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# Design of a Collection Management Decision Support Tool

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**Author Note**: Addison Ainsworth, Richard Thomas, Jacob Tuioti, Lance Dorman, and Brendan Straw are Cadets at the United States Military Academy. All five cadets are Systems Engineering majors. This work is the author's academic Capstone project in the Department of Systems Engineering (DSE). Colonel Brandon Thompson, Ph.D., the Program Director of Engineering Management in the Department of Systems Engineering, serves as the Capstone project's faculty advisor. The views expressed herein are those of the authors and do not reflect the position of the United States Military Academy, the Department of the Army, or the Department of War.

**Abstract:** This study aimed to integrate a novel environmental predictive model with an Unmanned Aerial Vehicle (UAV) path planning optimization tool to create a collection management decision support tool for the U.S. Army. The study evaluated a model that estimates a UAV sensor's field of view based on multiple parameter settings and a UAV path planning tool that calculates an optimal UAV routing plan. The team used systems engineering design and Agile methodologies to integrate the two disparate tools and analyze the results of parameter changes on UAV collection plans. Sensitivity analyses of model inputs demonstrated the importance of the integrated model as changes to parameters had a direct impact on UAV fields of view which resulted in changes to the UAV routing plan and collection coverage capability. The integrated decision support tool can be implemented by military intelligence collection managers to optimize UAV collection plans.

*Keywords:* UAV Path Optimization, UAV Field of View, System Integration

## 1. Introduction

Drone usage in the military has significantly increased with applications in surveillance, intelligence, reconnaissance, and targeting. The United States military now employs drones at the lowest unit echelons to provide precision targeting with high accuracy to minimize collateral damage. Unmanned aerial vehicles (UAVs) have become critical assets in modern military operations, supporting intelligence, surveillance, reconnaissance (ISR), and targeting missions. Their effectiveness depends heavily on sensor performance and the ability to efficiently plan flight paths over prioritized areas of interest. The sensor payload capabilities dictate drone usage that requires detailed planning to maximize efficient use of the limited resource (Quadt et al., 2024). The United States military conducts drone use planning in what is referred to as Collection Management. The Collection Managers typically rely on drone flight constraints such as available flight duration and target prioritization to develop flight plans and coverage of Named Areas of Interest (NAIs). However, parameters such as terrain effects and weather limitations are not consistently accounted for in collection management planning.

The United States Army Engineer Research and Development Center (ERDC) is currently conducting research to enhance drone collection management models. Specifically, the ERDC Cold Regions Research and Engineering Laboratory (CRREL) is developing tools to model the effects of terrain and weather on drone sensors. The novel expert propagation model to integrate battlefield sensor data with environmental predictive modeling (weather and terrain influences) is referred to as the Geospatially Relevant Intuitive Propagation Services (GRIPS) (Breton, 2025, Breton, 2026). CRREL collaborated with another ERDC team, the Institute for Systems Engineering Research (ISER), to build a UAV path planning optimization tool for future integration of the GRIPS application. The United States Military Academy capstone team then integrated portions of the GRIPS tool with the UAV Path Planning Optimization tool. This paper details the analysis and results of integrating a portion of the GRIPS tool with the UAV path planning tool.

## 2. Methodology

The USMA capstone research team utilized a systems engineering problem-solving methodology to develop a refined problem definition, conduct stakeholder analysis, and identify requirements for the integrated collection management decision-support tool. Following this initial phase, the team then transitioned to using the Agile Scrum method to iteratively develop the decision support tool through a series of Sprints.

## 2.1 Problem Definition and Stakeholder/Requirements Analysis

Critical to this capstone was the Systems Decision Process (SDP). This framework allowed the team to refine and scope the research problem and identify requirements for system integration. The team began defining the problem through meetings with the ERDC researchers. The initial proposed problem statement challenged the research team to provide operations research analysis to integrate battlefield sensor data and a UAV Path Planning tool with the GRIPS model. This process became difficult once the team was introduced to the GRIPS model, which is evolving and requires integrated services. These constraints made full integration challenging for the project.

The UAV Path Planning Optimization tool, hereafter referred to as UAV Path Planner, was designed to demonstrate the effects that changing UAV and sensor parameters have on NAI collection capability. However, the UAV Path Planner was developed as a standalone product with no requirements to incorporate the full suite of GRIPS inputs (Leonard, Richards, & Rinaudo, 2025; Richards, 2026). The research team identified the need to reduce the scope of the initial integration problem to deliver a path optimization tool that demonstrated the capabilities of GRIPS without requiring access to global terrain data or forecasted weather effects. As a result, the research team refined the problem scope to focus on developing a decision-support tool that demonstrates GRIPS capabilities without requiring full access to terrain and real-time weather data. The revised objective was to integrate key elements of GRIPS into the UAV Path Planner to support intelligence, surveillance, and reconnaissance (ISR) mission planning for military collection managers.

