Simulation-based UAS Swarm Selection for Monitoring and Detection of Migrant Border Crossings

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Abstract

The European migration crisis reached critical levels in 2015 due to a major influx of migrants taking the journey across the Mediterranean to Italy, Greece, and other European coasts. Migration flow rates across the Mediterranean have dropped in recent years, but fatalities have increased and border pressure is still high. Recent operations by local governments, international agencies, and NGO organizations have saved many lives and improved data collection practices, yet they have not been fully successful in responding to the high volume of travel and unexpected rate spikes in migrant trips. Different Operational Constructs and asset strategies have been studied resulting in relevant organizations investing in Unmanned Aerial Systems (UAS) for monitoring and detection. However, many questions about the most effective deployment of these assets still remain although. This study is centered on the development of a modeling and simulation environment, as well as a decision support tool for conducting system-of-systems comparisons of UAS swarm and surface fleet asset combinations. The environment is an agent-based simulation built in the In-House tool Janus, which leverages the NASA World-Wind SDK. The simulation tool and dashboard provide a trade-off environment for parametric analysis of swarm capabilities. A case study is performed for operations by the Italian Coast Guard off the coast of Libya. Results confirm the success of implementing UAS and coordinated swarm systems. Further analysis examines the trade-off of mission effectiveness and cost, with consideration of the resilience and robustness of the system-of-systems.

I. Nomenclature

$AFRL$	=	Air Force Research Lab
$ASDL$	=	Aerospace Systems Design Lab
$CONOPS$	=	Concept of operations
DES	=	Discrete-event simulation
ISR	=	Intelligence surveillance and reconnaissance
$ITAR$	=	International Traffic in Arms Regulation
LBU	=	Land Based UAV
NGO	=	Non-governmental organization
$NOAA$	=	National Oceanic and Atmospheric Administration
OEC	=	Overall evaluation criterion
OPV	=	Offshore Patrol Vessel
$OSCAR$	=	Ocean Surface Current Analysis Real-time
SAR	=	Search and rescue
SBU	=	Ship Based UAS
SoS	=	System-of-systems
UAS	=	Unmanned aerial system
$UV-CoRE$	=	Unmanned vehicle collaboration research environment

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II. Introduction

In the past four years, there has been an unprecedented migration influx towards Europe by way of land, air and the Mediterranean Sea. The people arriving to Europe belong to heterogeneous groups with different socio-economic backgrounds and motivations. The people often come from countries ravaged by war or famine and travel for weeks or sometimes months to process asylum claims in Europe. The situation has caught the world's attention due to the complex challenges that it imposes on the European Union Member States and the harsh conditions that the migrants face during their journey. Search and Rescue (SAR) operations in the Mediterranean have become one of the key responsibilities of multiple international organizations such as Frontex – the European Border and Coast Guard Agency. The authorities also face a heightened demand to protect Europe's security against terrorist threats, establish effective border control regulations, and fight against cross-border crime such as document fraud, human trafficking, smuggling.

According to Frontex [1], in 2015 the EU's external borders registered the largest number of illegal border-crossings ever recorded at more than 1.8 million. In particular, the Eastern Mediterranean region went from 50,000 detections in 2014 to about 885,000 in 2015, with most of the flow near the Aegean Sea. The countries of origin of most of these migrant arrivals were Syria (~56%), Afghanistan (~24%), and Iraq (~10%).

To address this rapid migration influx, the EU Member States adopted additional regulations, created new organizations, and established joint collaboration networks. The most successful joint-collaboration being the EU-Turkey agreement of 2016 [3], which resulted in a significant decrease for the number of illegal-border crossings detected in 2016 in the Eastern Mediterranean and the Western Balkans [2]. The Central Mediterranean region, however, experienced an increase in the number of migrants detected, which went from 150,000 migrants detected in 2015 to more than 181,000 detections in 2016. These trends are shown in Figure 1, which displays the number of illegal border crossings for each region for 2015 and 2016.

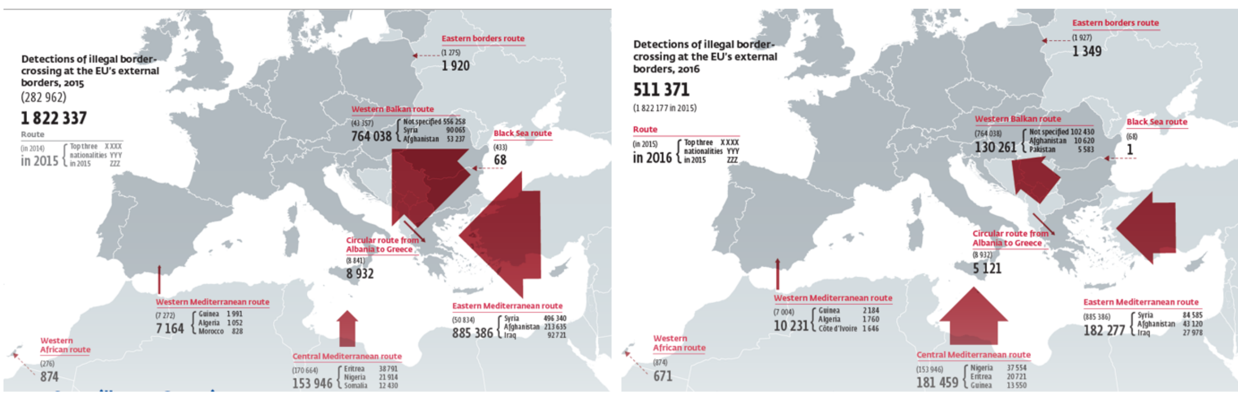

Figure 1. Migration Flow Levels 2015 (Left) [3] and 2016 (Right) [1].

