ILEOS: A Novel Intelligent Observing System Enabled by High Altitude Long Endurance Uncrewed Aerial Systems

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Most major global satellite surveyors of climate-relevant trace gases have relatively coarse spatial resolution or temporal sampling. While these data can be supplemented by fine-pointing satellites and aircraft, the spatial and temporal resolutions available from crewed aircraft is not sufficient to observe stochastic, ephemeral events that take place between observations. Emerging High Altitude Long Endurance (HALE) Uncrewed Aerial Systems (UAS) can operate for months at a time and loiter over targets to provide continuous daylight geostationary-like observations, allowing these new platforms to be integrated with existing satellites as part of a New Observing Strategy (NOS). To aid in the planning of future NOS missions, NASA is developing the Intelligent Long Endurance Observing System (ILEOS), a science activity planning system. ILEOS will help scientists build plans to improve spatio-temporal resolution of climate-relevant gases by fusing coarse-grained sensor data from satellites and other sources (e.g., terrain, forecasts), and plan HALE UAS flights to obtain finer-grain (high spatio-temporal) data. ILEOS will also enable observations for longer periods and of environments not accessible through in-situ observations and crewed aircraft field campaigns.

I. Introduction

The primary advantage of satellite platforms for collecting Earth observations is spatial coverage. However, current and near-term satellite data of atmospheric gases have resolutions that are too coarse in space and/or time for many scientific research problems (e.g., emissions estimation, source attribution) and applied research applications (e.g., human health exposure estimates, wildfire assessment). For instance, the state-of-the-art satellite, ESA's TROPOMI, has relatively coarse resolution – providing global daily coverage at spatial resolutions of 3.5×5.5 km^2 for nitrogen

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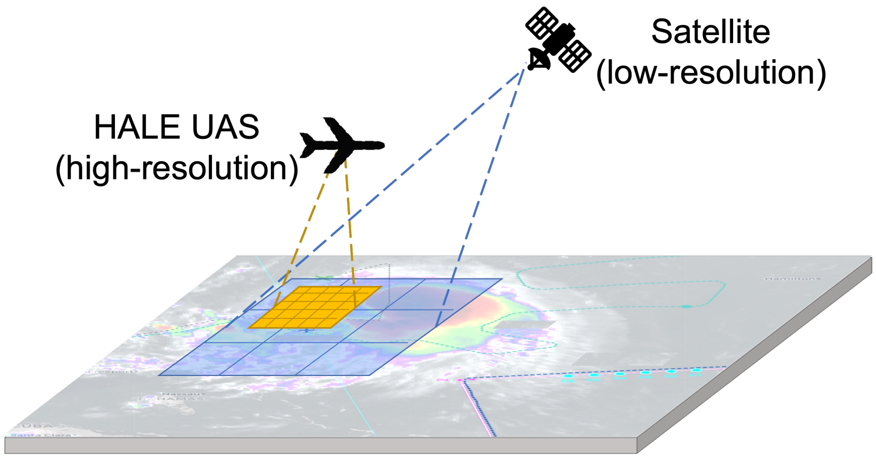


Fig. 1 ILEOS Concept of Operations

dioxide (NO_2) and 5.5×7 km^2 for methane (CH_4) [1]. GOSAT-1 has sparser coverage than TROPOMI with a footprint of 10.5 km^2 [2]. In contrast, these gases are emitted at much smaller, more complex spatial scales. For example, NO_2 is primarily emitted from fossil fuel sources, such that small scale variability depends on factors such as road density, etc. [3]. Methane (CH_4) is usually emitted during oil and gas extraction [4], and from wetlands [5]. In addition, most Earth-observing satellites are in sun-synchronous orbits, providing observations only once per day at the same solar time. Though some current and upcoming satellites are/will be in geostationary orbit, the issue of relatively coarse resolution remains (e.g., 2.1×4.7 km^2 for NASA TEMPO [6]).

The expense of collecting in-situ data with high spatial resolution limits this type of data collection to relatively small geographic areas and/or small periods of time. For example, large metropolitan areas often have few air quality monitors, which don't capture the complex spatial gradients found in the urban environment [4]. Intensive measurement campaigns can increase this density, as data are typically collected from numerous in-situ instruments on multiple platforms (e.g., aircraft, surface, and balloon [7]). However, these campaigns are "snapshots" of atmospheric composition because of their short durations (i.e., few days-weeks) and are limited to relatively small geographic domains for logistical reasons. In addition, they are expensive and require flight planning teams who analyze weather forecasts and discipline-specific model forecasts (e.g., atmospheric composition forecasts). As a cheaper option, low-altitude drones have successfully demonstrated the ability to collect data in challenging environments, such as offshore areas of energy extraction activities [8] and the Arctic-boreal zone [9], [10]. However, the limitations of low-altitude drones include the need for human operators and flight planners, along with their expense, and relatively short operating distances, times, and altitude ranges.

Emerging HALE UAS, such as those developed by commercial companies like Swift Engineering [11] and Aerovironment [12], are an emerging technology that may revolutionize earth observing. In particular, the Swift flies at $55 - 65K$ feet ($16 - 20$ km), can loiter over a single location and observe during daylight hours to provide continuous geostationary-like observations, and can relocate by flying at $45 - 55$ KTAS (knots true airspeed), providing a potential operating range of 1200 miles per day. HALE UAS can already carry instruments sized for CubeSats; as battery power density increases, they may soon be able to carry multiple, larger instrument payloads. Numerous instruments are able to measure climate-relevant gases and are likely to fly on near-term HALE UAS. Examples include the CHAPS-D instrument [13], (15 lb) that is being developed for a CubeSat form factor and is able to monitor NO_2 and other trace gases at 1 km^2 resolution [14], and the GHG-SAT-D imager [15] (33 lb.), which flies on existing GHGSat CubeSats [16]. HALE UAS offer the best of all worlds by leveraging (1) their ability to carry payloads with high spatial resolution, (2) their combined capabilities to continuously loiter like a GEO satellite, and (3) their ability to relocate freely like an aircraft, thereby enabling them to collect high spatial and high temporal resolution (high spatio-temporal) data (Fig. 1). This new vantage point will play an important role as part of a New Observing Strategy (NOS) to complement existing data sources. The goal of the NOS concept is to develop system architectures that will enable the optimization of measurements across a variety of platform vantage points (air, space, and ground) and dimensions (location, time) to build a more comprehensive picture of Earth Science phenomenon [17][18]. In recognition of the need to evaluate multiple technologies, a NOS testbed is under development [19] to evaluate and integrate new technologies.

