset, sensor, pilot, vendor or home airport, and operating altitude). Indeed, in the case of UAVs, vendor location and distance to the area of interest was not taken into account to determine the mission cost. Rather, mission cost was based on how much it costs to use a UAV of a certain type for a certain period of time. For manned aircraft, airport considerations are necessary to give sensible results. The implications of this new feature are important: an aircraft imagery solution with a very high resolution and a very talented pilot might be discarded because of the fact that the aircraft home airport is too far away from the area of interest. This concept could actually be retrofitted to the calculation of mission cost when using UAV assets as part of a future work. Indeed, it is probably relevant to account for the distance from the UAV vendor location to the area of interest when experimenting over large distances. This improvement requires a database upgrade: the information may be stored either in a vendor-independent database (e.g. aircraft,UAV, sensor characteristics) or a in vector-dependent database (e.g. for UAV vendor A: pilot/UAV/sensor schedule and pilot performance).

C. Satellite Imagery Analysis

Each imaging asset can provide pictures with a specific resolution or ground sampling distance (GSD). The resolution depends on the equipment utilized as well as the distance to the surface. For UAVs and manned aircraft, a vertical position from the asset to the target area can be assumed due to their proximity to the ground and the realistic approach of operating this way. Airborne assets are always tasked and operated for a specific mission and can therefore be adapted to satisfy the mission requirements.

Imagery satellites, on the other hand, operate in Low Earth Orbit (LEO) on a fixed trajectory. Furthermore, a single satellite is associated with much higher costs than a single aerial asset and therefore satellites as a whole are more limited in number and availability for a specific mission. Requiring the same minimal angle for images as may be achieved with aircraft or UAVs, would result in high costs due to the required priority in tasking in comparison to other missions. Those constraints result in the necessity to consider non-vertical pictures of target areas. To compare the unaffected resolution of aerial assets with the resolution of inclined pictures of satellites, the ground sampling distance of the satellite needs to be converted into a "True GSD" value. As outlined in the user guides of the satellites considered in this study (Pleiades and SPOT 6/7) [18] [19], the transformation is provided in Equation 1. It accounts for the viewing or incidence angle θ, the mean Earth radius R, the satellite altitude H (depending on the specific orbit), as well as the equipment-specific instantaneous field of view (IFOV) parameter. Table 1 summarizes the values used for the aforementioned parameters.

$$True\,GSD = 100 \times \left[\frac{(1+\frac{H}{R}) \times \cos(\theta)}{\sqrt{1-(1+\frac{H}{R})^2 \times \sin(\theta)^2}} - 1 \right] \times R \times IFOV \tag{1}$$

Table 1 Satellite specific values for "True GSD" conversion

		SPOT 6/7 [18]	Pleiades [19]
Mean Earth Radius R		6367.45km	
Satellite Altitude H		699km	695km
Instantaneous Field of View (IFOV)	PAN	$3.14 * 10^{-6}$	$1.00 * 10^{-6}$
	MS	$1.25 * 10^{-5}$	$4.00 * 10^{-6}$

D. Multi-Asset Alternatives Downselection and Ranking

To be able to compare UAVs, manned aircraft and satellites, we establish a list of common attributes that can be drawn from each asset specific filtering process. Indeed, each design and operating mode is different - satellites are orbiting around the Earth on specific trajectories whereas UAVs can be deployed anywhere. Thus, common inputs and outputs need to be used to ensure that the mission can be initialized the same way independently of the asset. Similarly, the outputs of the filtering process need to serve as inputs to the MADM process and need to be correctly evaluated by the algorithm.

The common set of inputs for each asset are required mission resolution, area of interest (boundary coordinates), mission type, and mission deadline for the decision-making process.

Using those common inputs, the filtering process is computed separately for UAVs, manned aircraft and satellites and the resulting outputs concerning actual GSD (related to the operating altitude for UAVs and manned aircraft and to the true GSD for satellites), mission cost, mission time and pilot experience (when applicable) are re-combined to obtain a single set of potential alternatives to perform the mission of interest.

