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ASSURE

Alliance for System Safety of UAS through Research Excellence

ASSURE A71 – Conduct Safety Risk Management Analysis on Small Unmanned Aircraft Detect and Avoid Systems

Final Report

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16. Abstract

[This report presents research aimed at improving Safety Risk Management (SRM) analysis for small Unmanned Aircraft Systems (sUAS) Detect-and-Avoid (DAA) technologies operating within the United States National Airspace System (NAS). As unmanned aircraft operations expand—particularly Beyond Visual Line-of-Sight (BVLOS)—DAA systems are critical to replacing the pilot's traditional *see-and-avoid* responsibility and enabling safe integration with existing aviation traffic.

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LIST OF ACRONYMS

ADS-B	Automatic Dependent Surveillance – Broadcast
ASTM	ASTM International
BVLOS	Beyond Visual Line-of-Sight
CONOPS	Concept of Operations
DAA	Detect and Avoid
DF	Detection Function
FAA	Federal Aviation Administration
FGA	Fast Geometry Avoidance
GNSS	Global Navigation Satellite System
LoL	Loss of Link
MIT LL	MIT Lincoln Laboratory
NAS	National Airspace System
NMAC	Near Mid-Air Collision
PRA	Probabilistic Risk Assessment
RAP	Risk Assessment Point
RUVS	Risk Uncertainty-Validity Spheroid
SLRS	Safety Limit Reward Sphere
SMS	Safety Management Systems
SRM	Safety Risk Management
sUAS	Small Unmanned Aircraft System
TCCA	Transport Canada Civil Aviation
UAS	Unmanned Aircraft System
YOLO	You Only Look Once

EXECUTIVE SUMMARY

This report presents research aimed at improving Safety Risk Management (SRM) analysis for small Unmanned Aircraft Systems (sUAS) Detect-and-Avoid (DAA) technologies operating within the United States National Airspace System (NAS). As unmanned aircraft operations expand—particularly Beyond Visual Line-of-Sight (BVLOS) operations—DAA systems are critical to replacing the pilot's traditional *see-and-avoid* responsibility and enabling safe integration with existing aviation traffic.

The objective of this research was to develop analytical tools and risk-assessment methods capable of identifying hazards, quantifying operational risk, and evaluating DAA system performance under realistic operating conditions. Current SRM processes largely rely on qualitative risk matrices based on likelihood and severity. While effective for many traditional aviation systems, these approaches are limited when applied to highly automated and dynamic technologies such as DAA systems. Therefore, this research introduced probabilistic, data-driven methodologies to support more rigorous and scalable safety assessments.

The research was conducted in three phases. First, the current state of DAA technologies and SRM practices was evaluated to identify safety gaps and operational challenges. This analysis highlighted several key issues, including the absence of standardized reliability metrics for DAA systems, limited empirical performance data, and uncertainty surrounding the effects of environmental conditions on detection capability.

Second, the study developed two probabilistic risk assessment frameworks tailored to DAA systems. The first introduces a DAA timing-distribution method that evaluates the probability of late or missed detection of intruding aircraft prior to a potential near mid-air collision. The second expands the traditional risk model and explores a three-dimensional framework incorporating potentiality, severity, and exposure, allowing risk to be quantified within a defined safety boundary.

Finally, the proposed methodologies were validated through high-fidelity simulation using a ROS2-Gazebo environment combined with large-scale Monte Carlo analyses. These simulations modeled aircraft encounters, sensor performance, and degraded environmental conditions to evaluate detection capability and avoidance effectiveness.

Results indicated that environmental visibility, sensor capability, and detection timing are among the most influential factors affecting DAA safety performance. The proposed frameworks provide improved methods for quantifying operational risk and offer scalable tools for evaluating DAA systems across a wide range of operational scenarios.

Overall, this research contributed to the development of new analytical methods, probabilistic modeling techniques, and simulation-based evaluation tools that enhance the ability to assess DAA safety. These findings support the development of future regulatory guidance, operational standards, and risk-management practices necessary to enable safe and scalable BVLOS operations within the NAS.

1 INTRODUCTION AND BACKGROUND

Over the past decade, improvements in autonomous flight control, onboard computing, sensing modalities, and communication architecture have significantly expanded the range of application viability for small Unmanned Aircraft Systems (sUAS). At a minimum, applications include infrastructure inspection, environmental monitoring, emergency response, precision agriculture, and logistics. As the operational domain continues to expand, the Federal Aviation Administration (FAA) faces a myriad of challenges in enabling full, scalable integration of sUAS operations into the United States National Airspace System (NAS), while maintaining the high safety standards and record that have characterized the NAS historically. The integration of sUAS into the NAS represents one of the most significant aviation milestones and transformations in aviation since the introduction of modern airspace and traffic management systems.

A central challenge in full and scalable sUAS integration is enabling operations Beyond Visual Line of Sight (BVLOS). Under the current regulatory landscape, sUAS operations rely on remote pilots and/or visual observers to maintain direct visual contact with the sUAS. This is required as a mechanism to comply with 14 CFR §91.113b, "see and avoid." In conventional crewed aviation, pilots visually scan the surrounding airspace to detect other aircraft and maneuver as required to avoid any airspace conflict and potential collisions. Alternatively, as sUAS are operated with greater levels of autonomy and no pilot on board, alternative technical and procedural mechanisms must be developed to provide situational awareness towards an equivalent level of safety.

Detect-and-Avoid (DAA) systems have emerged as the primary technological approach and key enabling capability to augment the collision-avoidance function traditionally executed by onboard human pilots. These systems fuse sensing technologies, surveillance data, aircraft state estimation, trajectory prediction algorithms, conflict detection algorithms, and maneuver decision logic to identify potential aircraft conflicts and initiate avoidance actions when necessary.

With respect to DAA system architecture and complexity, these systems often include cooperative surveillance sources such as Automatic Dependent Surveillance–Broadcast (ADS-B) and non-cooperative sensors such as radar or electro-optical systems, and navigation information derived from onboard global positioning system and inertial navigation systems. These data are fused to provide an estimate of the relative state of other aircraft with respect to the ownship and to determine whether a potential loss of well-clear separation or collision risk exists. A central requirement for enabling routine BVLOS operations is to ensure DAA systems can provide an equivalent level of safety to conventional methods for seeing and avoiding air traffic. Unfortunately, evaluating the safety performance of DAA systems presents significant analytical challenges.

The safety management policy and requirements established by the FAA are mandated in FAA Order 8000.369, Safety Management Systems. FAA Order 8040.6A: Unmanned Aircraft System (UAS) Safety Risk Management (SRM) Policy establishes the requirements for a UAS-centered SRM program and conducting SRM within an organization. According to the National Academies of Sciences (2018), the systematic approach to safety risk management has achieved a high level of safety for all users of the NAS. Unfortunately, the agency's current safety risk management approaches are qualitative and subjective. SRM is a structured process used within aviation safety management systems to identify hazards, analyze risk, and evaluate potential mitigations. Within the context of sUAS DAA systems, SRM analysis focuses on identifying conditions under which failures or degraded performance could lead to unsafe aircraft proximity or midair collision events. Unfortunately, the SRM tools available to the FAA are built around concepts and outcomes specific to crewed aviation and cannot adequately address the risks unique to DAA applications for sUAS. New approaches to risk assessment are needed to enable the FAA to truly understand hazards, risks, and other factors that contribute to risks associated with DAA systems.

Traditional aviation safety risk assessments/frameworks heavily rely on two principal variables: (1) likelihood and (2) severity. Within the SRM framework, hazards are categorized by the probability of an event occurring and the severity of its consequences. Although the traditional SRM framework has proven effective in many aviation contexts, it unfortunately falls short when applied to highly dynamic, automated systems, such as sUAS DAA architectures.

The primary objective and overall purpose of A11L.UAS.120: A71 - Conduct Safety Risk Management Analysis on small Unmanned Aircraft Detect and Avoid Systems was to develop analytical methods capable of evaluating hazards, quantifying operational risk, and assessing the safety implications of DAA system performance within representative operational environments. The project was structured sequentially into three primary tasks: investigating current risk assessment methodologies; identifying gaps in existing frameworks; designing and executing Monte Carlo simulation models; and presenting new approaches for quantifying risk associated with UAS DAA systems.

Task 1 focused on identifying potential safety hazards associated with DAA system operation to develop an initial safety risk management framework. This work established a structured approach to analyzing the interactions among system components, operational procedures, and environmental factors that may influence collision risk.

Task 2 expanded the analysis by examining risk modeling methodologies and exploring how variations in system performance parameters affect the probability of unsafe aircraft encounters. An important element of the Task 2 effort involved a sensitivity analysis to determine how variations in system characteristics and environmental conditions influenced overall DAA system performance. Factors such as sensor resolution, visual clutter, atmospheric visibility, and algorithmic detection thresholds were evaluated to determine their impact on detection probability and detection delay distributions. Therefore, the sensitivity analysis provided an important tool for identifying critical system parameters and highlighting key design trade-offs in the development of operational DAA architectures.

Task 3 further advanced the research by developing and applying a robust Monte Carlo simulation environment to evaluate the performance of DAA systems across a wide range of encounter scenarios. These simulations enabled scientists to investigate timing distributions, detection uncertainties, and maneuver execution dynamics that often influence the probability of successful conflict resolution. Despite significant advances in modeling and simulation, several research gaps remain in evaluating DAA systems. One inherent challenge is the availability of empirical data to validate sensor detection models under diverse environmental conditions. While simulation tools can approximate many aspects of system performance, validation against real-world observations remains essential for ensuring model credibility.

Together, these tasks provided a cohesive and refined understanding of DAA system safety performance. As sUAS operations continue to expand, the development of rigorous analytical SRM frameworks for evaluating DAA system safety performance will remain critical. The findings and methodologies presented in this final report contribute to this broader effort and support the FAA’s ongoing mission to ensure the continued safety and efficiency of the NAS. The analytical tools developed as part of this effort will support future evaluation of DAA technologies.

2 RESEARCH QUESTIONS

This research was guided by a series of research questions that framed the overall project and provided critical context when exploring SRM in relation to DAA systems. These questions represent knowledge gaps and areas of exploration where research may offer insights and answers that may further the goal of understanding the risks associated with the use of DAA systems and how to adequately understand those risks in the context of broader UAS operations in the NAS. To that end, the following questions were critical in framing research tasks, experiments, and research outcomes.

1. Through a sensitivity analysis, what portions of a DAA system design are most critical when it comes to mitigating collision risks?
2. Does this change for different DAA architectures or operations, such as Airborne DAA, Ground-Based DAA, Unmanned Traffic Management Surveillance Services as part of a DAA system, automated or manual DAA maneuvers, and Multi-vehicle DAA architectures and operations?
3. What risk assessment tools are recommended for industry DAA risk management?
4. Are they [risk assessment tools] different than the risk assessment tools recommended for FAA use?
5. What does a sensitivity analysis reveal about the effects of loss of link on DAA performance when considering different DAA architectures and operations?

   Examples include Ground-Based vs. Airborne, Manual vs. Automated avoidance, en-route vs. terminal operations, etc.
6. How should a suitable standard/accepted risk assessment on a DAA system be structured to provide meaningful insights into system design, performance, and safety optimization?
7. What variables or aspects of system design have the greatest impact?
8. What safety metrics are recommended for meaningful DAA system safety assessments? Consider assurance, performance, and system-to-system interactions.
9. What input-processing-output models or diagrams are most useful for identifying potential hazards?
10. How could guidance for Safety Risk Management Document assessments and UAS SRM policy be updated to satisfy the original intent of safety risk management and the risk management cycle?
11. What risk assessment tools and metrics are recommended for DAA system safety assessments?
12. What guidance is recommended for distinguishing between system safety and system-of-systems safety?
13. What risks are unique or more critical to different DAA systems? Consider a variety of different DAA systems and DAA operations.
14. How can SRM assessments better inform DAA standards and DAA development (as intended in the SRM cycle) rather than be an activity that is conducted after the design standard or system development is complete?

Research tasks and subsequent outcomes represent the research team's best efforts to address these questions. Answers to these questions will be mapped to research outcomes in Section 4.1.

3 RESEARCH TASKS

This project consisted of four research tasks, including this final report, to answer the research questions. These tasks defined the overall approach and timelines of the project, establishing deliverables, intermediate outputs, and final deliverables derived through an issue report, hazard identification/assessment(s), a sensitivity report, and simulation and modeling. The following sections and subsections highlight and summarize research tasks, emphasizing their overall contributions to this research and linkages to subsequent tasks and deliverables.

3.1 Task 1 – Issue Report

The Task 1 Issue Report explored DAA systems and functions in relation to the SRM process. This approach enabled the background report to identify existing issues and gaps in the operation of DAA systems in the NAS. It also framed this research against the growing demand for BVLOS flight operations and the need to identify and assess risks in a scalable, repeatable way. This is especially important given variation in UAS performance, DAA system integration, and mission profiles. The result is that there is no "one size fits all" when considering the risks associated with DAA systems and their operation. The full Task 1 Issue Report can be found in the accompanying Appendix A.

3.1.1 Approach to Identifying and Analyzing Risk – The SRM Process

The issue report adopted an approach for identifying and analyzing risk associated with DAA systems that was based on the SRM process, which is part of a larger component of a Safety Management System (SMS); See Figure 1.