HALE UAS will operate in what the FAA terms upper Class E airspace, (e.g., 60 K feet above mean sea level). The future use of this airspace creates a common desire to re-evaluate the current air traffic management approach and realize innovative solutions. To ensure safe and efficient service provision for current and future expanded operations, NASA and the FAA are exploring an upper Class E Traffic Management (ETM) concept [20]. Numerous workshops and studies on ETM have been conducted [21]. Future vehicle tests of ETM may also include HALE UAS simulating science missions, potentially as part of a NOS.

Although the development of these platforms advances the state-of-the art, additional work is needed to effectively leverage these new capabilities to build NOS that also push scientific discoveries forward. While previous investments have investigated scheduling fleets of satellites, aircraft, and both together, no technology has been developed to leverage coarse-grained data to identify new observing targets, and generate plans for HALE UAS fleets to obtain the desired high spatio-temporal resolution data needed to satisfy the objectives outlined above. Therefore, to fully utilize future payload capabilities, now is the time to begin integrating HALE UAS with existing satellite missions to enable NOS for climate-relevant gases 5-10 years hence.

II. Observation Scheduling for Earth Science

In this section we describe the problem of Observation Scheduling for Earth Science applications, starting with satellites, then moving to aircraft. The capability of scheduling observations for constellations of large satellites with payload re-pointing has been formulated for the French Pléiades constellation [22],[23] and COSMO-SkyMed constellation of synthetic aperture radars [24]. Schedulers for Cubesat constellations, such as the 200+ Dove spacecraft fleet [25] assume static orientation of the sensor in orbit and only schedule duty cycles for payload power. The D-SHIELD project [26], [27], [28] has demonstrated science activity planning of constellations of steerable spacecraft with multiple instruments and variable science priorities. Frank et al. [29] describes a notional scheduler for a geo-stationary satellite. This scheduler was used to evaluate different sensor designs for the GEO-CAPE design reference mission; it includes temporally varying preferences provided by Science Subject Matter Experts (SMEs), and a cloud-mask using GOES data to constrain observations. These technologies are not directly suited to flight planning for HALE UAS. Furthermore, none of these technologies incorporate automated target generation or 'cueing' from coarse-grained observations; nor do any of these technologies incorporate any explanation or user interfaces.

Numerous mission planning systems address the problem of covering an area using multiple UAS aircraft. [30–33] describe approaches to plan multiple vehicles tracking a target; simulation results are described. Shriwastev and Song [34] describes a multiple UAS coverage application with a focus on altering coverage when a UAS fails. These approaches are are not specific to Earth-science applications, but provide useful examples of novel UAS mission planning technology that employ multiple vehicles instead of a single vehicle, and are primarily simulation-based, with varying degrees of flight planning fidelity. A notable exception is [30], which demonstrates planning of a mixed team of UAS, including a real vehicle. Stecz and Gromada [35] address the problem of planning military reconnaissance missions for a single UAS in the presence of hazards / threats. This work includes treatment of exclusion constraints, priority of observations, and task and motion planning. However, the work was done in simulation for a low altitude vehicle. More suited to our application, Chakrabarty and Ippolito[36] address monitoring a fire with a UAS fleet. This work also demonstrated the use of multiple UAS, in a simulation environment. This work does not directly address scheduling of objectives to observe, as the objectives are all fixed in advance. None of the work described above addresses the problem of target generation, or 'cueing' from coarse-grained observations. While some of the work above includes user interfaces (e.g. [36]), none address the problem of explainability.

Numerous systems have been developed to plan and schedule satellites and aircraft (and other assets) simultaneously. [37, 38] have developed a coordinated automated planner that can handle a continuous stream of image requests from users, by finding opportunities of scheduling air or space assets to maximize collected utility. This approach addresses the problems of integrating multiple federated assets, and focuses on explicit representations of uncertainty. This work was demonstrated in simulation environments. Ferreira et al. [39] describes a system designed to manage underwater, surface and air vehicles for oceanographic survey missions, and has been used for numerous deployments of dozens of vehicles. The mission planning component used, NEPTUS [40], lets operators plan missions by hand, but includes no automated planning. In a similar vein to prior work cited above, these approaches do not address the problems of automated target generation, 'cueing' from coarse-grained information, or explainability of plans.

The problem of generating targets for Earth observations combines two elements. The first is the geospatial area of interest. Typically this a function of the sensor, and in the case of satellites, the orbits. In [29], for instance, scenes are statically defined due to the geostationary orbit of the GEO-CAPE mission. In other cases, points of interest must be covered by observations, as is done in D-SHIELD [27]. The second element of target generation is the priority of a scene; priority is a function of the scientific value of acquiring a scene, and is used to help planners select which scenes to observe, when not all scenes can be observed. There are few examples in the literature describing scene and priority generation schemes. Landsat 7's priority scheme [41] modifies a base priority compared to how often a scene was 'missed' due to excess cloud cover, best scene found so far, etc. Landsat benefitted from fixed scenes based on the LEO orbit of the spacecraft. Soil moisture models such as [42] and [43] produce error estimates, which are input to D-SHIELD's planner [27]. However, there is no attempt to generate explanations of plans and tie them to the model error estimates.

In recent years, explainability of automated and AI systems has become an increasingly important area of research. Examples of this interest include DARPA's XAI program [44] and workshop and tutorial programs at major AI conferences. Explainability is more than merely building user interfaces that describe plans, or show data. The seminal paper on explainable planning [45] describes a variety of techniques that must be developed in order to describe to a human operator why an automated planner produced the plan that it did. Since then, additional work on explanations for planning has been performed [46–50]. Explainability has not been applied to over-subscription planning, nor to planning problems with continuous domains. When it comes to the inputs to the planner, explanations may take the form of provenance, or configurations of the various analytic engines that produce the scenes, and priorities, consumed by the planner. In this context, provenance is defined as "information about entities, activities, and people involved in producing a piece of data or thing, which can be used to form assessments about its quality, reliability or trustworthiness [51]." Older work on provenance [52] is limited to merely describing where an artifact came from. Recent work on provenance [53], developed for DoD applications, is more applicable, connecting provenance of data artifacts to plan generation. However, none of this work has yet been applied to the problem we address, that of generating targets and observing plans for a HALE UAS.