Process Overview

An illustration of the multi-asset comparison framework is given in Figure 7. It is an expansion of the description provided in the background section but in a more sequential manner. The process starts with a main function that reads the user inputs and initializes the filtering process (second, third and fourth steps in Figure 7) and the Multi-Attribute Decision Making process (fifth step). In the filtering process, the second step starts with the initialization of all the required databases related to the vendor characteristics, the availability and compatibility information of the pilots, the sensors, the assets, and the performance information of the sensors, the UAV and manned aircraft assets considered in the study. For satellites, a request is made to the Geostore API according to the mission requirements in order to determine the possible space-based alternatives and their pricing. The compatibility and availability of each combination of assets is checked at this point. Some parameters are also introduced at that step in the process: those parameters will drive a wide variety of calculations such as the altitudes at which the trajectory is computed, the margin on the endurance, the maximum number of grid cells, etc. These parameters are not part of the user inputs but are a critical component of the framework. Indeed, changing these parameter values without precaution would give wrong results.

In the third step, the filtering process prepares for the endurance filtering computation for the aerial assets (aircraft and UAV). It starts off with the computation of the sensor characteristics. It takes the available information from the existing database and computes the missing elements. Those elements are stored in a database which is then used to find the combination of aircraft + sensor or UAV + sensor that can potentially achieve the mission. The endurance filtering process can then start and determine which pairs of asset-sensor can perform the mission (i.e. with the required resolution and enough endurance). The endurance filtering process is further expanded and visualized in Figure 8. The endurance filtering is divided into a sequence of actions: divide the area of interest into cells, compute the trajectory using the grid (Cubic spline trajectory for UAV or Dubins path for manned aircraft) with endurance computation, compute the trajectory from the airport and back (aircraft only) and generate the visualization files. The process in the third step ends with the aerial solutions with associated sensors and pilots that are available, compatible and with enough endurance and resolution. Based on the previous missions realized by the vendor and pilots, a scoring based on the performance and experience is extracted from databases. These values of pilot score and vendor experience are then added in the database to have a complete database. In parallel, the satellite solutions are generated using Geostore and the corresponding output is then reshaped in the right format to be able to be merged with aerial assets. The integration of the satellite solutions with both the UAV and manned aircraft solutions is described subsequently.