Unlike the Aegean Sea, this region is characterized by being a vast area of open sea. Migrants travel from all over the African continent for extended periods of time to arrive at the coasts of Libya and Egypt, where smuggling networks embark them in rafts that are often not seaworthy. The rafts sail with destinations towards Italy, or the island of Malta [4]. In addition, migrants are sometimes instructed to place distress calls so they can be rescued by either coast guard boats or NGO's vessels in the area.

Regardless of all the measurements taken, it is evident that this remains a critical humanitarian issue, aside from the growing concerns to EU's internal security. This requires to consider alternatives to improve the effectiveness of SAR operations. As a result, the present work focused on identifying opportunities for the inclusion of Unmanned Aerial Systems (UAS) to the current CONOPS. UAS are chosen since this is a mission that requires a persistent surveillance of a large area. These are accepted platforms for maritime ISR, while being smaller, lighter, and cheaper than manned systems. Furthermore, automation can be used to further increase the capability of these systems. In fact, Frontex itself recognized these opportunities, and is one of the drivers behind the European Maritime Safety Agency's (EMSA) decision to invest €67.1 million in Remotely Piloted Aircraft System (RPAS) services to support their current operations [5].

The application of UAS is promising, but there are many options available in terms of UAS type, performance, fleet size and composition. Their effectiveness is highly dependent on the way they are integrated with the current SAR operations and how they are used in coordination. This requires the problem to be looked at from a System-of-Systems (SoS) perspective.

III. Motivation

A. UAS Appeal

Unmanned Aerial Systems, or UAS, have dramatically increased in use over recent years. With the reduction in cost for small electronic sensors and high-density Lithium-Polymer (LiPo) batteries, the potential for high endurance Unmanned Aerial Vehicles (UAVs) has grown. A common use of UAVs in commercial applications is photogrammetry and mapping [6]. UAS are particularly good at this task because of their ability to carry cameras and other visual sensors at high altitudes for long periods of time and for a low cost. In general, UAS are good for what has been called, dirty, dull, dangerous" missions [7].

B. Rise in Swarm Applications and Research

Technical development of inexpensive communications, computation, and sensing devices has provided the framework for distributed control and coordination of networked multi-agent systems, or swarms [8]. The use of multi-agent robotics is now being researched and tested in many fields, both civil and military, largely because of their extreme versatility, redundancy, and reliability [9]. Inspiration for the concept of the swarm largely comes from nature, evident in the first major simulation by Reynolds in which flocks of 'boids' flew together using three rules: cohesion, separation, and alignment [10]. These rules, or micro-level behaviors, create macro level behaviors in the concept of self-organization [7]. In simulations, swarms can be achieved two ways: global laws using linear programming, low-level behaviors using agent-based modeling[11]. Three of the most important aspects of these systems which are directly related to their performance is communications, sensor functionality and formation control. Much research is aimed at this field of networked control of robotics that cannot be entirely discussed here. Studies are very common in areas such as optimizing coverage, organization formations, and heuristics for path planning [12] [13] [14] [15].

C. System-of-Systems

There are many available definitions for the concept of systems. The NASA Systems Engineering Handbook defines it as "*a set of interrelated components which interact with one another in an organized fashion toward a common purpose* [16]." Other definitions circle around the same terms, with some common themes being that in a system there is an existence of interacting elements and it fills a need. In the aerospace field, systems are becoming increasingly complex, and this has led to the use of the term *System-of-Systems* (SoS) to refer to "*groups of systems, each of which individually provides its own mission capability, that can be operated collectively to achieve an independent, and usually larger, common mission capability*" [17]. Therefore, a SoS is larger in scope and has complex integrations, while being more subject to uncertainty and risk in its operation. System-of-systems can be of many different types [18]:

1) Virtual: lacks central management or unique purpose and therefore exhibits a large scale behavior.
2) Collaborative: unlike the virtual system, in this arrangement systems interact willingly with each other voluntarily to fulfill a central purpose.
3) Acknowledged: similarly to the collaborative, here systems have recognized objectives, but they also have a management system and there is a set of resources for each system. However, each one retains some degree of independence.
4) Directed: finally, here the SoS is organized to fulfill a given goal, with a central management system that directs its operation, and even though systems remain independence, they recognize their sub-ordinance with respect to the manager.

The analysis of UAS acting in conjunction with other types of assets to conduct search and rescue operations requires an analysis from the SoS perspective. Indeed, there are many open variables in this problem that impact the UAS behavior, communication, and performance. Furthermore, the entire group of UAS can follow different organization architectures (e.g. distributed, hierarchical, leader-follower, etc.) [19]. As a result, there is a need to narrow down the problem, which can be seen in the following sections.

IV. Problem Formulation

A. Mission Analysis

To begin identifying a potential solution, the overall process of the Frontex maritime border patrol and response mission is inspected and found to have three main phases:

1) Deploy: A number of assets must be deployed in some pattern over the border/search area.
2) Detect: When migrant vessels make the journey, they must be located, classified, and identified.
3) Rescue: Once located, coast guard vessels are tasked with intercepting the migrants, rescuing and embarking, and disembarking them at an assigned port for completing medical treatment and processing asylum claims.

Detections may occur through visual contact, sensors such as IR or radar, or via satellite distress signals. However, if there are no assets active in a certain area, or if the migrants are outside of the detection range for some reason, the chain is broken and no rescue can occur, with potentially fatal consequences. Detecting the migrants is therefore a key to successful completion of this mission, and increased situational awareness may improve outcomes.