Previous similar work, such as INTEX-B[54] and D-SHIELD[27], has several limitations. While INTEX-B addressed the problem of planning for multiple, diverse sensors on a crewed aircraft, it lacked applicability to the operating domain and vehicle of interest for the identified science use cases below. The D-SHIELD work explores producing plans for the sensor payloads of a constellation of orbital satellites. It chooses which targets to observe and schedules when to observe them based on the satellites' locations, but does not develop a mission plan for moving a vehicle to specific high value target locations. In addition, neither INTEX-B nor D-SHIELD addresses explainability considerations.

III. Intelligent Long Endurance Observing System (ILEOS)

ILEOS features a combination of state of the art automated planning and scheduling algorithms, novel automated target generation technology, and innovative techniques for user control and review of the entire decision-making process. In addition, ILEOS incorporates environmental (wind, weather, airspace) data to ensure the creation of high-value flight plans for HALE UAS, thereby reducing costs associated with current field campaigns and surface in-situ sensing networks and ensuring that future science missions are able to explore the identified use cases of interest (Section III.A). Several data sources are taken from products that produce improved forecasts the closer you get to the date and time being forecasted. ILEOS has the potential to incorporate updated information to improve previously generated mission plans. Finally, ILEOS is designed with human operators in mind; plan explanation and data provenance features ensure science mission planners understand all key algorithmic choices made while generating plans. In summary, ILEOS is a key enabling technology for a HALE UAS oriented NOS to improve spatio-temporal resolution Earth measurements.

A. Use Cases for ILEOS: Relevance to Earth Science

While ILEOS has potential applicability to a wide variety of Earth science disciplines, we describe use cases for NO_2, an air pollutant and an important precursor to unhealthy levels of ozone formation, and CH_4, a greenhouse gas (GHG). Both trace gases have high relevance to the science and application priorities presented in the recent consensus study from the U.S. National Academies of Sciences, Engineering, and Medicine [55] (Decadal Survey). The Decadal Survey committee proposed competitive observational opportunities for several science and applications areas: (1) understanding the sources and sinks of carbon dioxide (CO_2) and CH_4, (2) the processes that will affect their concentrations in the future, and (3) assessing changes in NO_2, ozone and other gases, and the associated implications for human health, air quality, and climate. The ILEOS-enabled NOS could be effectively used, for example, to collect a rich dataset of observations with high spatio-temporal resolutions of:

- *NO_2 (proxy for combustion emissions such as CO_2) and CH_4 over oil and natural gas extraction areas of the Gulf of Mexico:* Observing these sources would allow for the estimation of these emission sources, e.g., point (large rigs), line (shipping lanes) and area (small wells; support ships).

- *NO_2 in urban areas:* Measuring these emissions down to the city block level is important for reasons of human health [3] and environmental justice [56]. NO_2 is a short-lived gas and has strong gradients in concentrations from sources, such as cars, trucks, and factories, leading to a wide range of potential exposures within an urban environment.
- *NO_2 generated from lightning:* This is an important ingredient for the formation of upper tropospheric ozone, a climate-relevant gas. Future HALE UAS could fly high above anvil storm clouds, collecting observations unobtainable from the surface, and are dangerous and expensive to collect using crewed aircraft.
- *Arctic-Boreal zone CH_4:* These sources are strongly influenced by the water table level and air temperature [9][7][10]. Both of these factors could be accounted for in the ILEOS observing strategy such that flights target areas likely experiencing high emissions.
- *CH_4 from various anthropogenic sources:* Sources include industrial processes and leaky natural gas distribution pipelines, in complex urban environments. The data may be used to pinpoint sources needing migration for safety reasons or to reduce the GHG footprint of urban areas.

B. ILEOS System Architecture

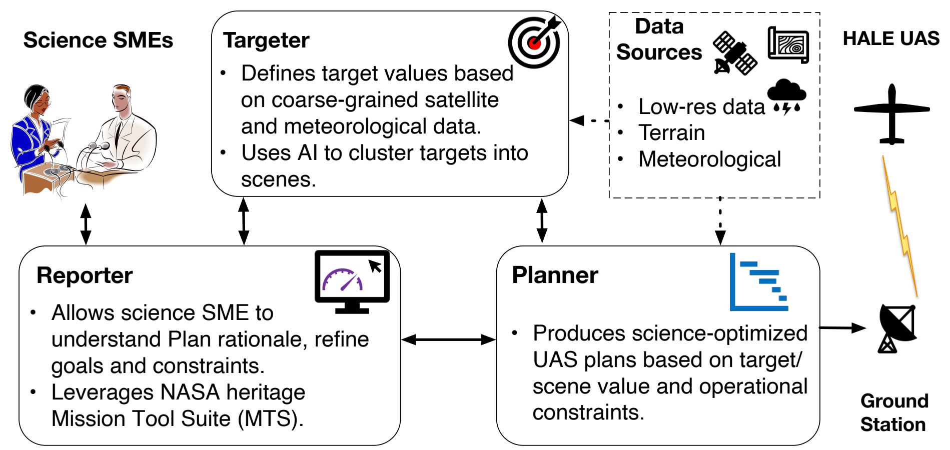


Fig. 2 The ILEOS system architecture includes three functional components: Targeter, Planner, and Reporter. These components leverage coarse-grained data and SMEs' domain knowledge to produce plans that maximize high spatio-temporal data collection.

ILEOS consists of three functional components (Fig. 2): the Target Generation Pipeline (Targeter), the Science Observation Planner (Planner), and Scientists' User Interface (Reporter). The Targeter identifies candidate target scenes for HALE UAS-mounted instrument observations. The Targeter leverages Science SMEs' domain knowledge to fuse available coarse-grained data from satellites and other sources into science value maps with targets of varying science value. The Planner uses automated planning and scheduling technology to automatically generate a flight plan to observe the best identified targets while enforcing all operating constraints for a HALE UAS.