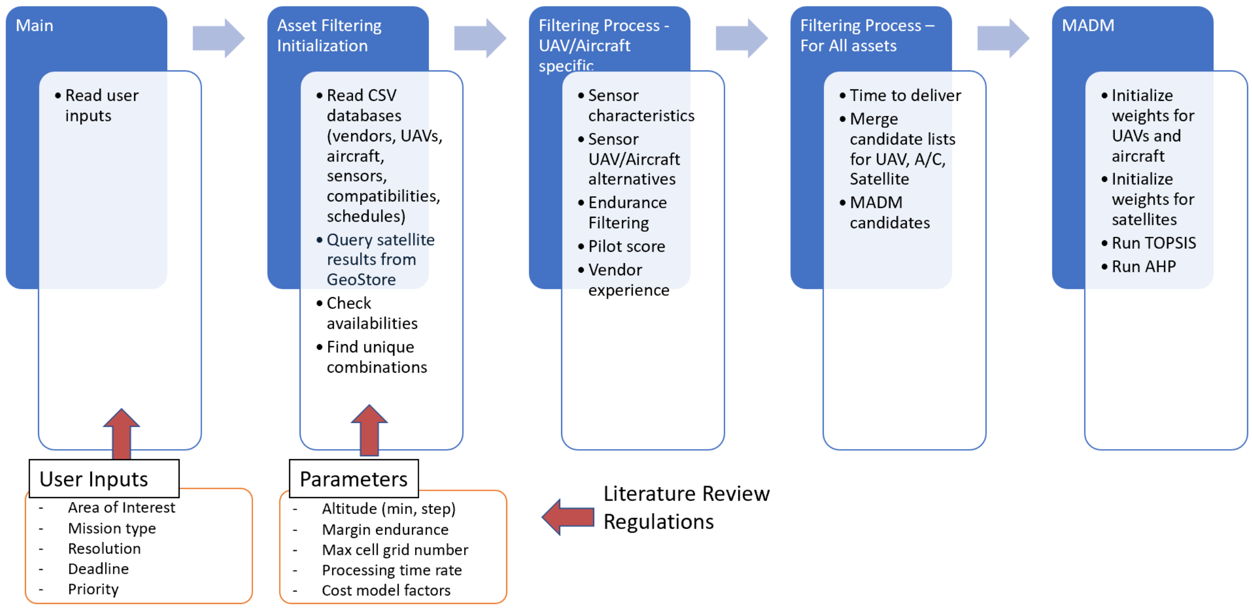

Fig. 7 The multi-asset comparison framework for Earth Observation

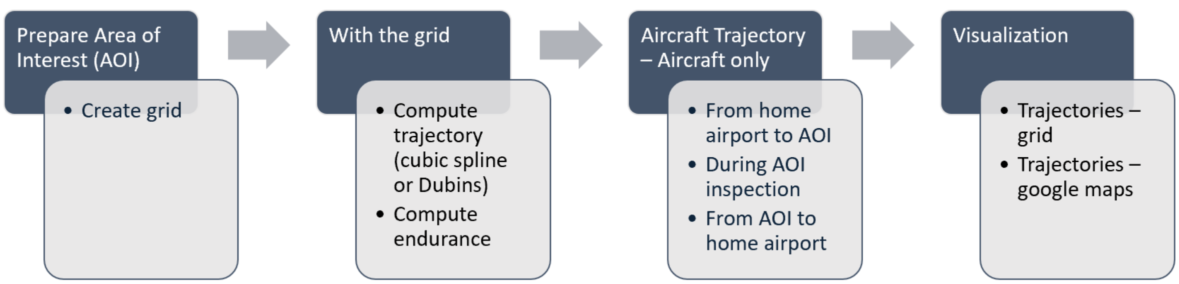

Fig. 8 Illustration of the endurance filtering sub-process

Satellite integration

In order to be able to compare satellites and aerial assets for the same mission with a given area of interest (AOI), a resizing of the AOI might be necessary before satellite solutions can be generated. Satellite imaging requests are usually required to be made for rather large areas, especially compared to the area a single aerial asset would be able to cover within a given timeframe. This means that, if the initial AOI is smaller than a given threshold, then this AOI needs to be artificially increased to obtain the relevant satellite alternatives information from the Geostore website, including true GSD, mission cost, and actual day when the AOI will be imaged by the satellite. For the generation of the enlarged satellite AOI, the minimum and maximum values for longitude and latitude respectively, are used to form a rectangle, which is then uniformly increased to meet the minimum area requirement. This process is visualized in Figure 9.

Cost Model

The cost model used for aerial assets is based on the the market values for UAV and manned aircraft services. These values are provided as a cost per square meter, a cost per nautical mile, a cost per megapixel as well as potentially some coefficients for some linear cost estimations. Several cost models were investigated as follows:

- *Linear model* which estimates costs using values like cost per hour, cost per session, cost per half-day, cost per full-day, cost per picture, cost per ft2, cost per Mpixel. A market analysis is necessary to provide values for that model.