B. UAS Solutions

Highly capable maritime intelligence, surveillance and reconnaissance (ISR) UAS exist today, for example the MQ-4C Triton employed by the US Navy, shown in Figure 2. The Triton is capable of being employed in maritime border monitoring missions while carrying payloads of sophisticated sensors at high altitude, for long periods of time [20]. However, this asset has large operating (BY2008 $8000/ flight hr.) and acquisition (BY2008 $160,000,000/unit) costs that may not be sustainable for a persistent mission[21]. Additionally, a SoS that is reliant on a few high-capability assets may be susceptible to considerable performance degradation when one of asset experiences unscheduled maintenance downtime.

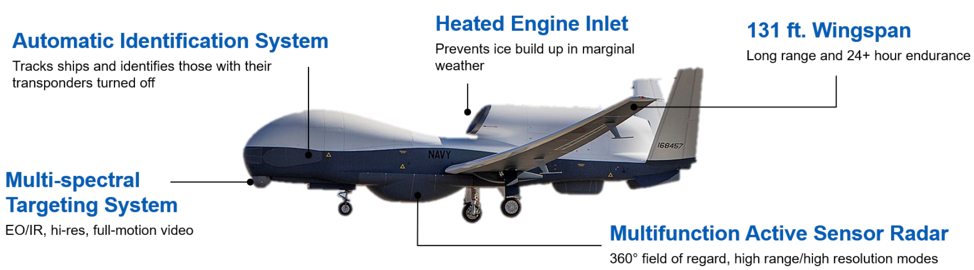

Figure 2. Northrop Grumman MQ-4C Triton [20].

Nowadays a large variety of lower capability, but more affordable UAS exist, such as those shown in Figure 3. A combination of these lower capability systems could be employed in place of a single high capability system. Choosing one or more of these platforms leaves a lot of decisions to be made. On the system level, the performance (endurance, range, speed) requirements must be generated. The specific sensor payload must be selected, and thought must be given to the launch and recovery process. On the SoS level, the fleet size and, if a combination of different systems is employed, fleet mix must be chosen. Where the assets are deployed from and how they work together must also be decided. In order to make these decisions, these different SoS alternatives must be compared.

(a) Boeing MQ-27A ScanEagle **(b) Tekever AR-5 Life Ray Evolution** **(c) Northrop Grumman R-Bat**

Figure 3. Lower capability, more affordable maritime ISR UAS.

C. Metrics of Success

Effectiveness must be quantified for this mission in order to compare the different SoS which are comprised of surfaces vessels and UAS. In the case of maritime border monitoring and response, mission success depends on two events: detections, and rescues. Detection rate is defined in terms of the percentage of migrants detected to total migrants launched because this measure describes how well the area is being monitored. Additionally, a fast and consistent detection capability is preferable, so the mean time to detection and the standard deviation of the detection times are also key metrics. Similar metrics can be defined for rescues. These metrics are important because the overall rescue rate describes the number of lives saved, and the faster rescue time reduces the risk of the loss of life.

Constraints on the SoS include the funds available for acquisition and funds available for sustained operating expenses. The key metrics can be related to the costs through an Overall Evaluation Criterion (OEC), given by the ratio of the benefits to the costs, normalized by a baseline SoS performance[22]. The weights $(\alpha, \ldots, \theta)$ on the metrics may be adjusted to bring focus on a specific one as desired. The equation can be seen in Equation 1.

$$OEC = \frac{\begin{array}{c}\alpha\left(\frac{\%\ Detected}{\%\ Detected_B}\right) + \beta\left(\frac{\%\ Rescued}{\%\ Rescued_B}\right) + \gamma\left(\frac{Mean\ Detection\ Time}{Mean\ Detection\ Time_B}\right)\\ + \delta\left(\frac{Mean\ Rescue\ Time}{Mean\ Rescue\ Time_B}\right) + \varepsilon\left(\frac{\sigma\ Detection\ Time}{\sigma\ Detection\ Time_B}\right) + \zeta\left(\frac{\sigma\ Rescue\ Time}{\sigma\ Rescue\ Time_B}\right)\end{array}}{\eta\left(\frac{Acquisition\ Cost}{Acquisition\ Cost_B}\right) + \theta\left(\frac{Operating\ Cost}{Operating\ Cost_B}\right)} \tag{1}$$

D. Research Questions

Based on these considerations, the primary research questions were formulated. First and foremost, which fleet, that is what quantity, type, and mix of UAS assets, offers the largest improvement in the key metrics? Secondly, how is the UAS fleet cost related to effectiveness? Answering the primary research questions results in the ability to make recommendations as to which assets are best suited to this mission. Data generated in pursuing these questions can also enable the exploration of ancillary research questions, such as whether there is a UAS cost-capability set which is consistently in the most effective SoS? If such a recurring UAS can be identified, it could indicate that the System-of-Systems architecture and mission are driving system-level requirements, and a system-level investment opportunity might be present. Additionally, perhaps swarms of low-cost UAS provide a more resilient capability than a fleet of a few high-cost assets. That is, perhaps a fleet of many low-cost UAS can mitigate the performance degradation experienced by a fleet of few high-cost UAS in the case of unscheduled maintenance of assets.

V. Methodology

A. Modeling and Simulation

To compare potential SoS architectures, it is necessary to evaluate their performance in the key metrics. The design space is very large, even for a very simplified range of variables as seen with the SoS level attributes in Table 1 and with the system level attributes shown in Table 2. Even with potential incompatibilities removed, the full-factorial Design of Experiments (DoE) produces over 4.4 million combinations. Comparing a few of these combinations on a one-off basis does not allow for sufficient exploration of the design space, and it is even more intractable to conduct real-world experiments at this stage. However virtual experiments employing a computational modeling and simulation environment, though not immune to the curse of dimensionality, allow for the comparison of many of these options in a rapid manner, enabling a more informed recommendation to be made.