The Reporter allows users to configure the Planner and Targeter. It provides the user interface for science mission planners to visualize science values, selected targets, flight plans, and other relevant information such as clouds and winds. The Reporter also allows mission planners to review the values of targets, and the underlying constraints and assumptions used to schedule measurements and generate a flight plan. Finally, it allows users to modify constraints (and ultimately science values for targets) to adjust science objectives and mission plans.

1. Targeter

The Targeter is responsible for identifying targets, known as scenes, for the HALE UAS to visit and their priorities. Each scene's priority is indicated by its science value given the available information. To determine the science value, a use case specific science constraint pipeline (defined by Science SMEs) is used to evaluate coarse-grained, climate-relevant gas concentration data available from satellites and other relevant sources (e.g., terrain, weather, temperature) and intelligently fuse that data to provide a score for how valuable (scientifically) a location (or pixel) is.

These locations are often at different scales than a full scene a sensor will scan. Therefore, multiple pixels and their science values are aggregated to form one scene and its value. Different science use cases require different algorithms for assigning science values. For instance, if the goal of observations is to reduce model error, scenes of high science value are those with high error; if the goal of observations is tracking a rapidly changing phenomenon, then scenes with high science values are those measured longest ago, or where change occurred most recently. The identified scenes and their scene values are sent to the Planner. The Targeter also records all key algorithmic decisions which, along with configuration information, are sent to the Reporter. This will allow the Reporter to explain scene value to users, providing traceability back to Targeter configuration choices and algorithm decisions.

The Targeter consists of the following steps: preprocessing, determining the science value, and scene generation. Fig. 3 illustrates the approach.

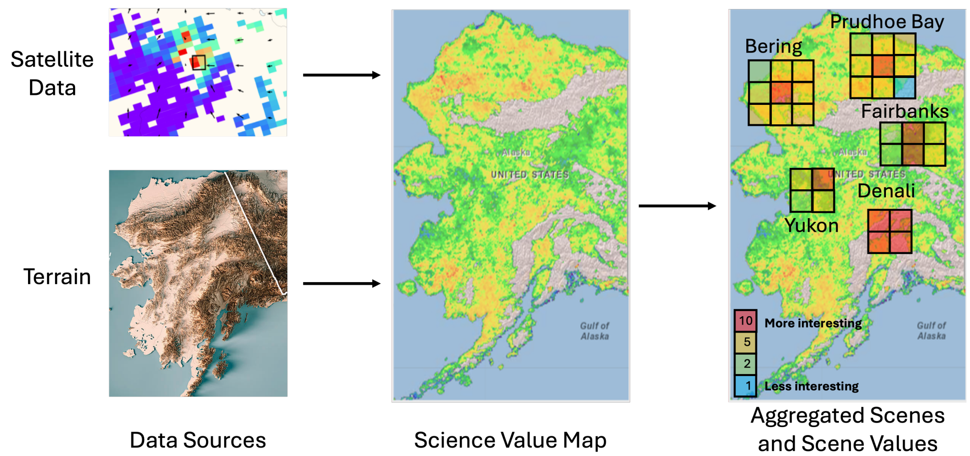


Fig. 3 The Targeter leverages a Science Value Module to preprocess the coarse-grained input data (left), intelligently fuse data together to determine the science value for all pixels (middle), and generate scenes (right).

To identify observing targets, the Targeter first assembles the different sources of available data, including satellite data (possibly from multiple satellites), wind, weather, and environmental data. The data are standardized to a common grid size, including coordinate transformations and interpolations as needed. The size is determined by the smallest resolution of the input data, or if computational time is a concern, the smallest resolution computationally viable. The result is a map of pixels with each pixel having data from multiple sources associated with it.

Once data from all sources has been assigned to the appropriate pixels by the preprocessor, the data is sent to the Science Value Module where each pixel's science value is computed using data from all sources associated with it. For example, for Arctic permafrost applications, CH_4 resulting from Arctic permafrost thaw has been shown to occur in close proximity to thermokarst [7], lakes or wetlands formed from permafrost thaw. Therefore, scenes will include data from GOSAT-1 CH_4 measurements, terrain, proximity to recently formed thermokarsts, and changing thermokarst geometry. The Science Value Module is generated a-priori by leveraging the science SME users' domain knowledge to intelligently fuse the available coarse-grained data together to produce science values according to the users' mission objectives. For the Arctic permafrost thaw example above, a scene may have high science value if CH_4 was observed by satellite, and is close to a thermokarst. While the Science Value Modules are use case specific, downstream Targeter algorithms (e.g., scene generation and scene value generation) are generic. In addition, each Science Value Module consists of an objective function that dictates the relationship between the input data and the science values. It includes several tunable parameters. These parameters can be adjusted by the user through the Reporter interface to make minor modifications to the science values produced after the Science Value Module is created, providing some flexibility without having to explicitly change science value and input data relationships defined by the objective function.

Science values are then passed to the scene identification module, where clustering is used to identify sets of similar points [57], [58]. Through clustering, pixels with similar science values that are close geographically are grouped together. This provides a basis for future explanations provided to users for why certain areas have higher priority (according to features identified via clustering). For the clustering portion of the Targeter, K-Means clustering is used. It assigns observations to one of K clusters based on the one with the closest mean [59].

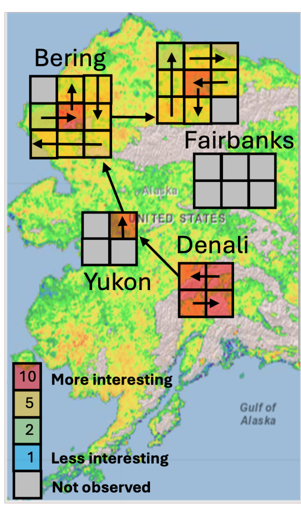
After clustering, larger scenes are created. In all the results shown below, scenes are assumed to be the size of the sensor footprint of the HALE UAS-mounted instrument. The sensor payload is assumed to be a push broom sensor and therefore the scene is the square with width equal to the swath of the sensor payload's scan. The value of each scene is aggregated from the pixels that are contained with it.