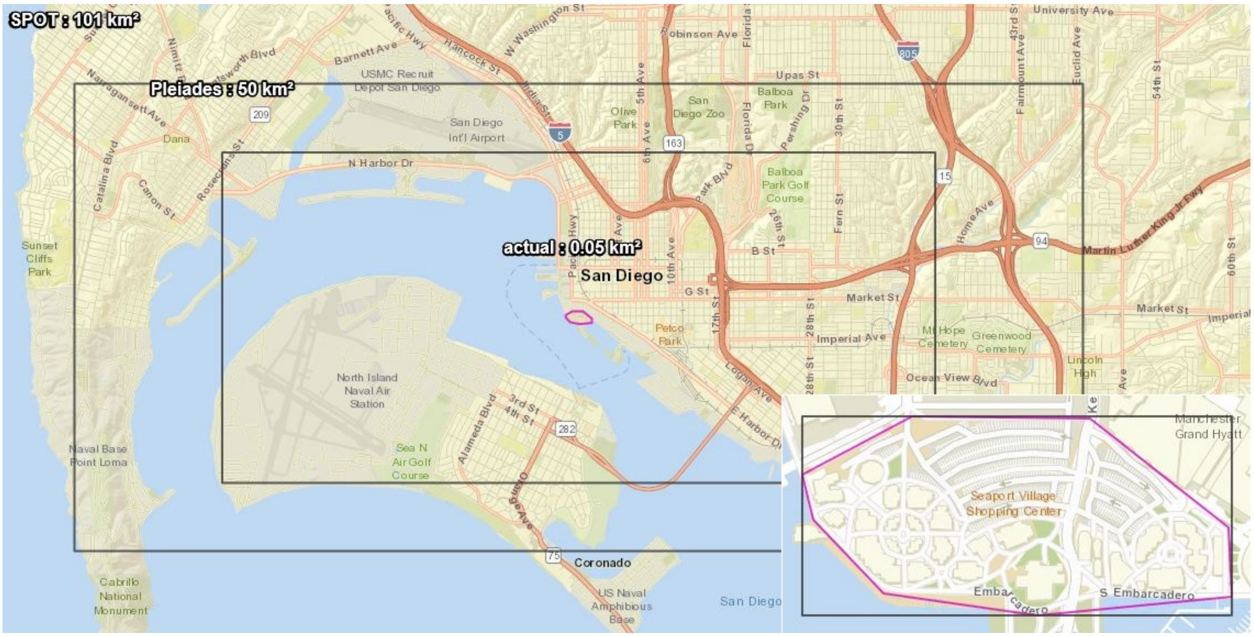

Fig. 9 Illustration of the AOI enlargement process

- *Relative scale model* which estimates costs using relative values from 1 to 9 – 1 being the lowest score and 9 being the highest score (UAV, sensor, distance to mission area, pilot experience/performance, vendor experience, number of images, image resolution, post-processing time or turnaround time, video length, video editing, etc.). A formula is necessary to convert the scaled values to real costs. That is mainly for aerial assets (UAVs and aircraft) as the Geostore API provides real cost values for satellite images. This model requires an extensive literature review about aerial imaging mission rates.
- *Regression model* which implies developing a surrogate model of mission costs using published rates for aerial imaging services depending on number of pictures, size/resolution of acquired data, type of acquired data (2D images, 3D images, visual images, IR images, videos, combinations of the above, etc.), mission scheduling flexibility, UAVs, sensor, etc. This model requires a literature review and a fitting analysis is needed to validate the model.

To test the proposed integrated process, the linear model was selected due to its simplicity. It yields sensible results and constitutes a good foundation for future model improvements. Linear formulas used are based on the rental cost of the aerial assets and a global margin taken to compensate travel expenses and mission complexity. Within the aerial asset category, there is a main difference between UAVs and manned aircraft. The cost of renting a UAV is not geospecific (i.e. not attached to a certain location) but rather it is fixed and encompasses the cost of renting the device plus any extra travel expenses which might occur. On the contrary, manned aircraft are geospecific and cost contains the information on the aircraft location. The cost of a manned aircraft mission is based on the distance between the area of interest and the home airport, as well as the average cost per unit distance.

Time to Deliver Data to Customer

This model was developed to estimate the amount of time required to post-process the data acquired during the imaging mission and to send the final product to the customer. An image processing phase is necessary to transform the raw image into a useful image. We investigated two ways to compute the time to deliver data to the customer:

- *Linear model* which estimates the time to process images as a linear function of the number of pictures taken. This model requires to set up a value for the cost of one Megapixel.
- *Regression model* which takes into account image size/resolution, type of acquired data (2D image, 3D image, video, visual image, IR image, etc.), vendor performance. A literature review is needed on image processing times depending on image size and resolution, type of acquired data, processing capability of the vendor, etc.

For model validation purposes and due to its simplicity, the linear model was used to estimate the time required to deliver data to the customer. It estimates the time to process images as a linear function of the number of pictures (or megapixels) taken. The "time-to-delivery" is a linear function of number of megapixels taken. The linear parameter was estimated using an average value based on market values. The regression model was not developed for this first framework but may be implemented as an improvement in the future.

Integration of multiple databases into a single database

Once the solutions are computed for UAVs, manned aircraft, and satellites separately, the fourth step of the process displayed in Figure 1 consists in computing the cost and "time-to-delivery" for aerial assets and merging the databases of candidate UAV, manned aircraft, and satellite solutions into one single multi-asset database. The combined set of UAVs, manned aircraft (with associated sensors, pilots, and operating altitudes) and satellite solutions may now be ranked using the MADM techniques described in the next section.