Table 1. Partial System-of-Systems-level design space.

Fleet Attribute	Option A	Option B	Option C	Option D	Option E
UAS Fleet Size	1	2	3	4	. . .
UAS Fleet Mix	Homogeneous	1:2	2:3	1:4	. . .
UAS Size	Group 1	Group 2	Group 3	Group 4	Group 5
UAS Launch	Runway	VTOL	Catapult	Hand	
UAS Recovery	Runway	VTOL	Net		
UAS Ship Integration	Land-based	Ship-based			
. . .					
Surface Fleet Size	Small	Medium	Large	. . .	
Surface Fleet Mix	Mix A	Mix B	. . .		

Table 2. Partial System-level design space.

System Attribute					
UAS Configuration	Fixed Wing	Rotary Wing	. . .		
UAS Sensor Payload	FMV	IR	LIDAR	SAR	. . .
UAS Cruise Speed	Low	High	. . .		
UAS Range	Short	Moderate	Long	. . .	
UAS Endurance	Moderate	High	. . .		
. . .					
Surface Vessel Size	Patrol Boat	Offshore Patrol Vessel			
Surface Vessel Speed	Low	High	. . .		

There are many potential models to use when developing a Modeling and Simulation (M&S) environment. Regression-based models are fast and accurate but rely on historical data. There is no such data available for this mission, and so such a model cannot be employed. The field of Operations Research (OR) often uses Discrete-Event Simulations (DES) to model processes in which resources are time-variant and limited. In DES, scenarios are simulated in terms of discrete events that occur in chronological order. Once an event is processed, the simulation jumps ahead to the next event with the assumption that no change of state occurs between events. This is a computationally efficient approach, and the ability to model processes such as assigning a patrol vessel to rescue a migrant boat or refueling a UAS are necessary for to simulate the mission of interest. A DES approach however faces several limitations. For one, the geographic component of numerous assets and migrants operating in the search area is critical, however not easily modeled using conventional DES. Because the key events of detection and rescue both depend on geographic proximity, locations must be tracked accurately, and therefore included in the state of the SoS. Additionally, events are unpredictable in the sense that a searching UAS does not encounter a migrant boat at a predefined time or location. When it does make a detection, it may leave the search pattern, triggering a series of events. Accounting for these dynamic events is difficult or impossible in a traditional DES approach.

B. Agent-Based Modeling

In agent-based models, systems are modeled as entities called agents with predefined behaviors related to their state that are simulated over time. In this continuous simulation approach, at each time step the agents move and interact according to their own behaviors, allowing them to interact and the simulation to develop without prior knowledge of the sequence of events. The ability to capture emergent behavior of the overall SoS is critical. Additionally, the fidelity of an agent-based model is flexible, allowing the simulation to be developed under time constraints and developed further later.

Various agent-based simulation toolkits exist. In selecting from them, the key factors beyond the ability to define custom behaviors inherent in any agent-based tool, were to model assets moving in realistic geographic space and provide visualization capabilities. The latter assists in debugging during development and gives deeper insight during analysis by allowing for the inspection of individual cases. One option considered is NetLogo, an open-source educational software that provides a generic agent-based environment. It does not come with any sort of geographic framework built in. Another option, AFRL's Advanced Framework for Simulation, Integration and Modeling (AFSIM) on the other hand is a sophisticated Operations Analysis tool that would lend itself to this type of simulation. However, it is ITAR restricted, which would limit the distribution and accessibility of the products of this effort. Fortunately, ASDL has developed an unrestricted alternative tool, Janus, formerly known as UV-CoRE. This Java-based framework provides hybrid discrete event-discrete time simulation capabilities and leverages the digital globe environment provided by the NASA WorldWind Software Development Kit. This combination of attributes makes it well suited for solving this problem.

C. Trade-off Environment

Given the nature of the problem and the agent-based simulation environment built, it was necessary to create a dynamic trade-off environment to visualize the results from the experiments. This environment was envisioned to be used by decision-makers to support them in choosing the right combination of assets that provides the most optimal results given different operational scenarios and goals. Therefore, the tool had to be capable of filtering data, exploring the solution space, and comparing between different alternatives. With these considerations, Figure 4 shows a schematic of the trade-off environment and its elements. The tool created was named SEAMASTER: Swarm-Enabled Autonomous Maritime Aerial Surveillance Tracking and Emergency Response.

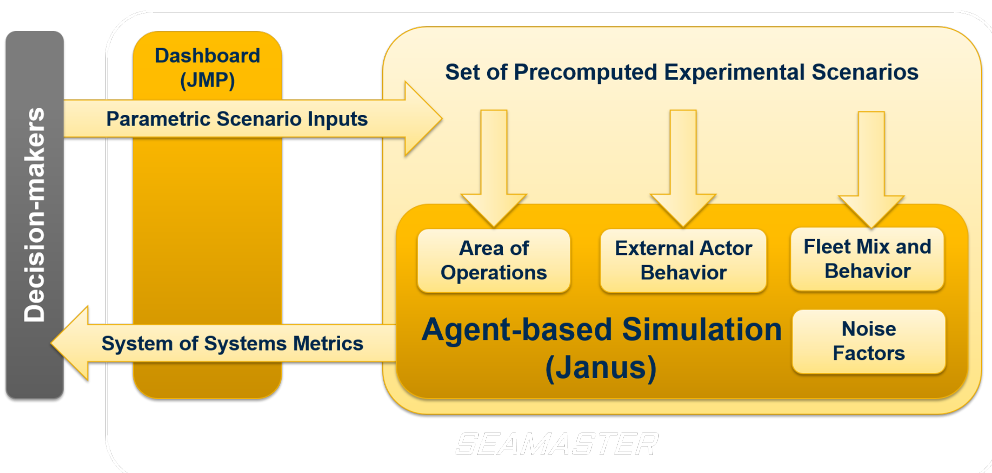

Figure 4. SEAMASTER trade-off environment architecture.