2. Planner

The Planner uses automated planning and scheduling algorithms to select the best targets from the set of scenes given by the Targeter and to produce a flight plan for a HALE UAS. In addition to scene priority, the Planner considers dynamic constraints (e.g., wind, clouds, and other weather variables), UAS location, and operating constraints such as air- and ground-speed and turning radius when generating plans. The Planner's output is a HALE UAS flight plan, scenes to observe, times at which the scenes are observed, and routes between each scene. The plans can be sent to a ground station, which communicates with the HALE UAS. Like the Targeter, the Planner records its algorithmic decisions which, along with configuration information, is sent to the Reporter. This enables users to ask questions about why a scene may or may not be included in the plan, why scenes are observed in a specific order, and why specific routes are taken. The Planner will ultimately allow SMEs to make modifications to the Planner constraints, and thus the plan itself.

The Planner's job is similar to that of a salesperson who must visit several cities but does not have time to visit all of them. First they decide which cities to visit on this trip and the sequence for visiting them. Next, they decide on the routes for travelling between cities, including where they enter/exit the city. Then they determine the sequence for visiting the customers within each city. All decisions must factor in dynamic conditions such as detours, constructions and traffic.

The Planner receives input from the Targeter, SMEs (directed through the Reporter), and external data sources. The Targeter sends the Planner a set of <scene, value> pairs, called scene choices. Scenes may have diferent values depending on the time of day they would be visited. SMEs use the Reporter to interact with the Planner to modify the scene value, if desired. This flexibility allows SMEs to apply expert knowledge not captured in the Targeter to inform the Planner's algorithms. The Planner's primary product is a plan, which is a scheduled sequence of selected scenes and flight plans for moving between. The Planner converts its inputs into a flight plan through several steps: preprocessing, scene scheduling, and high-level route planning (Fig 4). Note that the gray scenes represent scenes that were not observed because of the limited mission time. Inherently, this implies that they had lower value than those prioritized and included in the plan.



Scene Selection and Sequencing

Route + Motion Planning Output (UAS plan)		
Plan Step	**Action**	**Duration**
1	Observe Denali 3	30 mins
2	Observe Denali 4	30 mins
3	Observe Denali 2	30 mins
4	Observe Denali 1	30 mins
5	Traverse Denali to Yukon (Avoid T-Storm)	120 mins
6	Scan Yukon 2	30 mins
5	Traverse Yukon to Bering (Strong Headwind)	180 mins
6	Scan Bering 9	30 mins
...	...	...

Fig. 4 The Planner determines which scenes should be visited and in which order (left) and the detailed behaviors within each scene (right) with various vehicle operation and environmental constraints. Note that the gray scenes represent those that were not observed due to limited mission time.

In addition to constraints given by SMEs, the Planner will use available environmental data such as meteorological data (e.g., wind) and airspace constraints (e.g., no fly zones) when generating flight plans. Predicted winds will be used when generating flight paths to cover or traverse between scenes as in [60]. Predicted high winds or storms will be used to generate keep-out zones.

Each planning cycle starts with a preprocessing step to assimilate and convert external data sources, as well as Targeter input, into a format suitable for planning algorithms to use. These data products come in a wide range of data formats which depend on the tool used to produce the data and its intended use, but are typically not suited for use by planning algorithms.

The second step is scene selection and sequencing, which involves selecting a subset of scenes to observe and a sequence for observing them which satisfies all operating constraints. Vehicle specific operating dynamics are included as additional constraints when determining scene selection and sequencing. Each use case will specify the maximum plan duration, which constrains how many scenes can be observed each day. In general, a HALE UAS cannot observe all available targets due to various constraints, including effective ground speed, meteorology, etc. The Planner must identify and evaluate scene and schedule choices in light of these constraints, as well as scene priority. The Planner searches through all scene choices to select the subset with the maximum aggregate scene value, and a schedule for viewing them which does not violate any constraints. The problem is modeled as a Multi-Profit Orienteering Problem [61][62], which combines selection of a subset of tasks to perform and abstract route scheduling such that every target has multiple rewards depending on the time of day it is visited. A Mixed Integer Program was used to solve this problem, similar to [63].

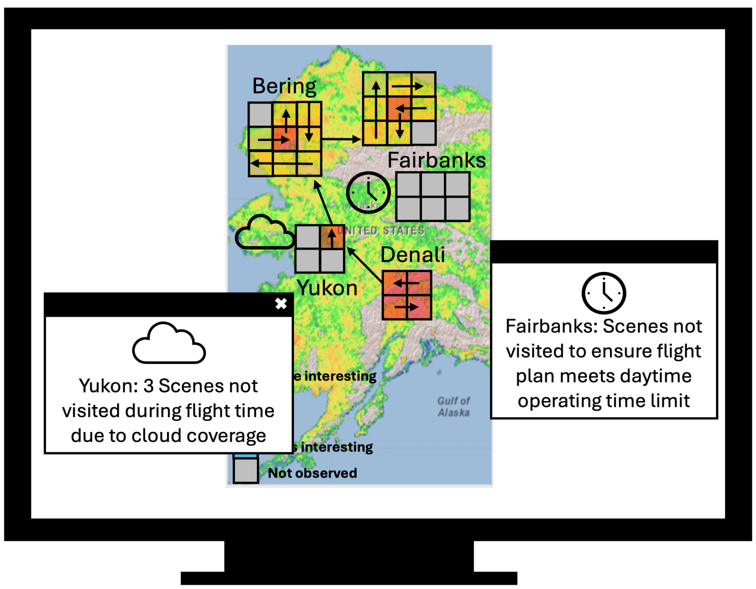


Fig. 5 The Reporter provides a unified interface for the user to interact with the Targeter and Planner components including viewing the applicable input data, generated targets and their associated science values, and generated mission plans. It also provides a way to understand the basis for the results so as to inform any potential iterations of the mission planning process.

3. Reporter

The Reporter provides a unified interface for both the Targeter and Planner. Through intelligent data visualizations and intuitive interactions with explanation and provenance features, the Reporter facilitates the review of configurations used by the Targeter to determine science values for scenes. This includes the ability to explore the impact of user configurations (e.g., SME-given thresholds) and input data. Similarly, the Reporter allows users to review the schedules generated by the Planner from the scenes provided by the Targeter and operating constraints. The Reporter also allows users to adjust the goals of the mission by modifying the parameters used by both the Targeter and Planner. Users are able to see data visualizations over varying levels of detail at their discretion for both the Targeter and Planner. As a result, the Reporter is able to provide necessary context for the user to understand the system decision making and goals without needing to understand all the low-level algorithms, thereby enabling them to maintain situational awareness as the mission progresses.