To support this effort, the team conducted stakeholder analysis through engagements with members of the U.S. Army intelligence community, GRIPS developers at CRREL, and UAV Path Planner developers at ISER. These interactions informed both system requirements and operational priorities. The findings from the stakeholder analysis identified gaps between the GRIPS modeling capability, the UAV Path Planner, and the requirements of intelligence collection managers. Each model or process contained critical information for the others but was not readily accessible. As a result, a redefined problem statement was proposed to integrate a subset of GRIPS capabilities within and updated UAV Path Planner incorporating system requirements for intelligence collection managers.

Based on the team's refined scope, the CRREL researchers developed a SWATH planning tool that incorporated portions of the GRIPS tool without the need for access to terrain models or real-time weather effects. The SWATH tool estimates the ground coverage swath width of a UAV sensor as a function of the quality of the imaging system, sensor field of view (FOV) capability, sensor height above ground level, and a scaled weather condition effect referred to as visibility. In practical terms, the tool uses these inputs to estimate the strip of terrain observed along a UAV flight path.

Discussions with the ISER team and a thorough analysis of the UAV Path Planner code resulted in a better understanding of the inputs and outputs of the model. The base UAV Path Planner included inputs such as UAV platform, number and location of NAIs, NAI priority score, flight duration, and UAV battery duration, representing energy or fuel for flight mission time. The tool then models the optimal route over the determined NAI nodes and returns a coverage percentage, both total and by NAI, estimated flight duration, and remaining flight time available. The issue was that the implied FOV of every UAV platform sensor was set as a fixed number regardless of UAV height above ground level, weather condition, or other parameters and the work detailed in this paper aimed to address this capability gap.

## 2.2 AGILE Scrum Methodology

Following key stakeholder engagements and requirements analysis, the team transitioned to an Agile Scrum methodology to begin integrating the SWATH and UAV Path Planner. The team divided the systems integration into multiple smaller projects that could be accomplished in two-week Sprints (Hema et al., 2020). This also allowed the team to troubleshoot updates to coding and to iteratively refine the collection management decision support tool.

### 2.2.1 Sprint 1: UAV Path Planner Analysis

In Sprint 1, the team conducted a thorough analysis of the UAV Path Planner to identify model inputs, outputs, and processing to enable integration of the SWATH tool. The UAV Path Planner tool generates an optimal route for a specified UAV and number of NAI nodes. The nodes represent a NAI designated by a polygon overlaid onto a portion of the terrain map. The tool's primary goal was to cover as many NAIs as possible, spending a certain amount of time on each node based on the node's size, UAV speed, UAV sensor FOV, and node priority relative to other nodes. For example, within the base nodes of the tool, a golf course would require a longer time to cover the node as compared to a single building if they were set at an equal priority. The UAV Path Planner calculates all possible paths, factoring in battery life, flight duration time available, and priority preferences to determine the optimal route that maximizes coverage over a certain area with a set number of programmed nodes. The main limitation of the tool was the fixed FOV value regardless of the UAV capabilities or sensor parameters. As a result, the team transitioned to Sprint 2 with the objective of identifying the proper FOV value based on the SWATH tool capabilities.

### 2.2.2 Sprint 2: SWATH Tool Analysis

In Sprint 2, the team delved into the SWATH tool, determining both its inputs and outputs. The researchers focused on two UAV sensors currently used by U.S. Army intelligence assets that have multiple zoom options resulting in different FOVs. The first sensor used was the WESCAM MX-8 which had three zoom levels or FOVs: narrow (NFOV), medium (MFOV), and wide (WFOV). The other sensor incorporated was the AERYON-Mk II which only had a single zoom or FOV (SFOV). UAV sensor height above ground level was a key parameter in the SWATH tool as it directly governs the sensor geometry seen in Figure 1 and consequently, the effective swath width, or horizontal field of view on the ground. The higher the drone flies above ground level, the larger the swath width. However, this is constrained by the quality of the imaging system and visibility from environmental conditions. SWATH also contains a probability of detection (POD) parameter that allows the user to set a target threshold from 0 to 1, where higher numbers represent a higher demand for task success. As the POD increases to achieve higher detections success, the model reduces the swath width to increase the probability of identifying the desired target within the NAI. Once the sensor swath width no longer allows for the desired probability of detection, the UAV is limited below that height. Environmental conditions of fog and rain are modeled by a visibility parameter (tau), which ranges from 0 to 1 in increments of 0.2, where 0 represents no visibility, fog = 0.2, rain = 0.4, and 0.6 to 1 represent clear conditions. The parameter tau governs the visibility of the sensor and, consequently, the effective swath width. The quality of the imaging system is determined by the sensor selection and the associated performance of the sensor. Variation of these inputs results in different effective swath widths.