As shown in Figure 4, a set of precomputed experimental scenarios were fed into the agent-based simulation engine. Each one of those scenarios is a case, representing a specific fleet mix or operational environment. The outputs were in the form of data that contained a description of each case, and the resulting key metrics as calculated after running the simulations. The next step in this process was to perform an analysis of the data and the creation of the trade-off environment capable of answering the primary research questions that guided this study.

Two options were considered for the creation of the dashboard. Plotly Dash is a Python-based tool that incorporates HTML and JavaScript components for the creation of web-based interactive data visualization applications. It is a relatively new product, and even though it offers attractive visuals and dynamic controls, it does not have any data analysis capabilities built in. JMP is a professional statistical software that provides the capability of managing data tables and performing several types of analysis in the data. Also, it has an application builder that allows arranging data and visuals for the creation of dashboard environments as desired. With these considerations in mind, it was decided that JMP's statistical analysis capabilities were critical for this project, and therefore it was used for the creation of the trade-off environment.

Therefore, the data produced from the simulations was compiled as a JMP data table, from which the dashboard, SEAMASTER, was built. It offers the capability of transforming data into actionable information. It does so by giving the user the flexibility in manipulating and filtering the data to obtain critical information about the SoS performance. Furthermore, each case is evaluated through an OEC, which provides a quantifiable measure of the effectiveness of the system in addressing the key performance metrics. However, it is evident that this is a complex multi-faceted problem that can be approached from multiple perspectives. In other words, different people have different priorities. Therefore, when considering what the most effective or desirable combination of assets is, it is necessary to incorporate feedback from the user. All these features were included into the dashboard, which is explained in more detail in the implementation section of this report.

VI. Framework Implementation

A. Simulation Tool

Janus leverages the capabilities of NASA's WorldWind SDK as well as the flexibility of the programming language JAVA. Figure 5 shows the main menu of the Janus tool where either visualization mode or batch mode can be setup for any of the available missions. In addition, other simulation and visualization parameters can be edited from the menu in Janus. Missions can be added by a process outlined in the Developer's Guide. The mission in question was named, "Maritime Migrant Monitoring". The mission accounted for various assumptions and simplifications.

The mission features simplified agent dynamics and asset coordination but keeps the flexibility to allow for future changes or upgrades. Higher-order dynamics models can be implemented in the waypoint navigation modules. Currently, the agents use first order, unicycle dynamics, with constant velocity and altitude. For now, communication is limited to friendly agents, including other UAS, surface vessels, and the home base, but is not limited by range. Detection sensors are modeled as perfectly accurate systems within the set detection radius. Upgrades of the sensors can be made in each respective sensor agent, thus making it easy to implement higher-fidelity simulations in the future.

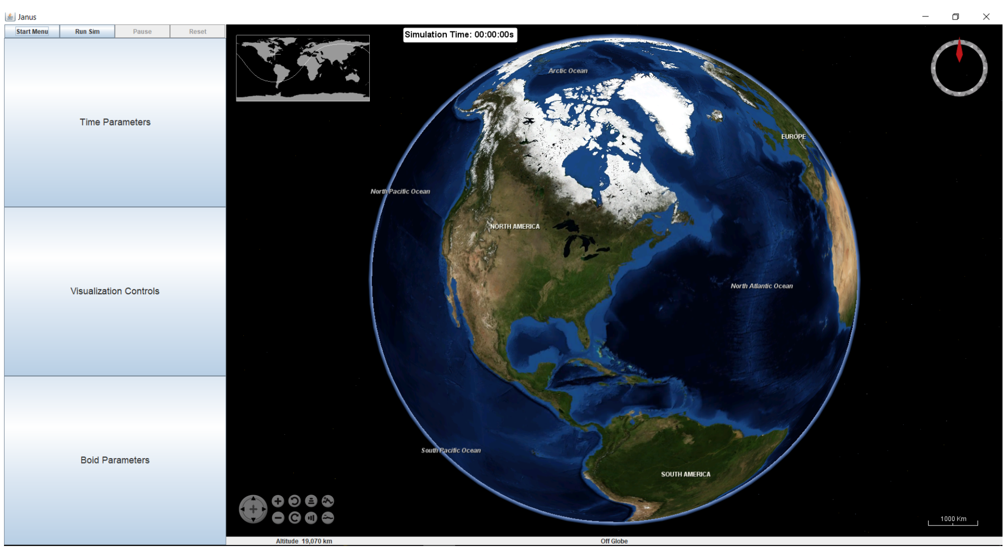

Figure 5. Main Menu of Janus.

B. Area of Operations

The selection of the Central Mediterranean as the area of focus was based on the recent shift in migrant flow and the potential applications of UAS to aid in SAR operations.