E. Candidate Solutions Ranking

Candidate solutions for each asset type (UAV, manned aircraft, and satellite) are ranked according to a multi-attribute decision making (MADM) process. In this study, the analytic hierarchy process (AHP) [20] is used.

Weighting Criteria

By definition, MADM techniques require decision criteria, or attributes, to compare alternatives. A challenge of implementing those methods in a multi-asset comparison case occurs when there are different kinds of attributes associated with each type of asset and those have to be harmonized, which is the case in this study. Six decision criteria are used in this algorithm to compare satellites and aerial asset-sensor combinations and their computed trajectories. The first criteria is Ground Sample Distance, or GSD. GSD corresponds to the resolution of the image acquired by a given sensor at a given altitude. For satellites, the True GSD is used as previously outlined. To maximize resolution, GSD must be minimized. The second criteria is cost, which must also be minimized. The cost of the mission is estimated based on the type of mission performed, the GSD, and the size of the area to be imaged. The third criteria is delivery time, which encompasses all the post-processing time required to process and deliver the raw pictures as a final image of the area of interest. Just like GSD and cost, MADM techniques seek to minimize delivery time when selecting the best alternative. For aerial assets, three additional criteria are included: pilot experience (which provides of a measure of the amount of similar missions performed by a given pilot in the past), pilot performance (which is related to the quality of the pictures taken and the pilot's UAV handling capabilities), and vendor experience (which is also a general score of the asset provider experience in handling similar missions). For satellites, these characteristics are set to a maximum under the assumption that human influence is negligible when it comes to satellite operations. The MADM techniques seek to maximize these three measures of human performance when ranking alternatives.

Multi-Attribute Decision Making Technique

The Analytic Hierarchy Process (AHP) organizes attributes into a hierarchy consisting of multiple levels. This way, only the relative importance, or weight, of each attribute within its level must be provided by the decision-maker. The weight of an attribute across multiple levels is obtained by successive multiplications of its weight at each level. The final result, or score, is the weight of the alternatives (lowest level), with respect to the final decision (highest level). The alternative with the highest score is the one selected, and a ranking of alternatives may therefore be obtained from the final score of each. AHP is ideal for problems with quickly identifiable hierarchies and a high number of attributes. In addition, AHP allows the easy inclusion of different decision-maker preferences and influences on the final decision.

The hierarchy implemented in this study consists of five levels. The first level, as for every AHP structure, is the final decision. The second level is the decision-maker level, which consists of each decision-maker's relative importance towards the final decision. The third level is the criteria level, consisting of "Cost", "Delivery Time", "GSD", and "Provider Score". The fourth level, the sub-criteria level, expands only from the "Provider Score" criterion, and consists of "Vendor Experience", "Pilot Experience" and "Pilot Performance". Finally, the fifth level consists of all the candidate alternatives generated by the asset filtering upstream of the MADM process. Here, the value of each alternative with respect to Cost, Delivery Time, GSD, and the three sub-criteria of the fourth level is normalized by the sum of the whole set. Thereby, the weight of a particular asset-sensor combination and trajectory with respect to each criteria is a direct function of its performance.

IV. Results

The multi-asset imagery framework is tested on five different use cases. The examples chosen are diverse enough to show the coherence of the results compared to logical solutions that one would think of. Plus, they are illustrating the variety of different options that may be handled by the proposed framework. For example, the size of the area of interest is varied from a small city of a few dozen houses to a complete city of 100,000 inhabitants. The tool allows the utilization of different weighting scenarii to conduct cost-, resolution- and time-critical missions. If such a scenario is specified, ranking gets dominated by the respective criteria (allocation of 99.82% weight alongside 0.06% for the remaining three criteria). For a balanced non-dominated assessment, the tool allocates equal weights (25% each) to every criteria. All cases were generated assuming a required resolution (GSD) of 1 meter for the images to be acquired, and a mission to be accomplished before DAY 12 (mission deadline).