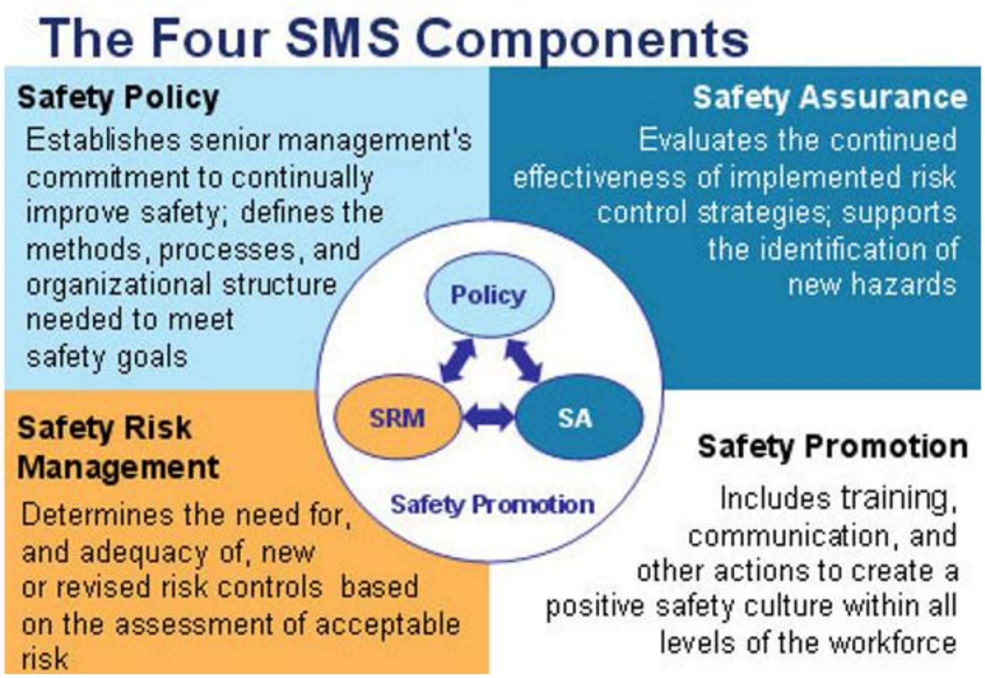

Figure 1. Safety Management System (SMS) Overview (Federal Aviation Administration, 2024).

Analyzing risk associated with DAA systems using the SRM process provided a simple, straightforward framework for describing risk consistent with aviation best practices. Figure 2 highlights the SRM process and its associated components. As shown in Figure 2, the SRM process provides a clear template for analyzing nearly any system in the context of assessing risk and overall safety assurance. Adopting this approach provided the research team with a pathway to better understand the functions of the DAA system, the hazards associated with its use, failure modes, and its overall safety risk. Moreover, this approach enabled the research team to reference FAA guidance within FAA Orders 8040.4C and 8040.6A. These orders outline SRM policy for conventional and unmanned [uncrewed] aircraft, respectively (Federal Aviation Administration, 2023a; Federal Aviation Administration, 2023b).

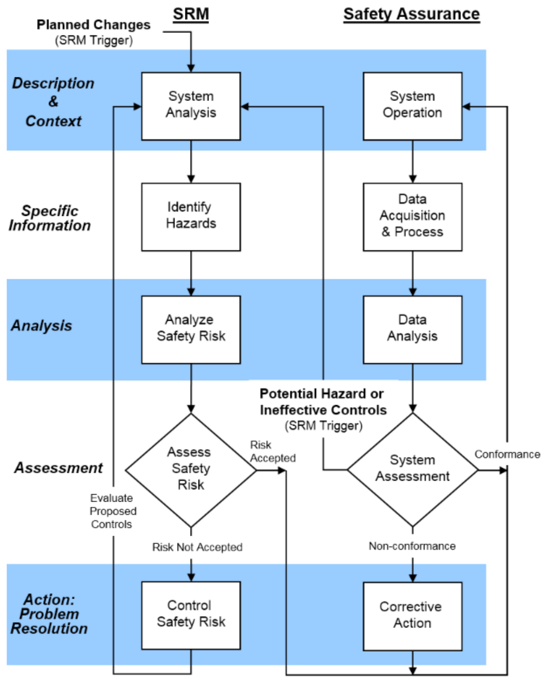

Figure 2. SRM Process and Safety Assurance Loops (Federal Aviation Administration, 2024).

Finally, this approach provided an avenue for identifying existing gaps or issues in DAA systems, including system functions, hazards, risks, and operational nuances that may affect NAS safety.

3.1.2 Identified Issues and Gaps

Issues and gaps identified in SRM for DAA systems stemmed from concerns about the reliability and limitations of DAA sensors, especially in complex environments. These issues and gaps were identified through a deeper analysis of ground-based and airborne DAA systems in the Task 1 report. These issues highlighted that different types of sensors struggle to detect intruders under variable weather conditions, and sensor performance may vary greatly across systems. Concerns extended to cooperative systems, such as ADS-B, and non-cooperative sensors alike. For example, cooperative systems may fail to detect traffic from non-broadcasting transmitters or from transmitters that may be turned off. Similarly, non-cooperative sensors may struggle to detect small aircraft or aircraft with signatures the system cannot detect or recognize. Moreover, algorithms that drive DAA systems may not be robust enough to distinguish aircraft from other environmental hazards, such as birds or ground clutter. There are also questions regarding DAA systems' current ability to integrate with existing traffic management systems. The research team identified a need not only to define performance metrics for DAA systems but also to validate system performance to ensure satisfactory function in real-world environments.

To mitigate challenges associated with isolating specific DAA system architectures and the aforementioned issues and gaps, the research team chose to describe the system in terms of the overall DAA cycle, a functional breakdown that is common to all DAA systems. Figure 3 shows an overview of this cycle.

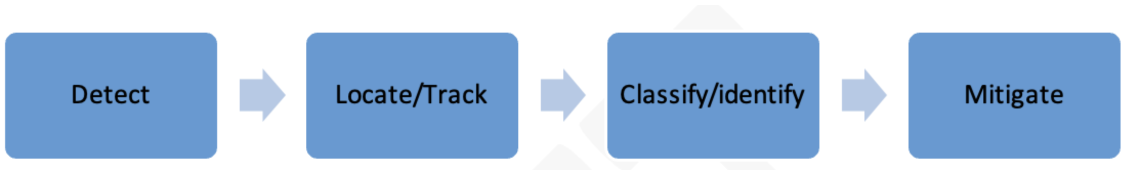

Figure 3. UAS DAA Basic Functions (McCrink et al., 2022).

The cycle shown in Figure 3 is common to all manner of DAA systems, regardless of sensor(s) or mode of operation. A similar process breakdown is outlined within ASTM F3442-25 *Standard Specification for Detect and Avoid System Performance Requirements* (ASTM International, 2025). Using the DAA cycle as a primary frame of reference for the SRM process enables the development of hazards, risks, and controls applicable to a wide variety of DAA systems.

3.1.3 Role of Industry Standards

An important component of this task was identifying where industry consensus standards fit within the overall construct for assessing risk associated with DAA systems. Industry standards are a critical component, as they provide a mechanism for translating best practices into the UAS industry to support compliance with FAA policy and regulations. They serve as a means of translating FAA-sponsored research into useful outputs for industry.

Presently, there are no current standards that specifically address the risks associated with DAA systems. However, some standards address operational risk assessments for UAS operations, such as ASTM F3178-24 *Standard Practice for Operational Risk Assessment of Unmanned Aircraft Systems (UAS)*. This standard emphasizes operational risk assessments for UAS in low-altitude operations (ASTM International, 2024). However, the standard does not address DAA requirements. While a standard outlining DAA performance requirements does exist, ASTM F3442-25 *Standard Specification for Detect and Avoid System Performance Requirements* (ASTM International, 2025), there is no standard for translating DAA performance directly to operational risk. Test methods to accompany ASTM F3442-25 are still under development by ASTM International at the time of this report – i.e., ASTM WK62669 *New Test Method for Standard Guide for Testing Detect and Avoid Systems (DAA) for Unmanned Aircraft Systems (UAS)*. ASTM F3224-25 and the new working document (ASTM WK62669) provide an avenue for original equipment manufacturers to define performance metrics for DAA systems. These metrics may be used to complement a notional risk assessment standard for DAA systems (Figure 4).

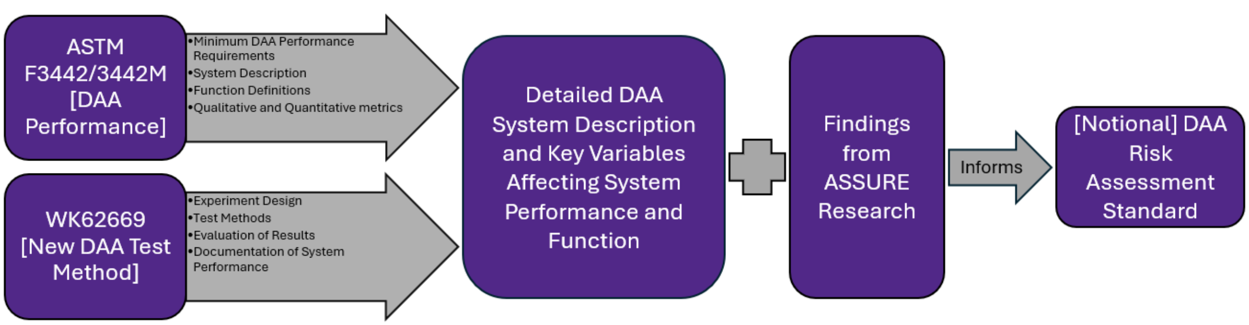

Figure 4. Framework for a Notional DAA Risk Assessment Standard.

Outputs from this research may complement the existing standards to inform avenues for assessing risk for DAA systems. This is especially true, as this research has identified the core functions of DAA systems as critical to understanding how they operate and their overall impact on NAS safety. A standard or process for assessing risk for DAA systems would account for DAA system functions and other factors that influence its operation within the NAS – e.g., rain, fog, and other factors that could disrupt the DAA cycle.

3.1.4 Task 1 Issue Report – Conclusions and Findings

The Task 1 Issue Report identified numerous issues and gaps relating to the SRM process as it applies to DAA systems. The report provided a starting point for follow-on tasks, and it offered a snapshot of the current state of DAA systems, risk assessment strategies, and critical issues that would impact future tasks. The following sections represent critical issues and gaps identified within the Issue Report.

3.1.5 Describing the System

Describing the overall reliability of various DAA systems is a challenging task, especially given unknowns regarding functionality and longevity of parts, components, sensors, etc. These unknowns are difficult to quantify, and they may vary from system to system. Differences in system design, function, and operational requirements also pose challenges when describing how DAA systems function and may fail.

DAA systems are not constructed to meet any specific standards or hard requirements; they are not certified to any known standards at this time. As a result, there are countless unknowns when assessing each system for overall function, performance, and reliability. The lack of accepted standards amplifies the challenge of identifying how DAA systems perform. While standards are currently being developed to define baseline DAA performance requirements and test methods, there is still work to be done to standardize and determine system performance and reliability for DAA systems.

3.1.6 Identifying Hazards

The most significant issues and gaps identified here relate to hazards associated with DAA system operation in highly variable environmental conditions, integration with existing air traffic control architecture, and technological limitations – e.g., challenges filtering out interference, noise, and other signals that may impact reliability. These issues and gaps stem from weather-related factors, such as rain, fog, and other phenomena that may disrupt or confuse detection. More data is required to understand how weather may affect DAA systems and to assess thresholds for interference, noise, and other factors that affect performance.

Additionally, the research team also found that integrating DAA systems with existing air traffic management systems may pose some challenges. These challenges relate to potential differences in how non-standardized DAA systems may use, present, and communicate data to a remote pilot. This data may not be in a format compatible with the standardized protocols used by air traffic systems. The result is a need to explore how DAA systems may interact with air traffic management systems and which data and protocols should be used.

3.1.7 Analyzing Risk

The Issue Report found that analyzing risk associated with operating DAA systems in the NAS is complex, nuanced, and difficult to quantify. This is largely due to comprehensive datasets that allow researchers to quantify the impact of DAA systems on air traffic, the NAS, and sUAS operations. The dearth of information and the rapid advancement of non-standardized sUAS and DAA systems prevent a detailed risk analysis and assessment of their impact on the NAS. The findings in the Issue Report underscore a distinct need for standards and data-driven approaches to understanding and quantifying DAA systems, their reliability, and their interactions with the NAS.

3.1.8 Assessing Risk

A critical gap for assessing risk for DAA systems is the limited exploration of how to fuse essential data elements to provide a reliable assessment. The Issue report made clear that more definition and fusion of the following six components – reliable data, accurate model(s), processes for analysis, algorithms that reliably reflect existing models, definitions of hardware/software, and applications to existing policy – are essential for accurate analysis of risk associated with DAA systems. Gaps in other areas reinforce this gap, underscoring the need for additional data, research, and the development of reliable analytical tools, models, and risk assessment considerations.

3.1.9 Controlling Risk

The lack of standardized risk controls presents challenges for controlling risk associated with DAA systems. While FAA Order 8040.6 provides some guidance, it offers no specific mitigations or pathways to accurately address failures, degraded operations, or off-nominal conditions. Gaps in other areas reinforce this gap, and it continues to reinforce a need for better data and analytical models.

3.1.10 Critical Themes and Concepts from the Task 1 Issue Report

The following represent prevalent themes and concepts the research team identified within the Task 1 Issue Report. These themes emerged from the literature and were often presented as issues or gaps. They reflect the current state of risk assessment for DAA systems and pointed the research team toward essential focus areas in subsequent tasks. The following themes and concepts are taken directly from the Issue Report:

1. There are no universally accepted reliability metrics for DAA systems.
2. There are currently no accepted standards for assessing the risk associated with DAA systems.
3. Data required to assess the risk associated with DAA systems is often incomplete, inaccurate, or unavailable.
4. Models driven by reliable data and a robust analytical framework are essential to assessing the risk associated with DAA systems.
5. The evolution of DAA technologies is occurring rapidly and extends beyond the current UAS operational guidance.
6. There is a need for effective verification and validation of DAA systems to ensure reliability.
7. Guidance and standards are needed to define and apply risk controls for DAA systems.