While detections in the Eastern Mediterranean fell dramatically from 2015 to 2016, the detections in the Central Mediterranean increased from 181,459 to 182,277 [1]. Also, the number of migrants from West African nations reached record highs in 2015 and 2016. Current conflicts in countries such as Libya and Sudan look to continue in 2018 according to The Assessment Capacities Project (ACAPS) [23]. A recent deal between the Italian and Libyan governments gave the Libyan Coast Guard equipment and the responsibility to blockade and rescue migrant boats from leaving the Libyan coast. However, in the recent months, it has been seen that the Libyan Coast Guard has assisted in the smuggling of migrants [24] and detained migrants in extremely poor conditions. In extreme cases, even selling migrants into slavery according to the New York Times [25]. These reasons present an opportunity to examine how to improve open ocean SAR operations in this area. The large area of operation, totaling more than 50, 000nmi^2, highlights the challenges large SAR operations confront. This area acts as a case study for examining the impact of UAS systems, which are well suited operating over a large area completing routine tasks.

One of the difficulties in planning the SAR mission is that migrants can launch their craft from a multitude of locations across the 1000-plus miles of coast line of Libya. Because of the ever-changing tactics and flows of migrants, this analysis relies heavily on historical data as show in in Figure 6. Geographical based data is sparse since historically detections come from a multitude of sources outside of published government reports [26].

The Base of Operations for this study is on the island of Lampedusa. Lampedusa contains a port large enough to handle Offshore Patrol Vessel (OPV) class ships as well as a runway long enough to accommodate the LBUs. Lampedusa's location provides the surface vessels and UAS the minimum possible refueling and migrant drop off time to maximize assets at sea.

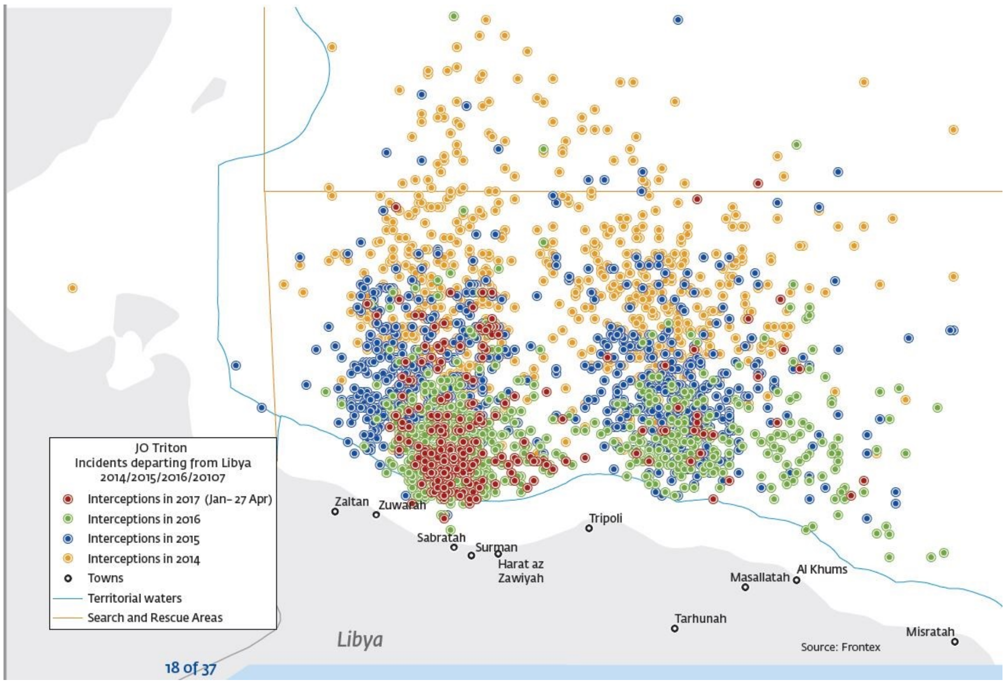

Figure 6. Migrant Sighting in the Central Mediterranean.

Besides the massive search area, weather conditions present a difficult and unique challenge. Migrant operation and modeling behavior will be covered in detail later. Migrants typically utilize underpowered vessels to traverse the Mediterranean. Ocean surface currents and ocean surface winds are the two factors that enable migrant vessel movement [26]. For this reason, even nominal weather that typically does not affect surface vessels requires accurate modeling.

All weather data for the central Mediterranean is obtained from the United States National Oceanic and Atmospheric Administration (NOAA). Two key databases are utilized. One database is WindSAT, which uses satellite microwave brightness measurements that can be used to determine ocean surface winds [27]. The second database is the Ocean Surface Current Analysis Real-time database (OSCAR). OSCAR provides near surface ocean currents to model migrant drift [28]. To calculate migrant vessel drift speeds from WindSAT wind vectors and OSCAR surface current vectors, vector calculations is used once wind effects are taken into account. To determine the effect of wind on the migrant boats, the Navy's equation for leeway speed on light displacement craft was used. The equation can be seen in Equation 2 where ω represents the wind magnitude and S_{drift} is the resulting drift speed [29]. The leeway speeds were added to the ocean current to calculate the actual migrant vessel drift speed and direction.

$$S_{drift} = 0.07 \times \omega + .04 \tag{2}$$

WindSAT and OSCAR databases provide date stepped latitude-longitude data in the form of NetCDF files which are