As the unified interface for ILEOS, the Reporter allows the user to ask questions about the priority of scenes, and the rationale for the target selection and scheduling (Fig. 5). To accomplish this, the Reporter leverages NASA's Mission Tool Suite (MTS) as a basis for the interface. MTS was developed as a mission operations and decision support environment for the NASA Airborne Science Program. The web-based MTS interface contains core capabilities for multiple users to simultaneously monitor real-time aircraft and satellite locations, view current or archived flight tracks, and view real-time sensor data from assets and external sources (e.g., weather products) through basic graphs and map overlays [64].

The Reporter takes inspiration from designs of provenance for planning. Similar to [53], the Reporter enable users to explore the input data sources, as well as the outputs from the Targeter and Planner to ask relevant questions such as (1) What are the science values of the scenes that the mission will plan to visit? What is the reward for visiting a particular scene? This provides a foundation for the users to review identified targets and produced plans and a method for ensuring that the user has the necessary information they need to make an informed decision should they want to modify any constraints (thereby modifying target priorities and/or plans). As a result, a mixed-initiative planning framework is produced where both the human and an algorithm contribute to the planning process, similar to [65].

IV. Use Cases

Two Greenhouse Gas (GHG) use cases were used to demonstrate the capabilities of the ILEOS architecture components: (1) validating the Bureau of Ocean and Energy Management (BOEM) inventory of NO_2 (as a proxy for co-emitted CO_2 and a precursor to tropospheric ozone) in the Gulf of Mexico region and (2) measuring CH_4 in interior Alaska. Results for the Targeter and Planner outputs will be shown for both use cases below and focus on the generation of initial mission plans.

A. Use Case 1: NO_2 in the Gulf of Mexico

When looking to collect NO_2 measurements, several factors play a key role. The first is the previously measured NO_2 value. The higher the value previously, the more interesting it is to revisit it to measure its diurnal variation. For this use case, both platform and non-platform emissions sources were were considered. Additionally, to ensure that effective measurements could be taken, scenes with lower aerosol optical thickness were assigned higher science value. Lastly, most NO_2 sensor payloads are affected by cloud cover. Therefore, scenes with lower cloud coverage were assigned higher values.

Fig. 6 shows a sample of Targeter input data for the Gulf of Mexico: (1) cloud coverage (left) and (2) combined platform and non-platform NO_2 emissions, measured columnar NO_2, and continental influence). The resulting science values for the scenes are shown in Fig. 7. The coast of the United States is shown as a solid black line and all area inland is assumed to be zero value as this use case is focused on locations in the Gulf of Mexico.

Given targets and their priorities (i.e., science values) produced by the Targeter, the Planner produces a flight plan. A

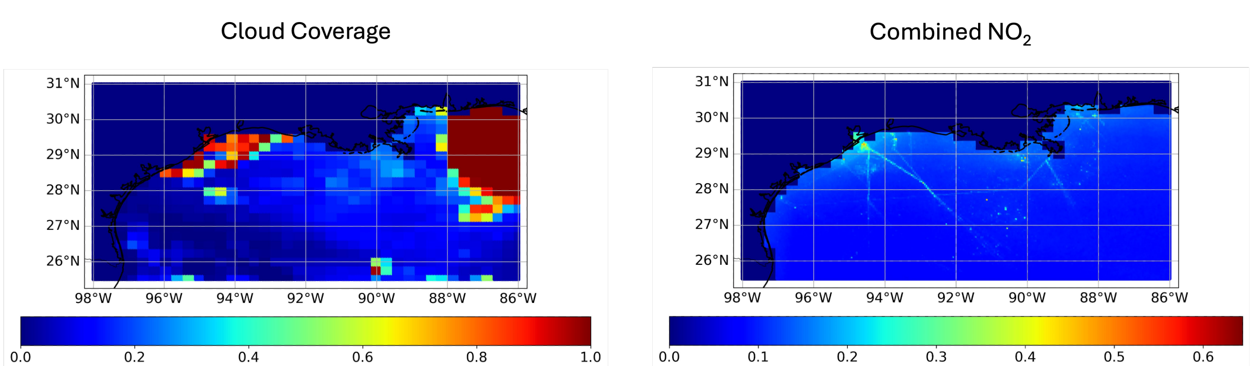


Fig. 6 Sample of Targeter input data used to determine the science value for scenes in the NO_2 use case. Note that cloud coverage is shown on a normalized scale and less clouds has a lower value (i.e., more science potential).

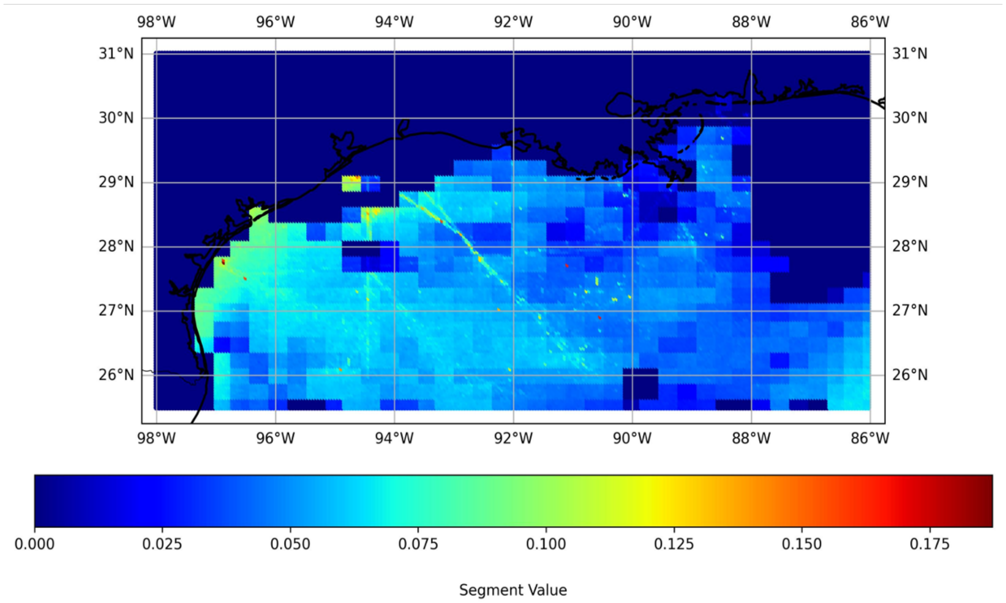


Fig. 7 Targeter produced scene values for the NO_2 use case. The coast of the United States is shown as a solid black line. All inland areas are given a value of zero as this use case was focused on offshore sources.

sample flight plan is shown in Fig. 8. This plan assumed a mission duration of 9 hours and utilized constraints resulting from the vehicle dynamics of a Swift Engineering HALE UAS (e.g., turn radius and nominal cruise speed). The result shows that the plan is focused around the hot spot area identified by the Targeter along the coast.