3.2 Task 2 – Draft Hazard Identification and Risk Assessment Processes for DAA Systems and Operations

Task 2 was built directly upon the gaps and issues identified in the Task 1 Issue Report and consisted of two distinct subtasks. The first, Subtask 2-1, directed the research team to explore and propose a probabilistic risk assessment framework suited to the unique characteristics of DAA systems and operations. The second, Subtask 2-2, focused on investigating the sensitivity of the proposed risk measures to variations in key system parameters and environmental conditions. Together, these subtasks resulted in the development of a novel timing-based Probabilistic Risk Assessment (PRA) methodology and a rigorous quantitative analysis of its responsiveness to factors such as fog density, camera resolution, and visual clutter. The findings from this task provided an essential empirical and analytical foundation for the simulation and testing activities in Task 3 and represent a significant step toward data-driven SRM for DAA-enabled sUAS operations. The full Task 2 report can be found in the accompanying Appendix B.

3.2.1 Subtask 2-1 – Hazard Identification and Risk Assessment Processes

This subtask resulted in the development of a novel PRA methodology tailored to DAA systems:

3.2.1.1 *DAA Timing Distribution Approach to PRA*

This method focuses on the probabilistic quantification of a key operational risk metric: the probability that a DAA system fails to detect an intruding aircraft before a Near Mid-Air Collision (NMAC) occurs. This risk measure is a function not only of the DAA system's internal performance characteristics, but of the specific Concept of Operations (CONOPS) in which it operates - including the trajectories of the ownship and intruder, the system's camera resolution and sampling rate, and prevailing environmental conditions such as fog and visual clutter. Knowing, for example, that a DAA system has a median detection delay of several seconds conveys little about actual collision risk without knowing the separation distances involved and the environmental context.

A foundational element of this approach is its grounding in the ASTM DAA Timing Standard (ASTM F3442/F3442M-23), which provides the regulatory and architectural reference for the timing constraints governing all DAA system functions. The standard defines 14 timing functions across three primary function categories - Detection, Alert, and Avoidance - each of which contributes sequentially to the total system response time. Figure 5 provides a visual summary of this timing architecture.

The Detection Function (DF) is the timing stage of primary focus in this research. It is responsible for detecting an intruding aircraft and providing the necessary data to the downstream Alert Function. DF timing performance is critically sensitive to the sensor update rate, the computational efficiency of tracking algorithms, and environmental factors, including radar clutter, optical noise from bright sunlight, and platform vibrations. These environmental sensitivities establish the direct link between the ASTM timing framework and the sensitivity analysis conducted in Subtask 2-2. The Alert Function (A1F) processes detection data and determines when to issue alerts to the avoidance system. The Avoid Function (A2F) computes and executes the avoidance trajectory after an alert is issued.

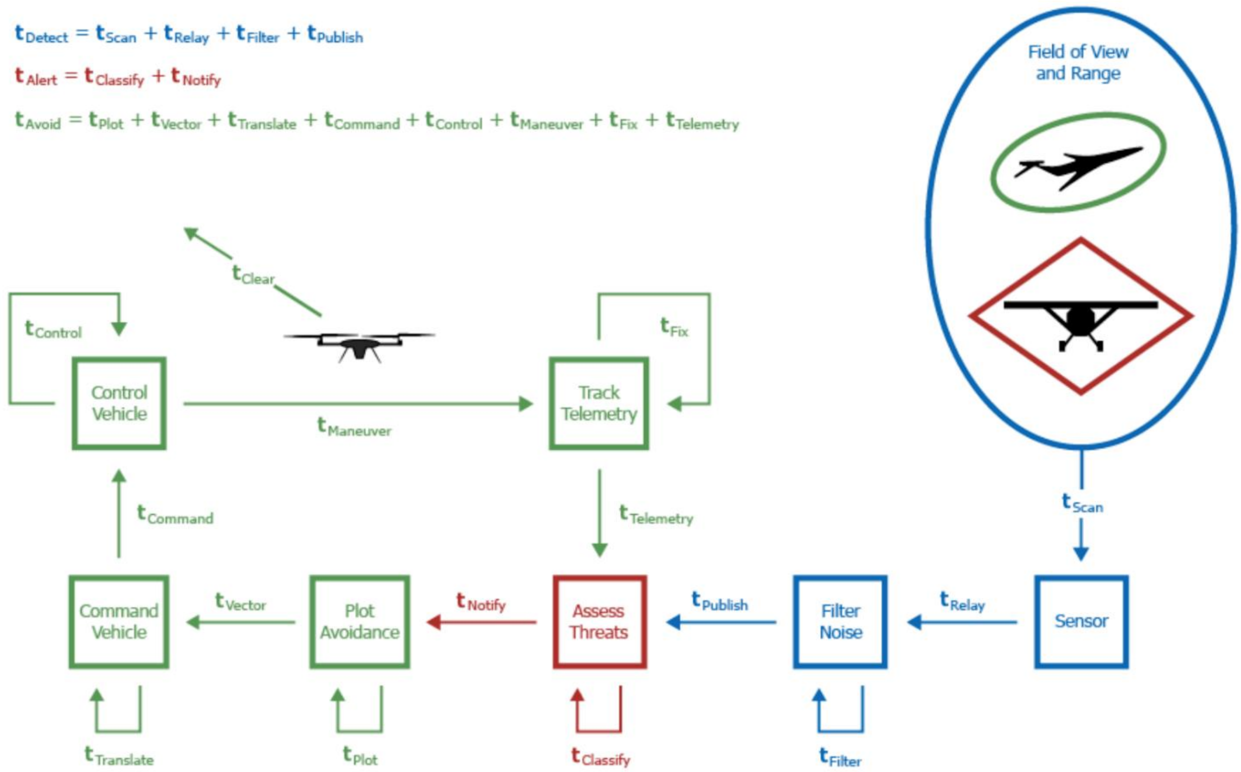

Figure 5. ASTM DAA System Timing Model (ASTM F3442/F3442M-23), illustrating the sequential timing functions governing detection, alert generation, and avoidance maneuver execution.

While the ASTM standard defines requirements across all three function categories, the current implementation in this research focuses specifically on the Detection Function and its timing characteristics. The Alert and Avoidance functions are reviewed here to establish the full regulatory context and to identify the downstream consequences of detection delays. However, quantitative modeling of those functions represents a natural and important extension for future work.

The methodology addresses this gap through an integrated three-tool pipeline:

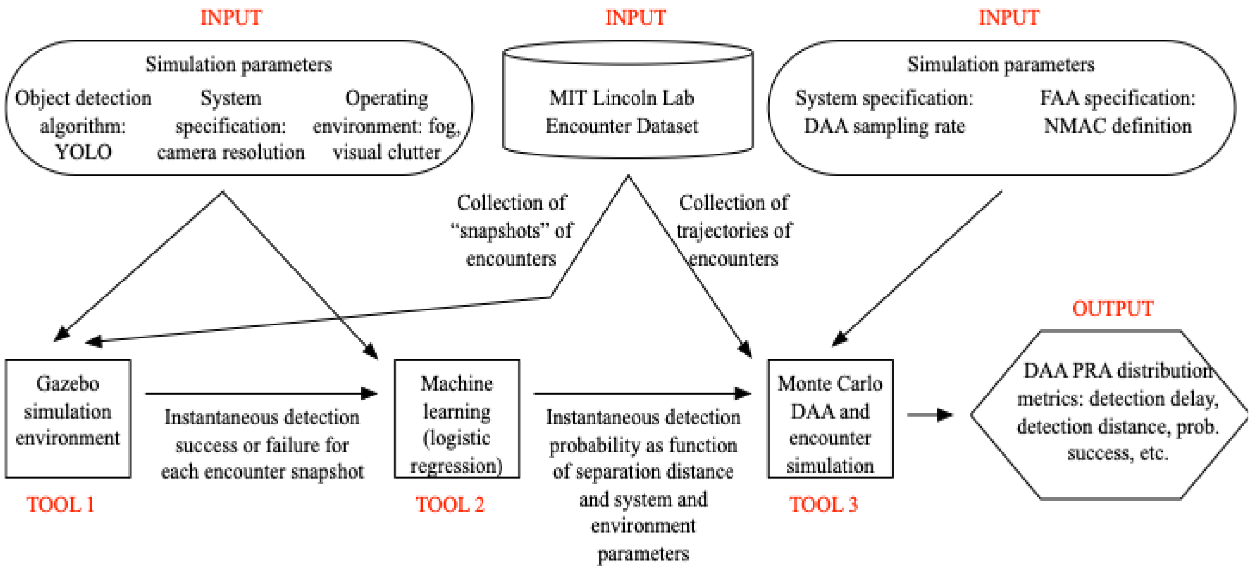

Figure 6. High-level overview of the DAA Timing Distribution approach to Probabilistic Risk Assessment.

3.2.1.2 *Gazebo Flight, Environment, and Detection Simulation*

The Gazebo simulation platform replicates the operational environment of a sUAS equipped with the uAvionix Casia X DAA system, which uses five 8.9-megapixel GigE cameras arranged to provide 360-degree horizontal coverage. Realistic aircraft trajectory pairs are drawn from the MIT Lincoln Laboratory (MIT LL) Manned Bayesian Encounter Model - a probabilistic model trained on radar surveillance data that captures real-world aircraft behavior in terms of altitude, heading, vertical rate, and turn rate. These trajectory pairs are classified by encounter type: relevant encounters in which an NMAC is possible, and NMAC encounters in which a collision course is established.

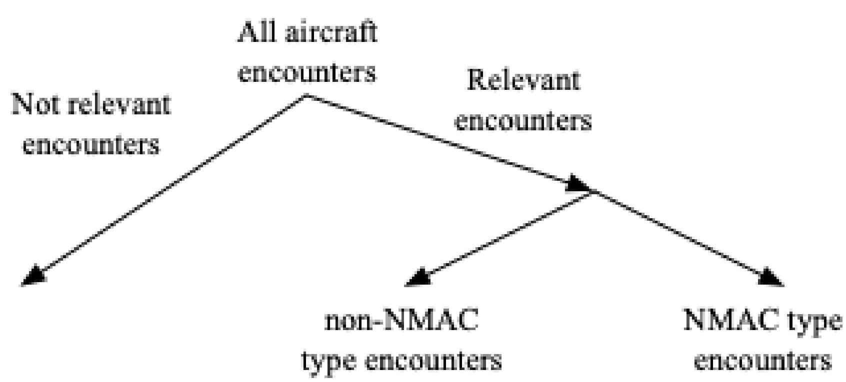

Figure 7. Encounter taxonomy used in the DAA Timing Distribution approach, distinguishing between relevant encounters and NMAC-type encounters used in the Monte Carlo simulation.

The DAA system's maximum detection capability is geometrically defined by a detection sphere (or, more precisely, a detection cylinder that accounts for horizontal and vertical separation distances separately) centered on the ownship. Detection attempts occur only when the intruder falls within this boundary.

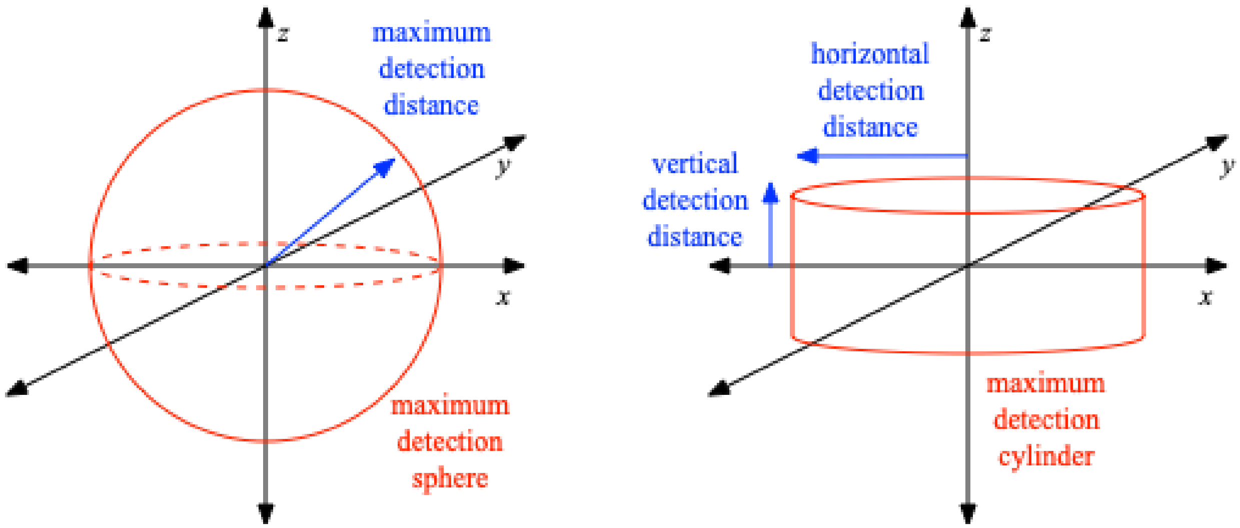

Figure 8. Maximum detection distance represented as a detection sphere (left) and a detection cylinder (right), the latter accounting for horizontal and vertical separation distances independently.

At randomly selected instants within each encounter trajectory, Gazebo simulates whether the You Only Look Once (YOLO) object detection algorithm successfully detects the intruding aircraft. These simulations are conducted with systematically varied DAA system parameters (e.g., camera resolution) and environmental conditions (e.g., fog level and visual clutter), producing a large set of labeled detection outcomes (Success or Failure) for each configuration.

3.2.1.3 *Machine Learning (Logic Regression)*

The labeled detection outcomes from Gazebo are used to train a logistic regression model that yields a parameterized *instantaneous detection probability* function. This function gives the probability that the DAA system will successfully detect the intruder at any given instant, as a function of the instantaneous separation distance between the two aircraft, the DAA system properties (e.g., camera resolution), and the operating environment (e.g., fog density, visual clutter). The approach identifies the instantaneous detection event as a random variable drawn from a parameterized Bernoulli distribution. By fitting this model across a systematic sweep of parameter values, the approach produces a continuous detection probability surface over the full parameter space, enabling credible prediction at conditions beyond those directly simulated in Gazebo.