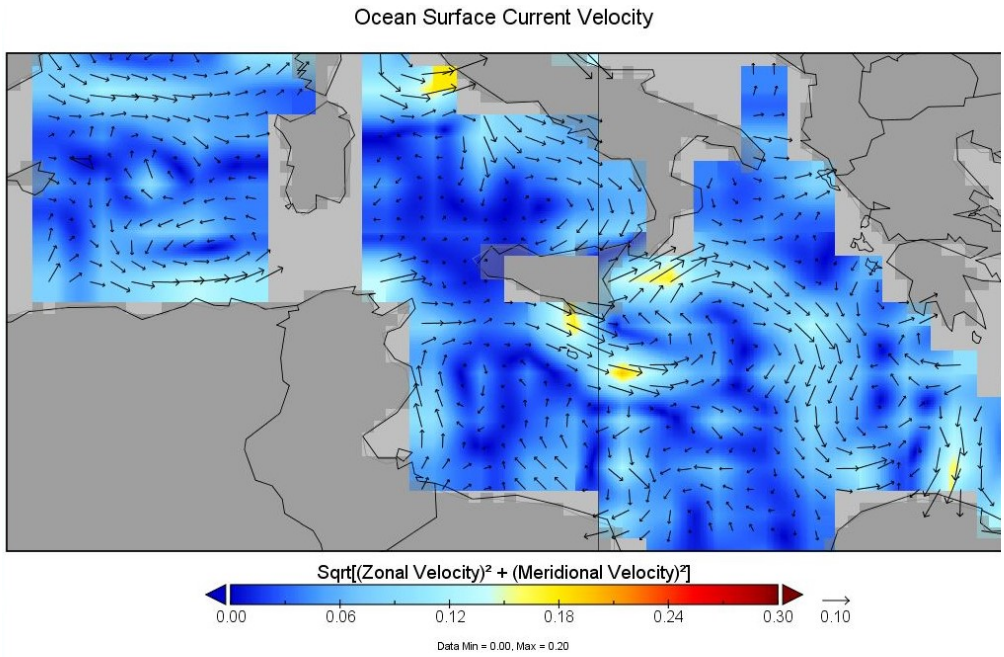

Figure 7. OSCAR Vitalization of Representative Ocean Surface Currents [30].

commonly use in climate and weather databases. These files integrate well in Janus due to Java's adaptability. The smallest time increment for historical ocean weather data available to the public is a 24-hour average of the weather measurements. Resolution is typically either a half to quarter latitude-longitude points. On a microlevel, these databases can be sporadic. However, if utilized across a large area and over a few days they provide a strong, historically based representation of ocean surface weather.

C. Agent Modeling

This section will discuss the processes for modeling migrant and Coast Guard surface vessels as well as currently produced UASs to increase the fleet's SAR capabilities in an effort to build capability into the Janus modeling environment. Specific aspects of modeling will be discussed, as well as the thought process behind each to outline the capabilities Janus has for modeling such a complex problem.

1. Migrant Boats

As previously mentioned, the focus on the migrant's central Mediterranean route from Libya to Italy is to highlight the challenges large SAR operations confront. Specifically, in the central Mediterranean, migrants could launch their craft from a multitude of locations across the 1000 plus miles of coastline that the migrants have historically used. Because of the ever-changing tactics and flows of migrants this analysis relied heavily on historical data.

Basic assumptions are made using the geographical data provided by Frontex. The first assumption is that information about migrant vessel sightings are representative of the full migrant patterns of the central Mediterranean. This translates to the assumption that sightings are made where the most migrants are floating and not because of migrant vessel sightings relation to commercial shipping lanes. The basis for this assumption is as follows. One, Frontex states that migrants seem to be irregularly distributed across the central Mediterranean. The second is that refugees' land-based migration across North Africa is related to smuggling routes from specific Libyan coastal cities [31]. Favorable ocean currents patterns are used to trace likely areas of departure from concentrations of migrant sightings. Detection locations shown in Figure 6 are applied regressively with likely migrant vessel float paths to find likely migrant vessel departure points. To ensure migrant vessels distribution matches that of the Frontex data, small perturbation in launch points is required. This introduces small dissimilarities between migrant vessels drift paths that would naturally occur, such as localized wind gusts and micro ocean currents. This combination of techniques allows the estimation of launch locations along the Libyan Coastline for use in Janus.

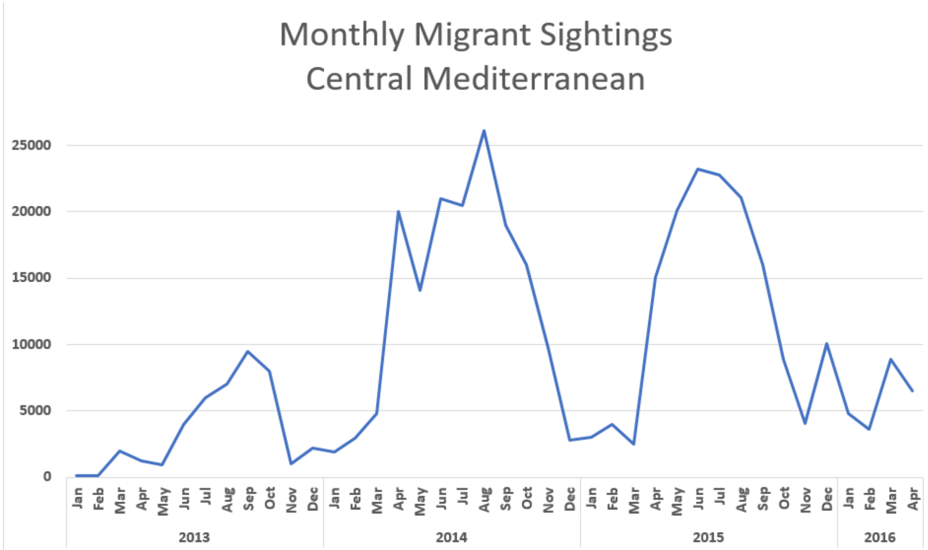

Figure 8. Historical Central Mediterranean Sightings by Month [31].