A. Exploration of weighting scenarii for a small area of interest

For the small area, the Seaport Village complex next to the Manchester Grand Hyatt Hotel in San Diego, CA (USA) with an area of 0.05 square-kilometers was used for this study. The results for the cost-, resolution- and time-critical missions are summarized in tables 2, 3 and 4, respectively. It is worth noting that a total number of 531 candidate solutions are obtained for each scenario, including all three asset types.

Table 2 Results for a small-size area with "cost-critical" weighting

Total Rank	Relative Rank	Type	Cost	GSD	Asset Name	Sensor Name	Time to delivery
1	1	UAS	89.51	0.075	DT18 HD-3G	DT18 HD-MamaBear camera	2
...							
3	3	UAS	91.31	0.045	DT18 HD-3G	DT18 HD-MamaBear camera	2
...							
321	1	MAC	1575.83	0.117	Cessna 172 Skyhawk	Waldoair XCAM B NIR EF 40MM F2.8 STM (2)	3
...							
405	1	Sat	3100	0.709	OnePlan Pleiades		10
...							
408	4	Sat	5600	0.860	OneDay Pleiades		1

Table 2 shows that UAVs are largely dominating the set of candidate solutions for the "cost-critical" mission and are ranked 1 through 320. The manned aircraft solutions follow (ranked 321 through 404) and the satellite solutions come last. This is because satellite pictures are much more expensive than pictures taken from cameras mounted on a UAV or on a manned aircraft.

Table 3 Results for a small-size area with "resolution-critical" weighting

Total Rank	Relative Rank	Type	Cost	GSD	Asset Name	Sensor Name	Time to delivery
1	1	UAS	444.1	0.011	Albris	eBee PLUS RTK/PPK SODA	2
...							
9	9	UAS	111.05	0.015	DT18 HD-3G	DT18 HD-MamaBear camera	2
...							
45	1	MAC	2051.93	0.05	Zenith STOL CH 750	Waldoair XCAM B Ultra 50MM fixed focal length + 85MM fixed focal length	2
46	2	MAC	8497.35	0.05	Zenith STOL CH 750	Phase OneÂ iXU-R 1000 iXU 1000 Schneider-Kreuznach fast sync 110 mm f 2.8	2
...							
515	1	Sat	3100	0.709	OnePlan Pleiades		10
...							
519	5	Sat	5600	0.861	OneDay Pleiades		1

Table 3 shows that, as image resolution becomes more critical, manned aircraft solutions become more interesting. The reason for that is that manned aircraft solutions can carry higher resolution cameras compared to UAVs and can therefore attain a similar image resolution, albeit a higher overall mission cost.

Table 4 Results for a small-size area with "time-critical" weighting

Total Rank	Relative Rank	Type	Cost	GSD	Asset Name	Sensor Name	Time to delivery
1	1	Sat	5600	0.861	OneDay Pleiades		1
2	2	Sat	5600	0.861	OneDay Pleiades		2
3	1	UAS	111.05	0.015	DT18 HD-3G	DT18 HD-MamaBear camera	2
4	2	UAS	94.83	0.030	DT18 HD-3G	DT18 HD-MamaBear camera	2
...							
23	1	MAC	8497.35	0.050	Zenith STOL CH 750	Hassleblad H6D-100c HCD 4 28MM	2
...							
31	9	MAC	1624.34	0.056	Zenith STOL CH 750	Phase One iXU-R 180 iXU 180 Rodenstock 90 mm f 5.6	2

Finally, Table 4 shows that if time becomes more critical, then satellite solutions are favored compared to UAV and manned aircraft options. This is due to both the fact that satellites can be more readily available to perform a mission compared to UAVs and manned aircraft which need to be available at the same time as their associated sensors and pilots, and to the fact that more post-processing is required on images taken from a UAV or a manned aircraft than from a satellite.