The MIT LL Bayesian Encounter Model underlying the trajectory generation is itself a Dynamic Bayesian Network that probabilistically relates aircraft state variables - geographic location, airspace class, altitude layer, air speed, acceleration, vertical rate, and turn rate - to produce realistic, statistically representative encounter geometries. This network structure is shown in the Task 2 report.

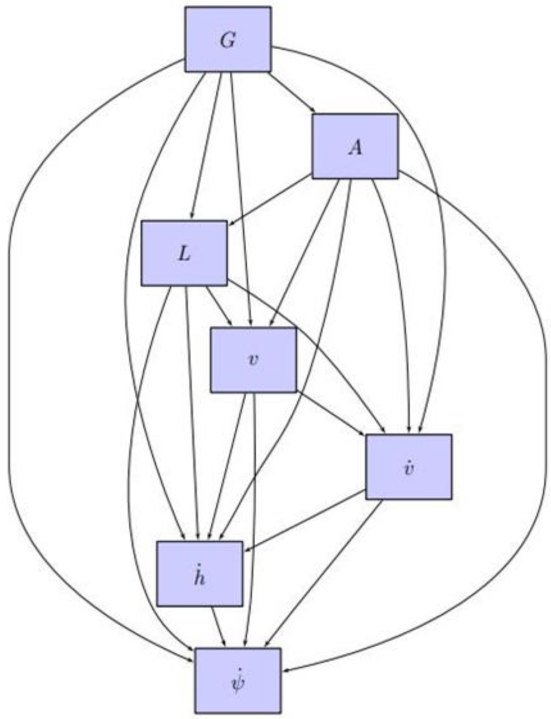

Figure 9. Bayesian network structure of the MIT Lincoln Laboratory Manned Encounter Model, used to generate realistic intruder aircraft trajectories for the DAA Timing Distribution simulations (MIT Lincoln Labs, 2021).

3.2.1.4 *Monte Carlo DAA Encounter Simulation*

Given the instantaneous detection probability model, a Monte Carlo simulator propagates a large number of encounter trajectories through time. At each discrete time step, a Bernoulli trial is conducted. If the separation distance is within the maximum detection range, the detection probability is evaluated using the fitted logistic model, and a random draw determines whether detection is registered at that instant. This process repeats at each time step, offset by the DAA system's sampling delay, until detection occurs, the separation exceeds the detection range, or the encounter ends. The resulting detection delay is a positive integer multiple of the sampling delay, and its distribution reflects both the encounter geometry and the environmental conditions in which it occurs.

An encounter is classified as a *success* if detection occurs before the first NMAC, and as a *failure* otherwise. The overall probability of successful detection - the proportion of simulated encounters where detection precedes an NMAC - is the primary risk measure. Supporting outputs include the full distribution of detection delays, the distribution of separation distances at the moment of detection, and the overall NMAC rate. This connection to the ASTM DF timing framework is direct: the sampling delay governs the granularity of the Bernoulli trial sequence, and the cumulative DF timing components determine the effective detection horizon available before a conflict escalates to NMAC.

This methodology offers several key advantages. The use of realistic MIT LL encounter trajectories ensures that simulations reflect actual sUAS operational environments, particularly in low-altitude Class G airspace. The Gazebo/YOLO simulation provides a faithful representation of detection algorithm behavior across diverse conditions. The logistic regression model enables computationally efficient parameter-space sweeping without requiring a full Gazebo run at every configuration. Moreover, the Monte Carlo framework fully captures the stochastic nature of detection events, producing statistically credible estimates of collision risk that are directly interpretable within a specific CONOPS and directly traceable to the timing requirements of the ASTM DAA standard.

3.2.2 Subtask 2-2 – Sensitivity Report

The second subtask directed the research team to investigate how the proposed risk measures change as key system parameters and environmental operating conditions vary. This sensitivity analysis was conducted for the DAA Timing Distribution Approach to PRA developed in Subtask 2-1 and produced quantitative findings directly relevant to DAA system design, operational planning, and regulatory guidance.

3.2.2.1 *Sensitivity Analysis for the DAA Timing Distribution Approach*

The sensitivity analysis for the second proposed method focused on quantifying how the instantaneous detection probability, the distribution of detection delays, and the probability of an NMAC change as a function of environmental operating conditions, specifically atmospheric visibility (parameterized as fog density) and visual clutter. This analysis was executed through the three-tool pipeline described in Subtask 2-1, with Gazebo simulations conducted across 40 discrete fog density levels and a range of clutter configurations, followed by logistic regression model fitting and large-scale Monte Carlo simulation (5,000 encounter scenarios per condition level).

The results of this analysis are organized around four primary performance metrics: detection rate, detection distance, detection latency, and NMAC rate.

Detection Rate. The overall probability of detecting an intruding aircraft before an NMAC was found to be highly sensitive to fog conditions, with a non-linear degradation pattern. Under clear conditions, the detection rate was robust and nearly complete. As fog density increased to a light level, the detection rate remained high at 93.33%. However, as fog density reached heavy levels, the detection rate fell to 46.43%, a decline of more than 50 percentage points. This finding establishes fog density as one of the most critical environmental parameters governing DAA system performance.

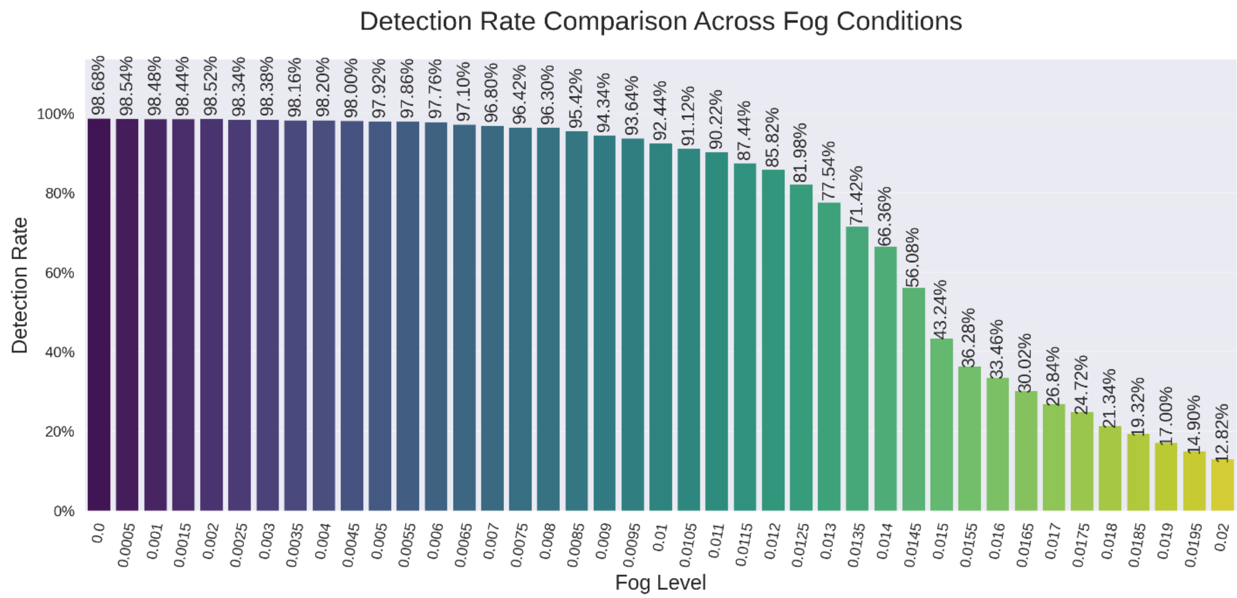

Figure 10. Detection rate across 40 fog density levels from Monte Carlo simulations of 5,000 encounter scenarios, demonstrating the non-linear degradation in DAA system performance under increasing atmospheric obscuration.

Detection Distance. The average range at which an intruder was first detected showed strong sensitivity and a dramatically non-linear relationship with fog density. Under clear conditions, the average detection distance was 1,447 meters. Under light fog, this declined modestly to 1,241 meters (a 14.3% reduction). Under moderate fog, the reduction was substantially larger at 31.2%, dropping to 996 meters. At heavy fog density, the detection distance collapsed to just 87 meters - a 94% reduction from clear conditions. This near-exponential decay in effective detection range with increasing fog concentration has direct implications for minimum operational visibility requirements in sUAS BVLOS regulations.

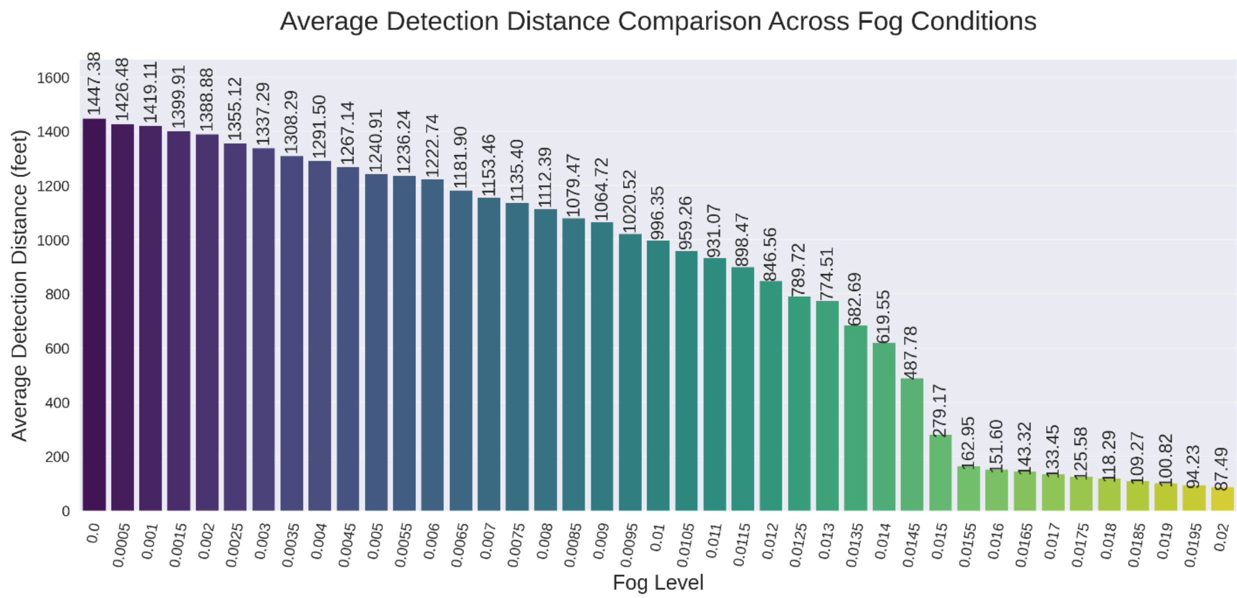

Figure 11. Average detection distance across fog density levels from Monte Carlo simulations, demonstrating exponential decay in effective detection range under increasing fog density.

Detection Latency. Unlike detection rate and distance, average detection latency exhibited a more linear relationship with fog density, increasing from 77.44 seconds under clear conditions to 81.26 seconds under light fog (a 4.9% increase), 88.56 seconds under moderate fog (14.4% increase), and 113.18 seconds under heavy fog (a 46.1% increase). The more gradual, linear nature of this relationship suggests that even partial fog conditions substantially degrade the system's responsiveness over time. That detection latency may be a valuable metric for setting operational weather minimums, in addition to the more commonly monitored detection rate.

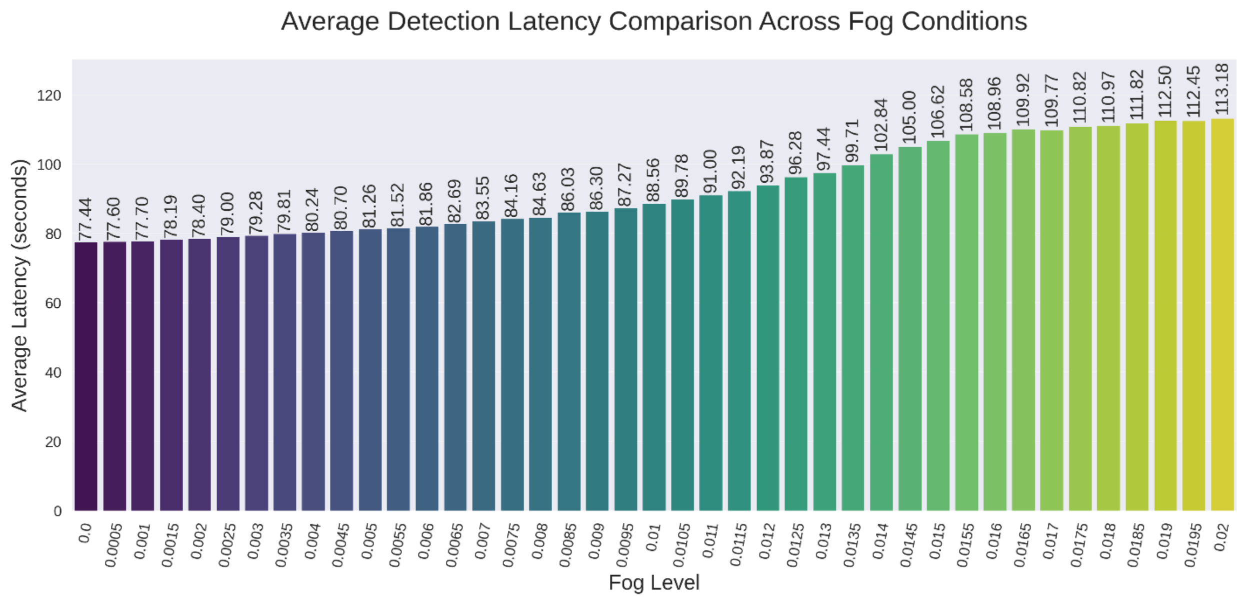

Figure 12. Average detection latency across fog density levels from Monte Carlo simulations, demonstrating a systematic and near-linear increase in DAA system response time with increasing fog density.