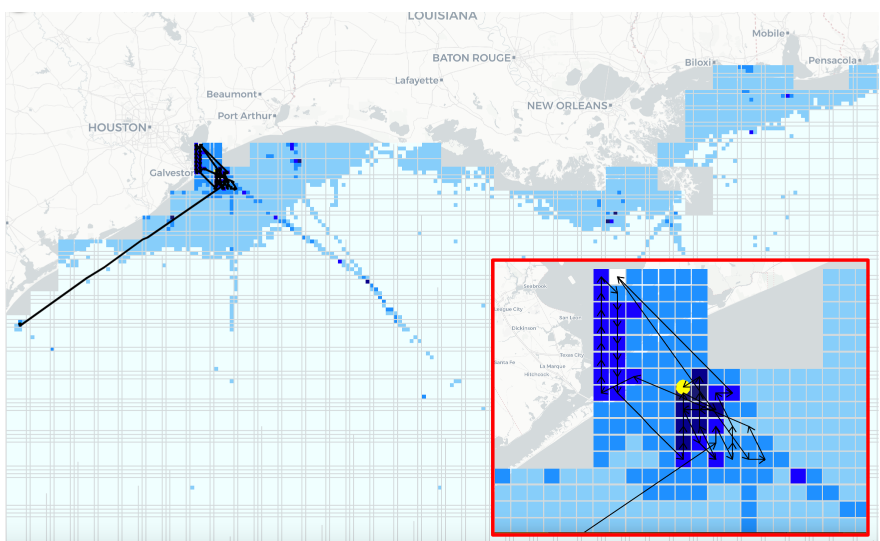


Fig. 8 Flight plan and chosen targets resulting from the Planner for the NO_2 use case. Each square represents a scene. The darker the blue of a scene, the higher its science value is.

B. Use Case 2: CH_4 in Interior Alaska

Permafrost thaw in interior Alaska can lead to the release of gases previously trapped within the frozen soil. Methane (CH_4) is a harmful GHG and is known to be one of the gases released. Typically, this gas release occurs in areas with specific land cover types (e.g., wetlands). Additionally, scientists are interested in areas where not only is CH_4 present, but those where there is a change in CH_4. Therefore, for this use case, land cover maps, satellite data detailing previous

CH_4 locations and variability over time were included in determining the science values. Like the NO_2 case, cloud cover was also considered due to its interference with sensor measurements.

Fig. 9 shows a sample of Targeter input data used for the CH_4 use case. The variance of measured CH_4 from the GOSAT-1 satellite and a map of the land cover types are used. Note that the original data resolution is different between the two data sources. All data is rescaled to the scene size before the science values are computed. The resulting science values are shown in Fig. 10.

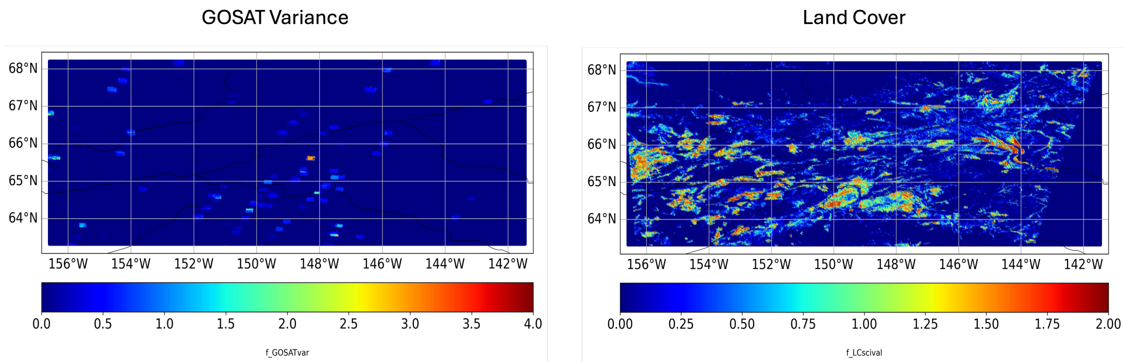


Fig. 9 Sample of Targeter input data used to determine the science value for scenes in the CH_4 use case. Note that land cover type is shown on a normalized scale and land cover that is more likely to have permafrost thaw has a higher value (i.e., more science potential) [66].

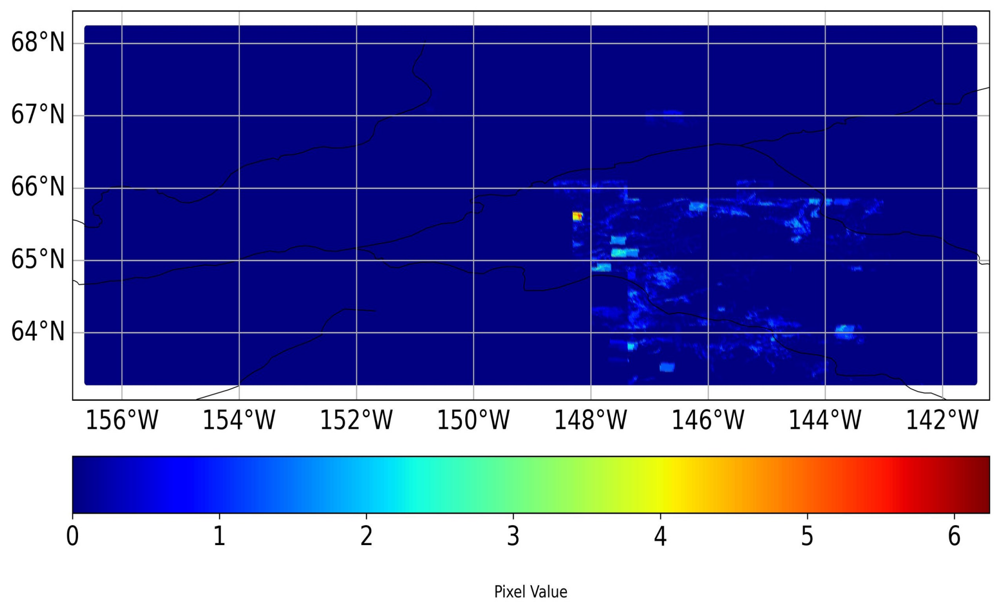


Fig. 10 Targeter produced scene values for the CH_4 use case.