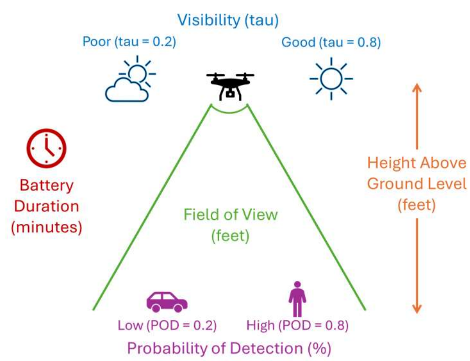


Figure 1: SWATH FOV Estimation Tool Conceptual Diagram

### 2.2.3 Sprint 3: UAV Path Planner and SWATH Manual Integration

In Sprint 3, the team aimed at improving the UAV Path Planner to more accurately model NAI coverage based on outputs from SWATH. For NAI completion time specifically, the model needed a FOV size measured in feet and effective platform speed to estimate the effective collection rate in square meters per second (Breton, 2026). The original UAV Path Planner's use of a fixed swath width or FOV did not accurately account for the time required over a NAI and produced inaccurate NAI coverage percentages. As a drone moves over an NAI, the effective FOV determines the number of flight passes needed to cover the node using a boustrophedon trajectory, or a non-overlapping back-and-forth pattern, and therefore impacts the flight duration spent over a NAI. A larger FOV reduces the number of passes required for full coverage of a NAI.

Integrating the two tools began with a series of sensitivity analyses. First, the team varied the height parameter in the SWATH tool for each sensor and drone, recorded the value of the effective FOV, and manually entered the corresponding value into the UAV Path Planner. For each iteration, the team recorded the total percentage covered (of all NAIs), total time, and the total distance the platform traveled. For all iterations, the remaining parameters were held constant in both the SWATH and UAV Path Planner. This manual, iterative sensitivity analyses allowed the team to establish a baseline for UAV performance while limiting confounding variables. This provided the team with a better understanding of the interaction between the two models and identified coding updates needed in both tools to enable full integration.

### 2.2.4 Sprint 4: UAV Path Planner and SWATH Integration

In Sprint 4, the team fully integrated the SWATH code into the UAV Path Planner. The team updated the user interface, Streamlit in Python framework, of the UAV Path Planner to allow collection managers to select sensor payloads, flight heights,

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visibility, probability of detection, and sensor FOV settings (single, narrow, medium, or wide), in addition to the original UAV Path Planner settings of UAV platform, UAV speed, and NAI priority. The integrated model utilizes the SWATH tool to calculate the resulting swath width based on the selected inputs, and then the UAV Path Planner calculates the optimal NAI coverage plan. The team then conducted sensitivity analyses by varying parameters and recording the resulting FOV and UAV Path Planner collection plan outputs. Figure 2 displays screenshots from the updated user interface with 2a displaying the parameter settings, 2b showing a UAV routing and NAI coverage plan, and 2c reporting the output summary to include time, distance, and coverage percentage (total and by NAI).

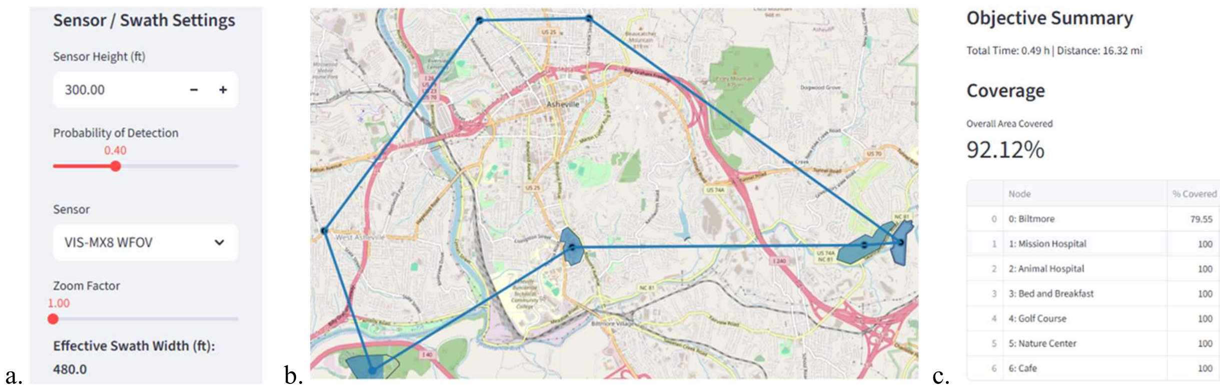


Figure 2: Integrated UAV Path Planner; a. Parameter Inputs, b. UAV routing plan, c. Model outputs