NMAC Rate. The most operationally significant finding of the sensitivity analysis concerns the NMAC rate - the proportion of simulated encounters resulting in a Near Mid-Air Collision. This metric exhibited an exponential relationship with fog density characterized by a distinct threshold behavior. Below a fog density of approximately 0.010, the NMAC rate remained consistently low, ranging from 0.02% to 0.22% - well within operationally acceptable bounds. At fog density 0.013, the NMAC rate rose sharply to 1.04%, representing a five-fold increase over the baseline. At fog density 0.015, the rate reached 2.70% - a 13-fold increase. At maximum simulated fog density (0.020), the NMAC rate escalated to 13.48% - a 67-fold increase over clear conditions.

The sharpness of this transition at fog densities between 0.012 and 0.013 constitutes a critical finding with direct regulatory implications. The data provide strong empirical evidence for a safety-critical environmental threshold at which DAA system performance degrades catastrophically within a narrow operational window. This type of quantitative threshold identification - precisely the kind of data-driven insight that the Task 1 Issue Report identified as missing from existing SRM frameworks - provides a concrete basis for establishing operational restrictions tied to atmospheric visibility measurements.

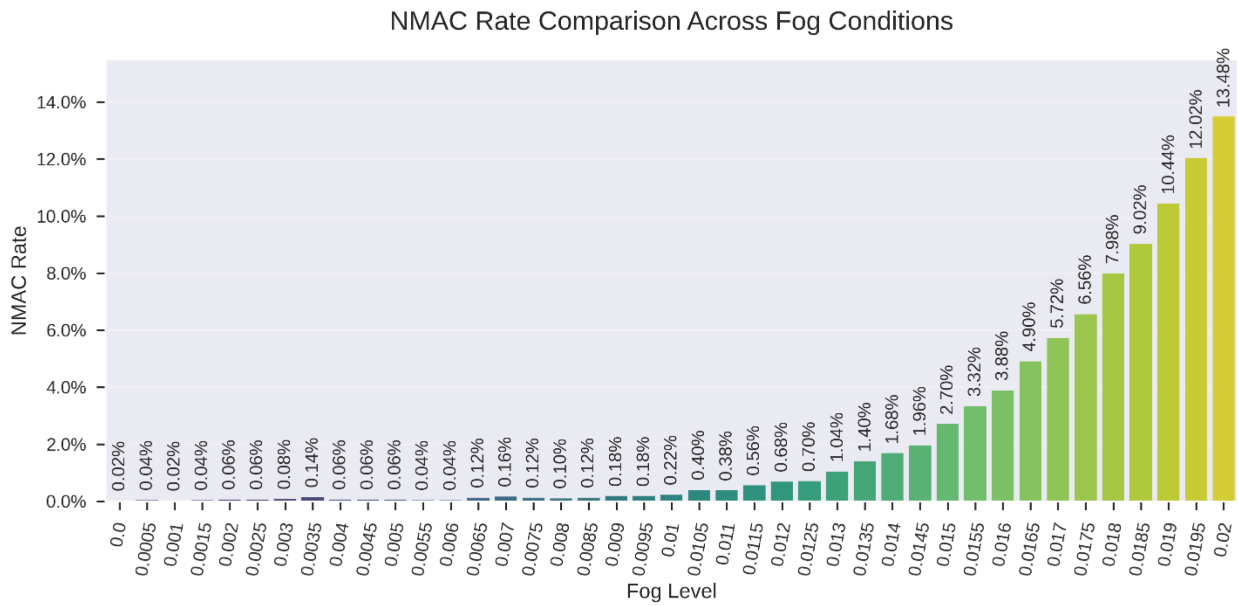

Figure 13. Fog levels applied in a New York City environment in Gazebo: a) No fog, b) Minimum fog, c) Medium fog, and d) High fog.

Together, the sensitivity findings across all four metrics establish several actionable conclusions. First, environmental conditions - particularly atmospheric visibility - are among the most critical and quantifiable determinants of DAA system safety performance, and their effects are non-linear in ways that make threshold-based operational restrictions both necessary and scientifically defensible. Second, the proposed DAA Timing Distribution methodology demonstrated the capacity to accurately predict detection performance across the full continuous parameter space, validating the use of logistic regression and Monte Carlo simulation as efficient and credible tools for DAA risk assessment. Third, the analysis identified the fog density range of 0.012-0.013 as a critical operational boundary, above which NMAC risk escalates rapidly, providing a concrete empirical basis for developing minimum meteorological conditions for BVLOS operations with vision-based DAA systems.

These sensitivity findings directly informed the simulation design and test conditions used in Task 3, ensuring that the Monte Carlo evaluation environment reflects the parameter ranges most critical to DAA system safety performance.

3.3 Task 3 – DAA Hazard Identification and Risk Assessment

This task tests the practical application of the templates and methods developed in Task 2. Monte Carlo simulations were used to test variables and encounter scenarios from Task 2 to identify their practical application and validate initial assumptions regarding the timing distribution PRA model. The following subsections present an overview and findings from Task 3, and the full report from Task 3 can be found in the accompanying Appendix C.

3.3.1 Subtask 3-1 – Simulation and System Requirements to Support Sensitivity and DAA Performance

3.3.1.1 *Objectives*

The objectives of Task 3.1 were:

- Determine the metrics, amount of data, and limitations for evaluating DAA performance.

- Develop a high-fidelity simulation framework for designing and evaluating DAA assessment methods.
- Integrate high-fidelity surveillance and navigation models into the simulation.
- Enable sensitivity analysis of DAA assessment methods through degraded operational conditions in a DAA simulation.

3.3.1.2 *Methods*

To develop a credible DAA simulation framework, Task 3 adopted metrics and conditions based on the detailed perspective provided by Transport Canada Civil Aviation (TCCA) to the ASTM WK62669 team. Based on TCCA insights, the A71 simulation identified the following requirements: simulations should prioritize challenging scenarios; systems should be evaluated at their operational limits; high-fidelity environmental conditions should be modeled; and tracking errors should be added to analyze DAA performance.

The simulation environment for Tasks 2 and 3 was developed as a modular ROS2-Gazebo system, enabling DAA algorithms to be integrated into the vehicles' guidance systems. This simulation framework allows the user to define environmental conditions, the number of vehicles, their trajectories, sensors, and guidance logic. The main simulation architecture is presented in Figure 14

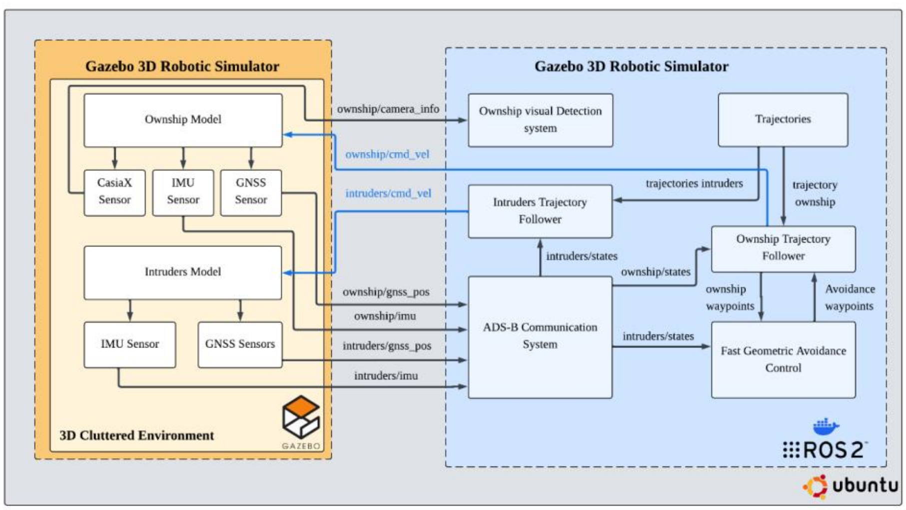

Figure 14. Simulation structure.

Inside its structure, the simulation is composed of the following elements:

- **Unmanned Aircraft model:** In Gazebo, every unmanned aircraft used in the DAA simulation is defined using a Cessna 172 3D model integrated with a small fixed-wing autopilot logic. In addition, each vehicle's characteristics, inertial properties, and sensors are presented using a Unified Robot Description Format file.
- **High-fidelity sensors:** The simulation environment uses custom Gazebo plugins that imitate high-fidelity sensors, which include Global Navigation Satellite System (GNSS), Inertial Measurement Unit, and ADS-B transmitters. Every sensor is designed to account for noise, delays, and tracking degradation.
- **Visual detection system:** For non-cooperative intruder avoidance, UAS are equipped with a 360° camera detection system based on the CasiaX onboard multi-camera configuration. Additionally,

the visual detection system uses the YOLO object detection framework to continuously search for intruders resembling fixed-wing UAS.

- **DAA Guidance algorithm:** For the avoidance maneuvers, the ownship uses the Fast Geometric Avoidance Control algorithm. This algorithm calculates optimal waypoints in real time to ensure the Ownship avoids entering the intruder's avoidance zone.
- **3D Gazebo Environment:** To test the intruder detection and sensor performance in dangerous-realistic scenarios, Task 3 defined five different cluttered environments (Empty World, New York, Hanscom Air Force Base, Sonoran Desert, and Rocky Mountains), where each map was tested with four different fog density configurations (None, Minimal, Medium, and High; Figure 15)

3.3.1.3 *Summary of Results*

Task 3.1 developed a high-fidelity, modular ROS2-Gazebo simulation framework designed to validate DAA systems, such as CasiaX, under rigorous environmental and technical conditions. By integrating a small fixed-wing Cessna 172 dynamics model, high-fidelity tracking sensors, and a 360° CasiaX-YOLO intruder visual detection system, the simulation can replicate complex, cluttered environments to generate comprehensive, high-precision safety analyses.

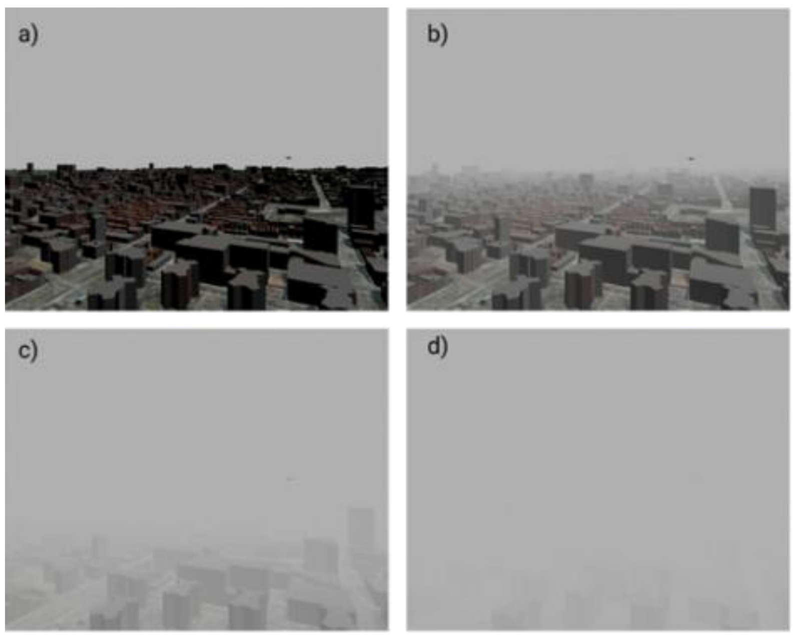

Figure 15. Fog levels applied in a New York City environment in Gazebo: a) No fog, b) Minimum fog, c) Medium fog, and d) High fog.

Overall, the simulation environment provided a realistic, robust, reproducible, and modular system for performing DAA maneuvers across the A71 project's tasks.

3.3.2 Subtask 3-2 – Safety Risk Management Analysis Document

Subtask 3-2 continued simulation tasks from subtask 3-1 and captured findings in a report. The following subsections discuss the objectives, methods, and results. This subtask built on findings from subsequent tasks to validate the timing distribution PRA model and inform overall findings.

3.3.2.1 *Objectives*

- Validate the simulation framework through extensive Monte Carlo simulations.

- Perform a comparison analysis between traditional risk assessment methods and the approach proposed in Task 2.
- Quantify visual intruder detection performance under degraded and occluded visual conditions.
- Evaluate DAA performance across complex avoidance and multi-intruder scenarios.

3.3.2.2 *Methods*

To analyze the UAS's intruder visual detection capabilities, 1,000 Monte Carlo simulations were run using the 1,000,000 available trajectories from the MIT Unmanned Aircraft Terminal Area encounters set. Each simulation trajectory was initialized at a random position near the Closest Point of Approach and propagated for 75 seconds. To determine the impact of occluded visual conditions, each simulation was performed in two environments: an uncluttered environment (Empty world) and a highly cluttered environment representative of the surroundings at Hanscom Air Force Base. Furthermore, each simulation was repeated with four levels of exponential fog (None, Minimal, Medium, and High) to evaluate the detection performance under reduced visibility. The resulting data was processed to create confidence detection distributions as a function of separation distance, which were compared against detection models defined in Task 2.

To evaluate the robustness of the detection system against hardware failures, a second set of simulations was performed in which two cameras of the CasiaX model were randomly disabled. The data obtained was also analyzed to examine the effects of occlusion on detection confidence, maximum detection range, and false-positive rates.

Finally, Task 3.2 tested the robustness of a Fast Geometry Avoidance (FGA) algorithm within the ADS-B-based DAA system by introducing high-risk conditions during an active avoidance maneuver. For instance, the simulation considered different DAA encounter geometries with multi-agent avoidance and ADS-B tracking errors due to GNSS dropout. Specifically, these simulations incorporate multi-intruder encounters and ADS-B tracking inaccuracies resulting from GNSS dropouts. This approach enabled an assessment of how degraded signals and tracking errors impact intruder localization and the generation of safe avoidance trajectories.