The Planned produced flight plan for the CH_4 use case is shown in Fig. 11. As with the NO_2 use case, the Planner assumed a mission time of 9 hours and used the constraints produced by the vehicle dynamics of the Swift Engineering HALE UAS. In addition to the plan, Fig. 11 also demonstrates that users can click on the plan to view additional information about the plan (e.g., duration, number of targets explicitly visited, etc.). Note that the number of targets shown is only those explicitly chosen by the Planner to visit (for their high value) and does not include the number of targets visited via fly-over while traveling between chosen targets.

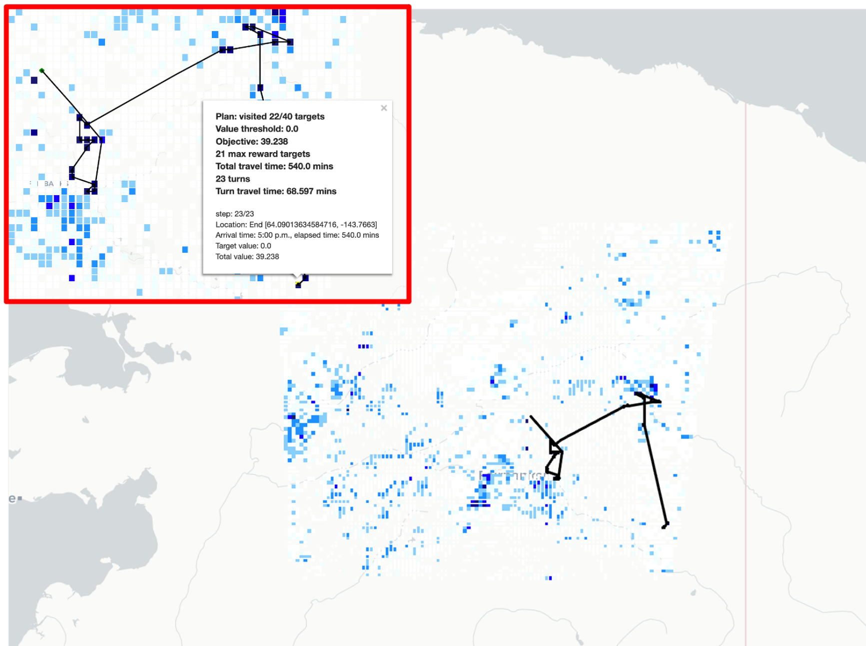


Fig. 11 Flight plan and chosen targets resulting from the Planner for the CH_4 use case. Darker squares are scenes with higher value. Additional details available within the Reporter for the plan are shown as a pop-up.

V. Discussion

The innovations resulting from the application of ILEOS to various application domains will enable coarse-grained sensor data to be used to increase the spatio-temporal coverage of targets of interest. With the long endurance capabilities of HALE vehicles, this has the promise of enabling scientists to ask research questions with longer timelines such as atmospheric changes over extended time periods after a significant event (e.g., volcanic eruption). In addition, it gives scientists the capability to potentially study more rapidly evolving dynamic events such as tracking NO_2 plumes.

The ILEOS architecture can be adapted to any vehicle (given its specific dynamic constraints) and any application domain (given its mission constraints and science value objectives). As a result, the ILEOS architecture has the potential to be incorporated into a much larger system that coordinates data collection across multiple platforms. These platforms could be heterogeneous and be tasked with collecting data at different simultaneously at altitudes (potentially even ground or underwater vehicles). Additionally, just like in the two use cases above where coarse-grained data was used as a basis to identify high value targets, data from HALE vehicles could be used as the “coarse-grained" data input to enable lower altitude vehicles to identify high value targets for their sensor payloads. As a result, ILEOS opens the door to the design of more sophisticated, hierarchical data collection networks where vehicles coordinate collection methodologies and objectives.

VI. Conclusion and Future Work

The Intelligent Long Endurance Observing System (ILEOS) provides a science activity planning framework that enables users to plan missions that maximize the collection of high science value data at high spatio-temporal resolution. This fills the gap of data currently collected from satellites and other sources. ILEOS intelligently fuses available coarse-grained data to identify targets with high science value by effectively leveraging SME domain knowledge to produce tailored science constraint pipelines. It then utilizes state-of-the-art planning and scheduling methods to maximize the number of visited high value targets within a mission and produce viable mission plans that adhere to vehicle and environmental constraints. Lastly, ILEOS provides an interface that enables users to focus on developing effective mission plans, without the need to understand the complex trade-offs between vehicle performance and mission objectives. The architecture has been successfully implemented for two GHG use cases: (1) NO_2 in the Gulf of Mexico and (2) CH_4 in interior Alaska.

Future work will focus on adding features that will improve the quality of the produced mission plan. One feature of interest is to enable users to provide more explicit prioritization of targets. Users' domain knowledge of the mission may dictate the need to visit specific targets regardless of their perceived science value. Additionally, work will explore how dynamically available data (such as updated meteorological data) can be used to update plans after they are initially generated. Lastly, additional capability will be added to the Reporter to let users ask for explanations generated by the Targeter and Planner to explain the reasoning used to generate a particular plan to observe a particular scene, with a specific value. More specifically, taking inspiration from the recent work on explainable planning [45], the Reporter will allow users to ask questions such as: Why is a scene observed? Why isn't a scene observed? Why is the flight path the way it is?

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