## 3. Results

The research team conducted sensitivity analyses to evaluate the impact of sensor performance on UAV routing missions. First, a baseline setting for each parameter was established with a battery duration (mission time) of 27 minutes, sensor height above ground level of 300 feet (ft), clear visibility (tau = 0.6), and moderate probability of detection (POD = 0.4). The baseline settings resulted in a horizontal field of view (FOV), or swath width, of 480 ft and a NAI collection 69.5%. The team then adjusted one parameter at a time and recorded the model outputs to include swath width, NAI coverage, flight duration, and distance traveled. This approach allowed the team to analyze the effect of each parameter in isolation. The research team then conducted scenario analysis varying multiple parameters to test the model and analyze results.

### 3.1 Sensitivity Analyses

The relationship between height above ground level and effective swath width was analyzed while holding all other parameters constant. The height above ground level was increased from 100 ft to 450 ft for three sensor zoom conditions, WFOV, MFOV, and SFOV. Sensitivity analysis of sensor height above ground level also showed significant difference following the integration of the SWATH tool. The UAV Path Planner tool had a default swath width of 300 ft across all missions not accounting for sensor performance in different heights above ground level which resulted in a constant 470 ft swath width. The integration of the SWATH tool provided a more realistic sensor performance. For each of the three sensor zoom options, the heights above ground level resulted in linear relationship with the calculated effective swath width. Figure 3 displays the highest swath widths were achieved under the WFOV ranging from 160 ft FOV at a UAV height of 100 ft up to a 720 ft FOV at a UAV height of 450 ft above ground level. There was little difference between the swath width of the MFOV using the MX-8 sensor and the SFOV using the Mk-II sensor. The resulting swath widths of each sensor are then used by the UAV Path Planner code to select the optimal NAI coverage plan. Figures 4 and 5 display the resulting NAI coverage percentages for various swath widths by battery duration and environmental condition.

The integrated model allows users to set the UAV battery duration to represent available flight duration, either fuel capacity or electrical power capacity of the UAV. A sensitivity analysis of battery duration revealed a generally linear relationship between available flight time and NAI coverage. Figure 4 displays the percent NAI coverage by swath width for battery durations of 15 minutes, 27 minutes, and 35 minutes with the WFOV, clear environmental conditions, and moderate POD. Limited to 15-minute flight time, the highest NAI coverage achieved was 35.5% with a UAV height above ground level of 450 ft and a resulting swath width of 720 ft. A 27-minute flight time achieved a 100% NAI coverage at the maximum tested height above ground level of 450 ft and 720 ft swath width. Increasing the flight time to 35 minutes allowed the UAV to cover all NAIs at heights above 350 ft and swath widths greater than 560 ft.