3.3.2.3 *Summary of Results*

The 1,000 MIT encounter set simulations determined that, as fog density increases, the maximum detection range and average confidence detection decrease. In an uncluttered environment, the mean detection range fell from 1,335 ft to 724 ft as fog density increased. On the other hand, cluttered environments like the Hanscom Air Force Base reported higher mean detection ranges (1,821 ft to 1,203 ft) as presented in Figure 16.

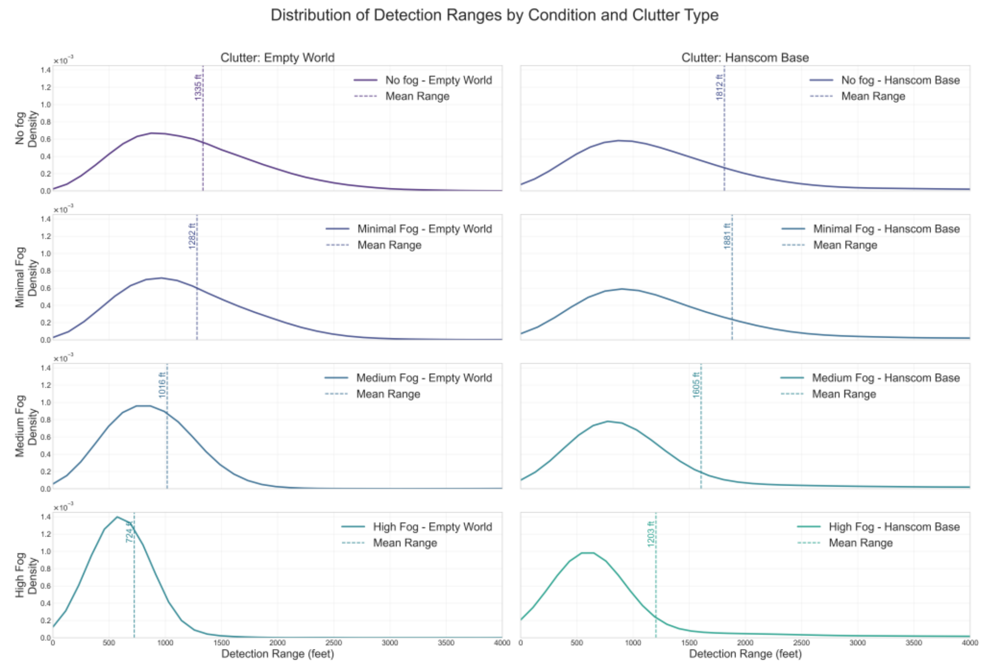

Figure 16. Distribution of Detection Ranges by Condition and Clutter Type for the 1,000 MIT encounter set simulations. Kernel density estimates show the probability density of detection ranges, with dashed vertical lines indicating the mean detection range.

These higher detection ranges are attributed to a high false-positive rate (~23%) in the visual detection system, leading to fewer total intruder detections. Figure 17 presents the overall success rate, showing that in uncluttered environments, the success rate approaches 100% at close ranges (400-800 ft) across all fog conditions, but drops below 20% beyond 1,000 ft in the no-fog condition. Conversely, in cluttered environments like Hanscom, visual noise reduces the close-range success rate to ~80% regardless of fog density and to 20% beyond 800 to 1400 ft, depending on fog density.

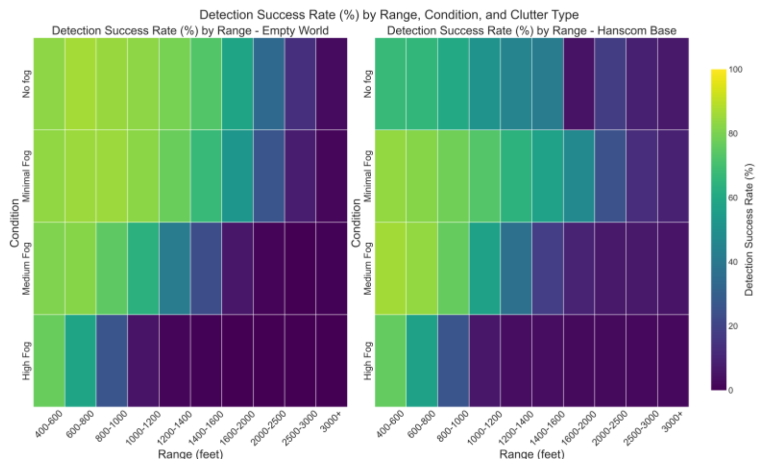

Figure 17. Detection success rate (%) as a function of range and fog conditions for Empty World (left) and Hanscom Base (right) environments. Color intensity indicates detection probability, with yellow representing high success rates and dark blue representing low success rates.

On the other hand, for degraded hardware scenarios, the system showed a significant reduction in detection volume. Figure 18 shows that total detections dropped approximately 50% compared to the nominal CasiaX configuration, reaching a minimum of 8% for the minimal fog conditions. However, the lower number of objects inside the image resulted in a lower false-positive rate, which decreased to 12% across most fog levels.

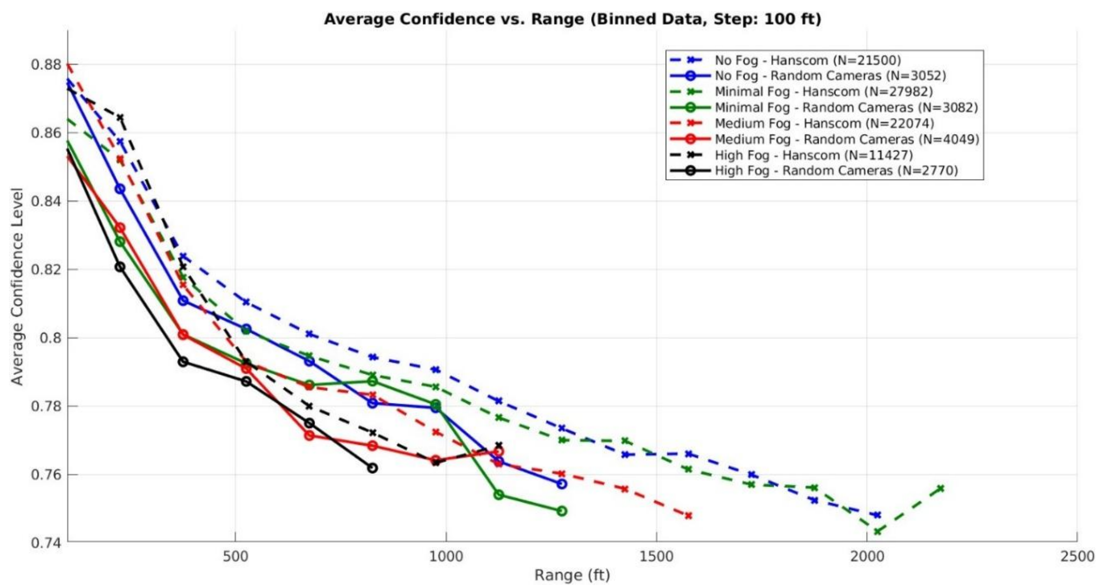

Figure 18. Average confidence detection levels vs range for different fog conditions in the Hansom Air Force Base and the Hanscom Air Force Base with random camera simulations.

The exception occurred during high-fog conditions, when false positives reached approximately 20% of total detections. These results show that reducing the field of view of the cameras reduces the visual clutter from environmental structures, but it also reduces the successful detection range and confidence level.

Finally, the FGA algorithm, integrated with the ADS-B broadcast system, proved effective at resolving multi-intruder encounters but was sensitive to sensor failure. Under nominal conditions, the DAA algorithm successfully avoided multiple intruder scenarios, including single- and multiple-intruder scenarios, even when the avoidance zones overlap, as demonstrated in Figure 19.

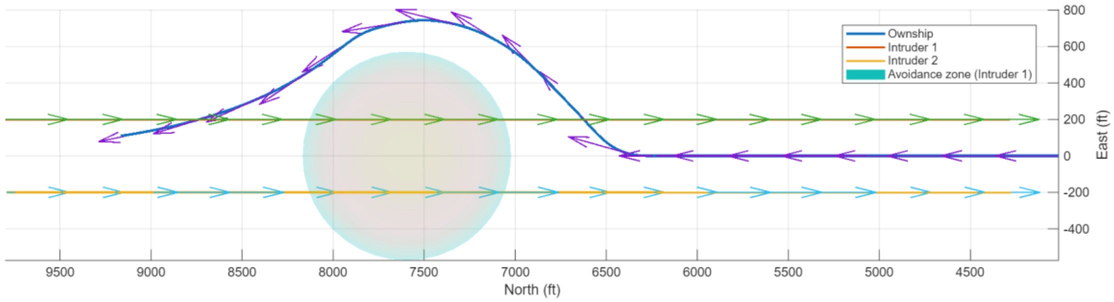

Figure 19. Multi-intruder DAA scenario: Two intruders approaching from the opposite direction and surrounding the ownship.

However, the introduction of GNSS dropouts affected trajectory avoidance by causing the ADS-B tracking localization estimates for both ownship and intruders to diverge. The slow convergence following a dropout often forced the algorithm to detect the avoidance flag or create large conservative avoidance maneuvers, as illustrated by Figure 20.

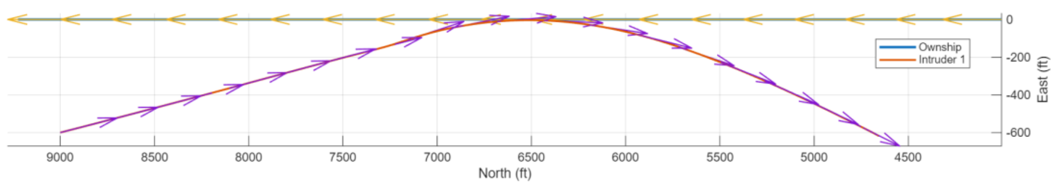

Figure 20. Lateral avoidance maneuver with GNSS dropout in Gazebo, where the ownship failed to recognize the avoidance flag.

Furthermore, slight penetrations into the avoidance zones by the ownship suggest that higher safety coefficients should be applied to maintain adequate separation during avoidance maneuvers.

4 CONCLUSIONS

This section presents conclusions and recommendations resulting from each task and subtask. The conclusions and recommendations highlighted provide both direct and indirect answers to the guiding research questions. The conclusions and recommendations provided also offer a starting point for future work and additional exploration of risk assessment methodologies and best practices for assessing risk in DAA systems.

4.1 Summary of Findings by Task

The following represent findings and conclusions for each task. The findings and conclusions support broader research objectives and address research questions. A more detailed breakdown of research questions and research findings can be found in Section 4.2.

4.1.1 Task 1 – Background Report

The Task 1 Background Report established critical elements for future tasks. Of note, the Background Report identified themes in literature and the application of DAA technologies that required further investigation and consideration when identifying hazards and developing a risk assessment process for DAA systems. As discussed in Section 3.1.10, the following themes were identified within the Task 1 Background Report:

1. There are no universally accepted reliability metrics for DAA systems.
2. There are currently no accepted standards for assessing the risk associated with DAA systems.
3. Data required to assess the risk associated with DAA systems is often incomplete, inaccurate, or unavailable.
4. Models driven by reliable data and a robust analytical framework are essential to assessing the risk associated with DAA systems.
5. The evolution of DAA technologies is occurring rapidly and extends beyond the current UAS operational guidance.
6. There is a need for effective verification and validation of DAA systems to ensure reliability.
7. Guidance and standards are needed to define and apply risk controls for DAA systems.

These themes guided the exploration of hazards and helped the research team develop models and simulation inputs for Tasks 2 and 3. More importantly, this task identified gaps and areas requiring further exploration of hazards and risk assessment methodologies.

4.1.2 Task 2 – Draft Hazard Identification and Risk Assessment Processes for DAA Systems and Operations

Task 2 advanced the project from the qualitative gaps identified in Task 1 toward a more structured, data-driven, and probabilistic framework for evaluating DAA safety. Rather than relying solely on traditional likelihood-severity-based risk matrices, Task 2 developed and evaluated a probabilistic approach that more directly captures the operational behavior and performance of DAA systems under realistic encounter conditions.

A central contribution of Task 2, and a major focus of Drexel's work, was the development of a timing-based probabilistic risk assessment framework for DAA systems. This approach reframed DAA risk as an operationally meaningful metric: the probability that a DAA system fails to detect an intruding aircraft before an NMAC occurs. In contrast to deterministic timing budgets or single-point detection thresholds, this method recognizes that detection performance is inherently probabilistic and must be evaluated in the context of encounter geometry, system characteristics, and environmental conditions.

The timing-based framework is grounded in the ASTM DAA Timing Standard. It focuses on the Detection Function as the portion of the timing chain most sensitive to sensor performance, algorithm latency, and environmental degradation. Detection is modeled as a sequence of probabilistic events over time, where at each time step the likelihood of detection depends on factors such as relative separation distance, sensor resolution, update rate, and environmental effects including fog, lighting, and visual clutter. Using high-fidelity simulation environments and Monte Carlo methods with representative encounter trajectories, this approach generates detection-time distributions and estimates the probability of successful detection prior to NMAC. As a result, it provides a direct, quantitative link between system performance, operational conditions, and collision risk.

Importantly, this probabilistic timing framework enables sensitivity analysis across both system and environmental parameters, demonstrating how degraded visibility, sensor limitations, and operational constraints can significantly alter detection probability and timing margins. These insights are critical for identifying performance limitations, informing system design, and supporting the development of mitigation strategies in later tasks.

Overall, Task 2 demonstrates the value of simulation-based and probabilistic approaches for DAA safety assessment. By linking detection performance directly to encounter dynamics and environmental conditions, the timing-based framework provides a practical and scalable foundation for data-driven SRM. It supports the continued development of performance-based DAA standards.