Table 5 Results for a remote area with "resolution-critical" weighting

Total Rank	Relative Rank	Type	Cost	GSD	Asset Name	Sensor Name	Time to delivery
1	1	UAS	1172.98	0.574	DT18 HD-3G	DT18 HD-MamaBear camera	2
...							
3	4	UAS	1149.74	0.604	DT18 HD-3G	DT18 HD-MamaBear camera	2
...							
27	1	Sat	3100	0.709	OnePlan Pleiades		10
...							
59	5	Sat	5600	0.861	OneDay Pleiades		1

B. Impact of area remoteness on geospecific assets

When considering different areas of interest, the location of the area relative to the geospecificity of the manned aircraft vendor is a relevant factor for candidate feasibility analysis. Geospecificity thereby relates to the association of a home base with a certain vendor and thereby also with the corresponding assets. For such a remote area, the forest area around and including the campus of the University of California - Santa Cruz in Santa Cruz, CA in regard to vendors located in the Los Angeles area was used for this study. Table 5 shows results for this case study. The results include only candidate solutions for UAVs and satellites, but not for aircraft. The absence of aircraft solutions comes from the fact that the distance of the area from all vendors and the corresponding flight time exceeds the endurance of the available assets. It should be noted at this point that UAVs are not implemented with vendor locations and the distance between area and vendor is not considered within the cost model. A similar approach could be implemented in the future for UAVs by calculating travel costs from/to the vendor locations to/from the area separately from the operating costs for the actual imaging mission of the area of interest. Satellites act as non-geospecific assets, since they actually provide global imaging capabilities.

C. Study of asset feasibility for a large area of interest

The technical feasibility related to the use of a certain kind of asset, besides the operational feasibility determined by availabilities and compatibilities, is driven by the size of the AOI. Aerial assets require a land- or air-based travel from the vendor location to the AOI and back, as well as a certain mission trajectory to accurately image the area. Those factors yield time constraints that might conflict with the time required to image a given area. For a large-size area, a part of the Los Padres National Forest outside of Santa Maria, CA with an area of 210 square-kilometers was used for this study. Table 6 shows results for this case study, which only includes satellite candidates. This is because the aforementioned constraints for aerial assets were violated and therefore potential solutions became infeasible.

Table 6 Results for a large-size area with "resolution-critical" weighting

Total Rank	Relative Rank	Type	Cost	GSD	Asset Name	Time to delivery
1	1	Sat	7980.87	0.709	OnePlan Pleiades	10
...						
5	5	Sat	14417.05	0.861	OneDay Pleiades	1
6	6	Sat	14417.05	0.861	OneDay Pleiades	2
7	7	Sat	14417.05	0.861	OneDay Pleiades	3
...						
17	17	Sat	14417.05	0.861	OneDay Pleiades	12

V. Conclusion and Future Work

This study is an extension of an Unmanned Aerial Vehicle comparison framework developed by Choi et al. to downselect and rank unmanned aerial vehicle solutions (with the associated sensors and pilots) for a specified Earth observation mission. The expanded framework allows the comparison of heterogeneous Earth observation imagery assets: unmanned aerial vehicles, manned aircraft, and satellites. It takes into account each system characteristics and operational capabilities, and features methods to assess their performance based on a handful of common attributes. To be more specific, the filtering process includes manned aircraft and satellite assets, and the ground sampling distance computation was adapted to the case of satellites using the concept of true GSD. Regarding trajectory calculations, aviation regulations and aerial asset physical constraints provided by the manufacturers were used to compute the Dubins trajectory for manned aircraft. The filtering process is composed of the following steps: first, a compatibility and availability check of the assets is performed; second, an endurance filtering process is implemented; third, the mission cost and time to deliver data the customer are computed; fourth, from a set of user inputs and predefined model parameters, alternatives based on different asset types (UAVs, manned aircraft, and satellites) are evaluated and ranked. The user inputs are mission type, area of interest, desired resolution or Ground Sampling Distance, deadline to complete the mission. The predefined model parameters include values like the post-processing data rate and the different altitudes at which assets may fly. The comparison criteria are cost, time to deliver the pictures to the customer, picture resolution, vendor experience and pilot experience/performance. The proposed framework enables the end-user to rank multi-asset alternatives based on relative importance of the time, cost, and resolution metrics. The framework was successfully tested on a number of test cases ranging from a small area which favors UAV solutions to a larger area which favors satellite solutions.

Future work could include the assessment of multi-asset operations, not only limited to multiple assets of the same type but also missions including the utilization of different kinds of assets. When considering a larger scale mission, an Area-of-Interest (AOI) may be divided into sub-areas that may be tackled by separate assets. By adapting the established multi-attribute decision making procedure, the aforementioned considerations can be included in a comprehensive decision-making analysis.

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