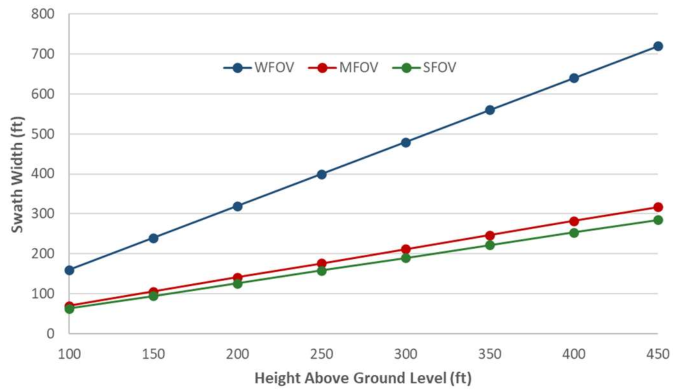


Figure 3: Sensitivity Analysis for Height Above Ground Level and Swath Width

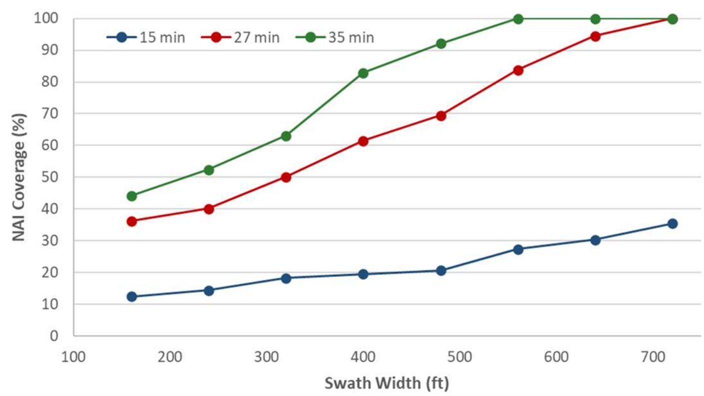


Figure 4: Sensitivity Analysis for NAI % Coverage by Battery Duration and Swath Width

Three environmental conditions representing sensor visibility were tested to determine their effects on swath width and resulting NAI coverage. The SWATH framework links environmental conditions to system performance by reducing the swath width of the UAV sensor at a rate so that higher altitudes result in higher degradation of sensor swath width under fog or rainy conditions. In addition, UAV Path Planner code reduces the speed of the UAV under rainy conditions which further limits NAI coverage ability. Figure 5 displays the NAI coverage percentage by swath width under normal (clear), fog, and rain environmental conditions. Of note, the relationship of swath width to NAI coverage has similar slopes under normal and fog conditions above 300 ft heights above ground level. The rain condition slope is slightly less as expected due to the reduced speed of the UAV. At lower heights above ground level, the model calculated different routing patterns resulting in higher NAI coverage at heights below 300 ft than heights at 350-400 ft.

The final sensitivity analysis involved adjusting the probability of detection (POD) which represents the desired task success rate on a scale of 0 to 1, with higher score representing an increased percentage of success. This parameter can be used by intelligence collection managers to task UAVs with detecting missions (low POD), identification missions (medium POD), and recognition missions (high POD). The expectation was a higher percentage of POD would result in a narrower swath width to provide a better opportunity of identifying and recognizing a target of interest. However, results showed that POD had little effect on swath width until the POD was set above 0.8 representing a high requirement for task success. The swath width remained at 470 ft until a POD of 0.9 and 0.95 reduced the swath width to 368 ft and 257 ft respectively. This is likely due to sensor limitations within the SWATH tool that restrict the swath width more than the POD under the current settings. However, the expected decrease in swath widths at the highest POD settings and the steep decline from POD 0.9 to 0.95 indicate that the model is able to effectively reduce the swath width under conditions that require increased focus.

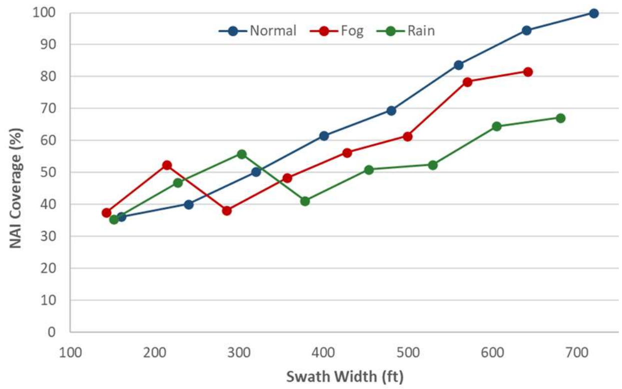


Figure 5: Sensitivity Analysis for NAI % Coverage by Environmental Conditions and Swath Width

## 4. Conclusion

The goal of this project was to integrate the UAV Path Planner with capabilities of the GRIPS-derived SWATH tool to provide intelligence collection managers with a reliable decision-making tool. The integrated UAV Path Planner provides a more realistic UAV routing plan within the tool by incorporating environmental factors, sensor capabilities, and UAV parameter settings. This distinction is operationally important because a military planner relying on the default 300 ft FOV assumption may underestimate the effective sensing capability of the UAV, leading to overly conservative planning and ineffective use of the limited UAV assets. On the other hand, the sensitivity analyses demonstrated that the original UAV Path Planner overestimated NAI coverage under poor visibility, when high probability of detection was required, or when sensor parameters were set to narrow FOVs, resulting in a false sense of intelligence collection coverage. This could lead to allocating additional assets or overestimating required mission time. The findings and updated UAV Path Planner will be useful to the Army intelligence community, as this provides a base collection management decision support tool integrating weather effects, sensor capability, probability of detection weighting, and UAV parameters within a path planning optimization tool to more realistically estimate percent coverage of NAIs. Future updates to this integrated model should incorporate additional GRIPS capabilities by introducing terrain effects on sensor capability and resulting NAI coverage estimations.

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