4.1.3 Task 3 – DAA Hazard Identification and Risk Assessment

The results of Task 3 demonstrated that a high-fidelity, modular simulation framework can effectively support the evaluation and validation of DAA systems under realistic and challenging operational conditions. With the integration of detailed aircraft dynamics, advanced sensing models (including GNSS, IMU, ADS-B, and vision-based detection), and configurable environmental scenarios, the ROS2-Gazebo-based simulation environment enabled repeatable and scalable testing of DAA performance. The framework successfully reproduced complex encounter scenarios and degraded conditions, providing a robust platform for safety analysis when real-world data are limited. Consequently, simulation tools can be used as a credible and essential tool for developing and assessing DAA architectures.

The analysis performed in Task 3 showed that DAA performance is highly sensitive to environmental conditions and sensor limitations. Increasing fog density and environmental clutter significantly reduced detection range, confidence levels, and overall detection success rates. While cluttered environments sometimes produced higher apparent detection ranges, this was largely driven by increased false positives rather than improved true detection performance. Additionally, hardware degradations, such as partial camera failures in the CasiaX DAA system, substantially reduced detection coverage and reliability, even though they occasionally lowered false-positive rates by limiting visual noise. These findings highlighted the trade-offs between detection sensitivity and robustness and emphasized the importance of maintaining sensor integrity and accounting for environmental complexity in DAA system design.

Finally, the evaluation of the FGA algorithm in degraded operational scenarios for ADS-B systems demonstrated that although the system performs well under nominal conditions, including multi-intruder encounters, it is vulnerable to navigation and tracking errors. GNSS dropouts degraded ADS-B state estimation, leading to delayed or inaccurate conflict detection and overly conservative or ineffective avoidance maneuvers. In some cases, this resulted in slight violations of avoidance boundaries, indicating the need for more conservative safety margins. Overall, the findings show that reliable DAA performance depends on the coupled interaction of sensing, estimation, and guidance systems, and that high-fidelity simulation combined with probabilistic risk assessment provides a powerful approach for quantifying these effects and informing safety-critical design decisions.

4.2 Research Questions Addressed

Research Question 1: *Through a sensitivity analysis, what portions of a DAA system design are most critical when it comes to mitigating collision risks?*

Through the sensitivity analysis from Monte Carlo simulations in Task 3, the portions of a DAA system design that proved most critical for mitigating collision risk are the end-to-end sensing–tracking–avoidance chain, with the strongest sensitivities concentrated in (1) visual detection robustness to environment, (2) sensor integrity, and (3) navigation/tracking robustness that drives DAA system conflict detection and guidance timing.

Visual detection robustness: Collision risk is most sensitive to the reliability with which the vision system detects intruders in fog and clutter. As fog increases, detection range and confidence drop; in cluttered scenes, "longer" apparent detections are often driven by false positives (~23%), which degrade usable detection and can confuse downstream logic. For example, in the case of the CasiaX DAA system, perception performance under realistic visibility and clutter conditions, as well as false-positive control, is critical.

Sensor integrity and coverage, or camera degradation: When cameras are degraded (e.g., two CasiaX cameras disabled), the system loses coverage and detection volume (~50% drop; as low as ~8% detections in some cases), reducing time-to-detect and, therefore, time-to-avoid. False positives may decrease due to reduced clutter, but safety is dominated by the loss of field of view and detection opportunity.

Tracking/estimation feeding avoidance (ADS-B + GNSS dropouts): The FGA avoidance logic works well in nominal multi-intruder encounters, but GNSS dropouts degrade ADS-B tracking and delay or distort conflict detection, leading to overly conservative maneuvers and occasional boundary penetrations. In this case, robust navigation/tracking under dropouts and uncertainty-aware safety margins are critical for reliable collision avoidance.

Reference – Subtask 3-2.

Research Question 2: *Does this change for different DAA architectures or operations, such as Airborne DAA, Ground-Based DAA, Unmanned Traffic Management Surveillance Services as part of a DAA system, automated or manual DAA maneuvers, and Multi-vehicle DAA architectures and operations?*

Yes. The proposed 3D risk assessment model is highly adaptable and explicitly accommodates both human-in-the-loop (manual) pilot-operators and fully automated DAA system architectures. In automated architectures, the algorithm directly processes variables to execute course corrections. In contrast, in manual maneuvers, the data is translated into simple visual cues (such as the red-yellow-green matrix) to assist human decision-making.

Reference – Subtask 2-1: Draft Hazard Identification and Risk Assessment Processes for DAA Systems and Operations

Research Question 3: *What risk assessment tools are recommended for industry DAA risk management?*

Under 3.2.1 - Subtask 2-1 – Hazard Identification and Risk Assessment Processes – Instead of just exploring general alternative methods, the research initially proposed two distinct, novel PRA methodologies for DAA systems.

This tool models risk as a three-dimensional Risk Assessment Point (RAP) rather than using a flat matrix. The recommended metrics for this assessment are three variables, each scaled from 0 to 1:

1. Potentiality: The instantaneous probability of a hazardous condition occurring.
2. Severity: The potential consequences or impact of the hazard.
3. Exposure: The duration of the UAS remains vulnerable to the hazardous condition.

To assess the confidence and safety of these metrics, the tool also uses a Risk Uncertainty-Validity Spheroid (RUVS) to visually represent data uncertainty and a Safety Limit Reward Sphere (SLRS) to define the boundary of acceptable risk.

Reference – Subtask 2-1: Hazard Identification and Risk Assessment Processes for DAA

Research Question 4: *Are they [risk assessment tools] different than the risk assessment tools recommended for FAA use?*

Section 3.2.1 within Subtask 2-1 expressed a model that expanded the traditional two-variable risk matrix (likelihood and severity) into a three-dimensional model. Potentiality replaced likelihood, representing the probability that a hazard exists at a specific instant. Severity remained the impact of the hazard. Exposure is introduced to measure exactly how long the unmanned aircraft remains vulnerable in a hazardous condition (such as a potential collision course). This creates a 3D RAP, allowing risk to be visualized and aggregated over entire fleets or individual missions.

While Method 1 was investigated in Task 2, method 2 - DAA Timing Distribution Approach to PRA was emphasized as efforts moved into Task 3. Method 1 was suggested in Section 5 Future Work.

Research Question 5: *What does a sensitivity analysis reveal about the effects of loss of link on DAA performance when considering different DAA architectures and operations?*

Examples include Ground-Based vs. Airborne, Manual vs. Automated avoidance, en-route vs. terminal operations, etc.

A sensitivity analysis generally shows that Loss of Link (LoL) degrades DAA performance through whatever part of the architecture depends on that link, and the impact can look very different depending on the DAA architecture (ADS-B/cooperative vs CasiaX vision/non-cooperative) and the operation phase (cruise vs close encounter vs active avoidance).

In the ADS-B (cooperative) DAA architecture, LoL is most critical when it disrupts navigation/tracking quality (e.g., GNSS dropouts that corrupt the ownship/intruder state estimates used by the ADS-B conflict logic). From the Task 3 results, GNSS dropouts caused ADS-B localization estimates to diverge and converge slowly afterward, which led to delayed/inaccurate conflict detection, overly conservative or ineffective avoidance maneuvers, and even slight penetrations of avoidance zones, implying that LoL conditions demand larger safety coefficients/margins and robust fallback behavior during and immediately after a dropout.

In vision-based (non-cooperative) DAA architectures, such as the CasiaX DAA system, LoL manifests as a loss of sensing coverage or confidence (e.g., partial camera failures or degraded conditions), directly reducing detection volume, detection range, and detection reliability. In task 3, the camera-degradation runs showed large drops in detections (on the order of ~50% fewer detections vs nominal, with some cases much lower), meaning LoL-like degradations reduce “time to first reliable detect,” shrinking the window available for safe maneuvering, even if false positives sometimes decrease when the field of view is reduced.

Reference – Subtask 3-2.

Research Question 6: *How should a suitable standard/accepted risk assessment on a DAA system be structured to provide meaningful insights into system design, performance, and safety optimization?*

The risk assessment structure must be tailored to each end-user.

For Automated Routines: The structure should process a continuous spectrum of 3D mathematical probability calculations (Potentiality, Severity, Exposure) using machine learning and AI. This allows the system to autonomously evaluate the RAP against the SLRS and trigger fail-safes without human intervention.

For Pilot-Operators: Because complex 3D models can be difficult to interpret quickly, the assessment structure must translate the complex data into an intuitive, cognitive-load-friendly interface. If the RAP and RUVS are safely inside the SLRS, the pilot sees a Green (safe) indicator; if the uncertainty extends outside the SLRS, they see Yellow (mitigations required); and if the RAP breaches the SLRS, they see Red (unsafe/halt).

Reference – Subtask 2-1: Draft Hazard Identification and Risk Assessment Processes for DAA Systems and Operations.

Research Question 7: *What variables or aspects of system design have the greatest impact?*

The variables with the greatest impact are the ones that determine (1) time-to-detect, (2) track accuracy/uncertainty, and (3) how conservatively and reliably the system turns that information into avoidance guidance. Based on the results in Task 3, the biggest drivers are: sensor performance and coverage (e.g., field of view, detection range vs. visibility, clutter/false-positive rate, and sensor health/degradation), estimation and tracking quality (e.g., GNSS integrity, dropout handling, latency, update rate, and how uncertainty grows with horizon), and decision/avoidance tuning (e.g., alert thresholds, replanning rate, and fallback behaviors when confidence drops). Environment and operations strongly modulate these factors; for example, fog and clutter reduce confidence and range for vision systems, while GNSS dropouts degrade ADS-B state estimation and can delay conflict detection or force overly conservative maneuvers, so designs that explicitly model uncertainty, adapt margins, and maintain redundancy across sensing and tracking typically have the largest safety benefit.

Reference – Subtask 3-2.

Research Question 8: *What safety metrics are recommended for meaningful DAA system safety assessments? Consider assurance, performance, and system-to-system interactions.*

This research established a PRA to inform the FAA on transitioning from qualitative safety assessment methods to a quantitative approach to safety risk assessment. Specific metrics examined as part of subtasks 1-2, "Sensitivity Analysis," included detection rate, detection distance, detection latency, and NMAC rate. These metrics were identified in Task 2, assessed via the sensitivity analysis in subtasks 1-2, and evaluated in Task 3.

This approach reframed DAA risk as an operationally meaningful metric: the probability that a DAA system fails to detect an intruding aircraft before a NMAC occurs. In contrast to deterministic timing budgets or single-point detection thresholds, this method recognizes that detection performance is inherently probabilistic and must be evaluated in the context of encounter geometry, system characteristics, and environmental conditions.

Reference – Subtask 2-1; Subtask 2-2; Task 3.

Research Question 9: *What input-processing-output models or diagrams are most useful for identifying potential hazards?*

For this research, the most useful diagram for identifying hazards was the DAA system cycle/timing model shown in Figure 5. This model provided a truly system-agnostic approach to understanding how various degraded operations and failures affected the DAA cycle. This research established a framework for assessing the risk associated with DAA systems, focusing on the timing of individual functions within given systems. This enables risk to be viewed as a quantity that either adds to or removes from a system's capability to complete a DAA cycle, remain well clear, and avoid an intruder aircraft. Evaluating DAA systems in this way provides a way to adapt models to fit nearly any DAA system while maintaining a standard approach to risk assessment.

Additionally, Monte Carlo simulations allowed the research team to explore the efficacy of this approach. The simulations provided quantitative assessments of the critical variables identified in the subtask 2-2 sensitivity report. They supported the notion that timing budgets can be used to identify, classify, and assess the risk associated with DAA hazards. The timing budget model establishes a framework for further exploration of DAA system function and risk, and for identifying critical hazards that may be unique to specific DAA System architectures.

Reference – Subtask 2-1; Subtask 2-2; Task 3.

Research Question 10: *How could guidance for Safety Risk Management Document assessments and UAS SRM policy be updated to satisfy the original intent of safety risk management and the risk management cycle?*

Quantifying "Gain" (Risk vs. Reward): SRM policy should be updated to officially evaluate the *gain* (or reward) of a specific flight relative to its risk. Regulators should use the SLRS dynamically; a critical life-saving mission (e.g., organ delivery, search and rescue) warrants an expanded SLRS for higher risk tolerance, while a low-urgency luxury delivery warrants a tighter SLRS.

Transitioning to Data-Driven Methods: Policy should encourage a shift across the "Safety Risk Assessment Methodologies Quadrant." Assessments should move away from *A Priori & Qualitative* methods (which rely heavily on Subject Matter Expert guesswork) toward *Post Hoc & Quantitative* methods (utilizing actual historical flight data) to continually improve the accuracy and validity of the risk variables.

Reference – Subtask 2-1.

Research Question 11: *What risk assessment tools and metrics are recommended for DAA system safety assessments?*

Task 2 recommends a shift toward more quantitative, adaptive, and data-driven methodologies for DAA system safety assessments. To properly evaluate DAA systems, traditional qualitative tools - such as static likelihood-severity matrices - should be replaced or augmented with probabilistic, simulation-based frameworks that capture system behavior under realistic operational conditions.

Recommended Tools:

The primary tool identified in Task 2 is a multi-stage simulation-based framework, which integrates encounter modeling, detection algorithms, and probabilistic evaluation. Rather than relying solely on limited testing or static assumptions, this approach enables scalable and repeatable evaluation across diverse operational scenarios.

This framework consists of three key components:

1. High-Fidelity Simulation Environment (e.g., Gazebo)
   Realistic encounter trajectories are simulated under varying environmental conditions, including fog, lighting, and visual clutter. Detection algorithms (e.g., YOLO-based vision systems) are evaluated in this environment to produce detection outcomes at each time step.
2. Data-Driven Detection Modeling (Machine Learning)
   Simulation outputs are used to construct a probabilistic model of detection performance. Detection success is modeled as a function of separation distance, system parameters, and environmental conditions, yielding an instantaneous detection probability.
3. Monte Carlo Encounter Simulation
   The probabilistic detection model is embedded within a Monte Carlo framework that simulates full encounter trajectories. Detection is treated as a sequence of probabilistic events over time, allowing estimation of detection timing and overall encounter outcomes across many scenarios.

Recommended Metrics:

Task 2 emphasizes the use of probabilistic and scenario-dependent metrics that directly relate system performance to safety outcomes:

1. Probability of Detection Before NMAC (Primary Metric)
   The probability that a DAA system successfully detects an intruder before a Near Mid-Air Collision occurs is the most critical safety performance measure.
2. Detection Time / Detection Delay Distribution
   Instead of relying on a single detection time, the framework produces a distribution of detection delays, capturing variability across encounters and conditions.
3. Detection Probability as a Function of Distance and Environment
   Detection performance is evaluated as a function of separation distance, visibility, and system characteristics, allowing assessment under different operating conditions.

4. Encounter-Level Success and Failure Rates
   Each encounter is classified based on whether detection occurs within required timing thresholds, enabling estimation of overall system risk.
5. Detection Separation Distance
   The distance at which detection occurs provides insight into available reaction time and system effectiveness.

Reference – Subtask 2-1.

Research Question 11: *What guidance is recommended for distinguishing between system safety and system-of-systems safety?*

The framework suggested in the Future Work section below uses the concepts of Potentiality, Severity, and Exposure to distinguish between these domains. An operator has high managerial authority over internal "system safety" within a closed domain (e.g., managing aircraft engine failures via quality control). However, they have limited managerial authority over external interactions in an open "system-of-systems" domain (e.g., weather changes, bird strikes, or the flight paths of other aircraft that cause mid-air collisions). Recognizing which variables fall outside the system boundary helps properly classify whether a hazard belongs to system safety or system-of-systems safety.

Reference – Subtask 2-1; Final Report subsection 5.

Research Question 12: *What risks are unique or more critical to different DAA systems? Consider a variety of different DAA systems and DAA operations.*

Based on the results reported in Task 3, specifically sub-task 3.2, different DAA architectures have different risks that become more critical depending on the operation phase (detect–track–decide–avoid) and the encounter geometry. Cooperative, ADS-B DAA, is most sensitive to data integrity and availability. For example, GNSS errors/dropouts, latency, and tracking inaccuracies can delay or distort conflict detection, leading to overly conservative or ineffective maneuvers. Non-cooperative DAA (e.g., CasiaX) is dominated by environment and sensor-health risks: fog, clutter, and occlusions reduce detection range and confidence, and false positives/false negatives can either overwhelm tracking logic or, more critically, cause missed detections; partial sensor failures or reduced field of view sharply shrink detection volume and time-to-avoid. Across all systems, the most critical operational moments are close-range encounters, multi-intruder conflicts, and active avoidance under degraded sensing/tracking, where uncertainty grows quickly, and safety margins, replanning rate, and fallback behaviors largely determine separation assurance.

Reference – Subtask 3-2.

Research Question 13: *How can SRM assessments better inform DAA standards and DAA development (as intended in the SRM cycle) rather than be an activity that is conducted after the design standard or system development is complete?*

SRM assessments can better inform DAA standards and system development by being integrated into the design process through simulation-based evaluation frameworks. Rather than applying SRM as a post-development activity, Task 2 demonstrates that meaningful and accurate simulation enables prediction of DAA system safety performance early in the development cycle.

By incorporating high-fidelity simulation environments, representative encounter trajectories, and probabilistic detection models, developers can evaluate how a DAA system is expected to perform across a wide range of operational scenarios before finalization. This allows safety performance - such as the probability of detection before NMAC and detection timing margins -to be assessed during system design, rather than after implementation. As a result, SRM becomes a predictive tool, enabling designers to understand in advance how well a system will perform from a safety risk perspective.

Importantly, simulation supports iterative design feedback. System parameters such as sensor capabilities, detection algorithms, and sampling rates can be adjusted, and their impact on safety metrics can be evaluated immediately through repeated simulations. This allows SRM assessments to influence design decisions directly and helps ensure that safety requirements are incorporated into the system architecture from the outset.

Additionally, simulation enables evaluation under varying environmental and operational conditions, such as changes in visibility, clutter, and encounter geometry. This provides insight into system limitations and supports the development of both robust design standards and appropriate operational constraints.

Reference: Subtask 2-1 and 2-2.

5 FUTURE WORK

While the DAA timing distribution approach and associated sensitivity analysis demonstrate strong potential for probabilistic risk assessment, several key areas remain for future development to improve realism, accuracy, and applicability.

DAA Timing Distribution Approach to Probabilistic Risk Assessment: Future Research

The current framework focuses on the detection function, while downstream components, such as the Alert and Avoidance functions, are treated qualitatively. Future work should extend the framework to incorporate the full DAA timing chain, enabling end-to-end assessment of detection, alerting, and avoidance performance and their combined impact on NMAC risk.

Moreover, while the current methodology leverages simulation and machine learning to estimate detection probability, it remains largely dependent on synthetic data. Future efforts should incorporate real-world flight and sensor data to validate and refine the probabilistic models, thereby improving accuracy and reducing uncertainty.

The sensitivity analysis highlights the strong influence of environmental conditions such as fog and visual clutter on detection performance. Building on this, future work should explore adaptive DAA system configurations, where detection thresholds and system parameters are dynamically adjusted based on operating conditions to improve robustness in degraded environments.

Exposure-Based Approach to Probabilistic Risk Assessment: Future Research

Tailoring the system for distinct end-users, future development of the risk assessment model must be customized to cater to two primary end-users with different needs:

- Pilot-Operators: For human operators, the complex 3D risk assessment must be translated into an intuitive, human-factors-friendly interface to manage cognitive load. Future interfaces will simplify 3D data into a traditional color-coded matrix: Green (acceptable risk), Yellow (mitigation and higher-level authority acceptance required), and Red (unsafe; halt operations).
- Automated Routines: Unlike human pilots, automated UAS algorithms can process robust mathematical probability calculations across a continuous spectrum. Future work will leverage

machine learning and artificial intelligence to allow these automated routines to ingest real-time data (sensor readings, weather, flight parameters) and autonomously execute fail-safe mechanisms or course corrections when critical risks are detected.

Visualizing Confidence and Uncertainty

Because the calculations for potentiality, severity, and exposure currently rely heavily on subjective expert judgment, future iterations will implement RUVS.

- The RUVS is an error spheroid that surrounds the 3D RAP to visually represent the validity, uncertainty, and weight of the data used in the calculation.
- A smaller RUVS indicates high validity and low uncertainty (e.g., calculations backed by robust quantitative flight data). In comparison, a larger RUVS warns stakeholders that the risk assessment is heavily uncertain and may require additional mitigations. These example visuals are illustrated in Figure 21.

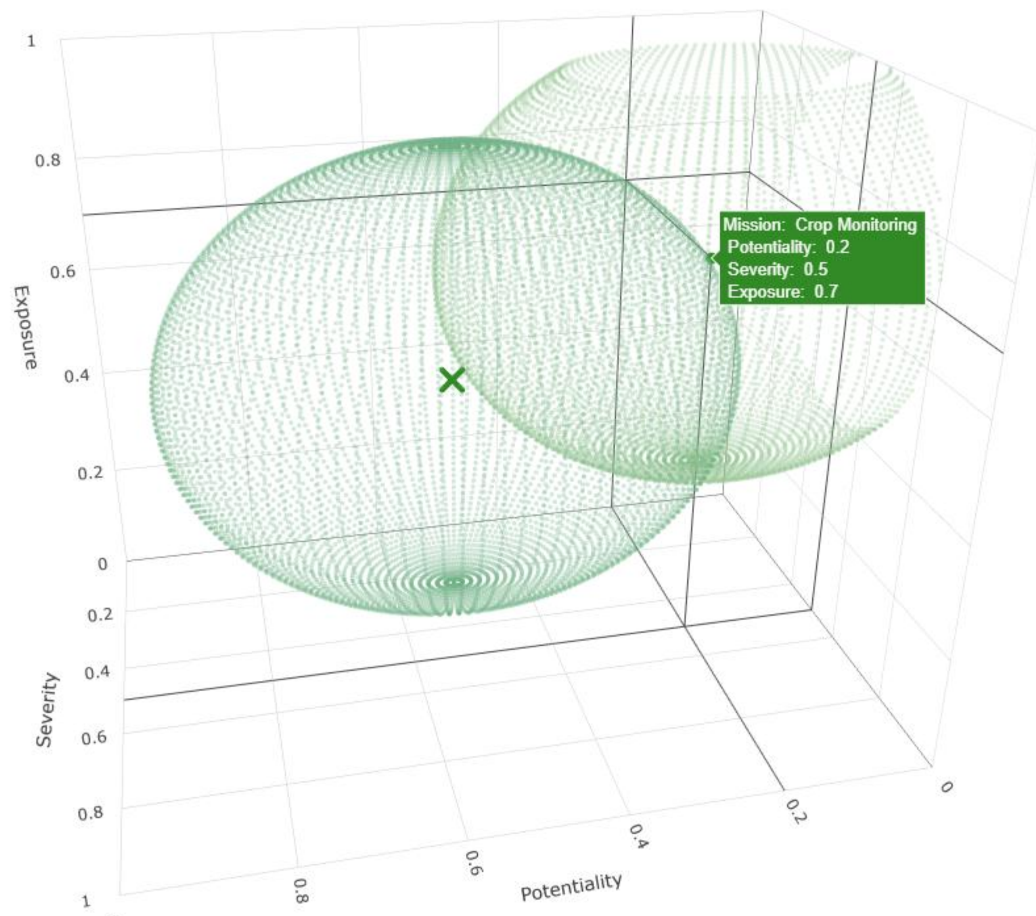

Figure 21. Example graph of RUVS and SLRS, showing Potentiality, Severity, and Exposure metrics per mission (here: Crop Monitoring).

Balancing Risk Versus Reward

To account for the "Gain" or reward of a specific flight, future frameworks will utilize SLRS. The weight of the mission Gain is illustrated in Figure 22.

- The SLRS represents the boundary of acceptable risk; if the RAP or the RUVS penetrates or exceeds this sphere, additional mitigations are required.
- The size of the SLRS will be dynamic, expanding for high-stakes, critical missions (such as delivering emergency medical supplies) to allow for higher risk tolerance, and contracting for less critical, routine missions.

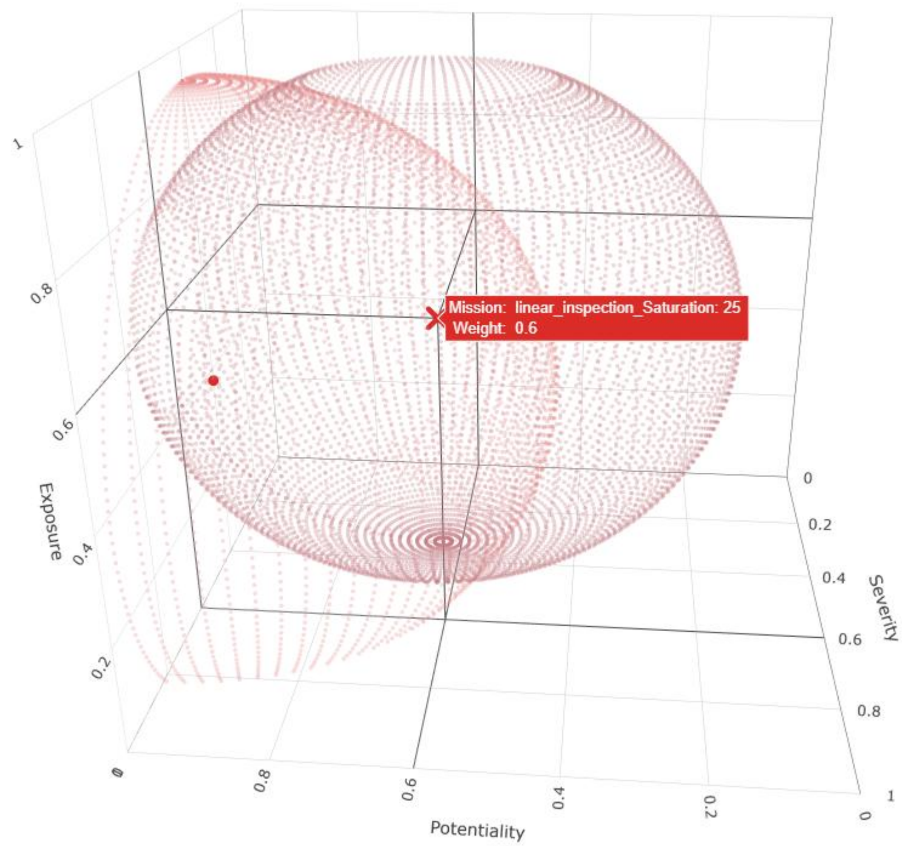

Figure 22. Example graph of RUVS and SLRS, showing the mission's gain weight metric. This example mission is pipeline inspection.

Transitioning to Data-Driven Methodologies

To improve the accuracy of the variables used in the 3D model, future work must transition risk calculations across the Safety Risk Assessment Methodologies Quadrant. Currently, much of the data relies on A Priori and Qualitative methods (predictive, subjective Subject Matter Expert judgments).

The future goal is to achieve Weighted Confidence by moving toward Post Hoc and Quantitative methods, utilizing actual historical flight data to objectively identify risk patterns and trends, thereby reducing human error in the calculations.

Extensive Real-World Testing

While the 3D model resolves historical issues (such as the "denominator issue" in factoring duration into risk), its underlying complexity may be difficult to explain to operators accustomed to simple two-variable matrices. Therefore, extensive real-world testing and modeling exercises are required to ensure the theoretical advantages translate into safer, practical UAS operations before widespread adoption.

6 REFERENCES

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