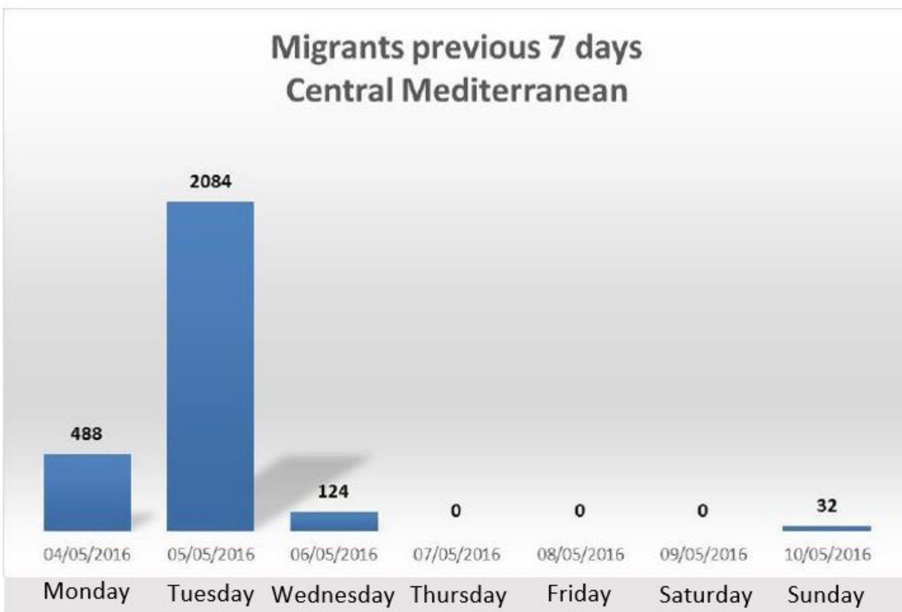

Figure 9. Typical Central Mediterranean Weekly Migrant launches [31].

Migrants leave Libya when weather conditions are favorable as well as within common cyclic human patterns. Migrant flows in the Central Mediterranean wildly vary throughout the year due to both poverty and humanitarian crisis as well as seasonal weather patterns. These cyclic migrant patterns are even dependent upon the day of the week. As seen in Figure 9, migrants tend to base their departure on a typical week starting with departures on Sunday and finishing out departures by mid week. The reasoning behind this is not fully known, but it has been hypothesized that this relates to either religious customs centered around Sunday or established smuggling methods [31].

The last aspect to mention is modeling migrant vessel's potential to capsize. Capsizing happens frequently due to the migrant vessels being overloaded with passengers as well as being unfit to ocean travel [26]. Modeling capsizing is difficult because refugee migration data cannot accurately account for the number of migrants lost at sea. Because of this, capsizing was modeled using a discrete likelihood function that increases likelihood of capsizing with increasing time. The probability of capsizing is estimated from the known deaths of migrants at sea. Known death of migrants at sea is approximated because the actual migrant deaths at sea is unknown.

2. Assets: Coast Guard Boats

Since this model was constructed against Operation Trident, Italian vessels were used as the baseline for this simulation. Frontex data provided assets amounts and vessels classes. The surface fleet for SAR operations consisted of some number of Offshore Patrol Vessels (OPV) and Smaller class Patrol Boats [32]. The OPV are modeled after the Italian Luigi Dattilo (CP-940) 310 feet OPV [33]. This vessel is large enough to hold up to 4 average sized migrant vessels for extended trip engagements as well as launch multiple UAS with catapults from the deck.

Figure 10. Luigi Dattilo OPV [33].

The smaller patrol vessels have the ability to launch, resupply, as well as disembark migrants to the OPVs. The patrol vessels take advantage of this capability due to the large search area and distance from the home port. This typically renders patrol vessel impracticable in these operations without OPVs. Frontex does not supply asset tactics in their data. Tactics and operational constructs for this simulation are supplemented from the US Navy's Able Vigil mission in 1994 that preform a similar operation to rescue Cuban migrants attempting to float to Florida [34].

Examples of tactics includes utilizing typical SAR patterns such as the ladder pattern defined by the Navy document found in Reference [29] and OPV and patrol vessel timing and interaction. Dynamic vessel search patterns were developed for use in the model to maximize the capability of the fleet when assets are refueling or unable to contribute to search operations. The dynamic search patterns maximize the ocean surface covered at each time step without leaving search gaps. Dynamic searching provides the most utility during times of heavy migrant flow because of the OPVs requirement to offload migrants at home port once the vessel is full. OPVs require two hours at port to offload migrants and resupply the ship, with a three hour travel time from port to search area. This could cause significant gaps in the search patterns without dynamic pattern calculation.

The most important capability of surface vessels is the ability to rescue migrant vessels. A hierarchical chain of actions is used to model operational constructs from Operation Abil Vigil. First action in the order of importance is for an OPV to launch a patrol vessel to pick up the migrants when detected. Next, if the closest OPV already has a patrol vessel deployed, the OPV itself will move to pick up the migrants. This is because migrants are time critical targets. If the closest OPV has its patrol boat deployed, is full of migrants, is traveling back to home port or is waiting on its final load of migrants from a patrol vessel, the second closest OPV is tasked. The second OPV will enter the same logic chain to determine if it can pick up the migrants. This logic chain in continued until there are no longer vessels available to be tasked to rescue sighted migrants. The complicating factor is the logic chains that rely upon integrating with migrant sightings, UAS tasking, and UAS availability. This will be discussed in the next section.

3. Assets: UAS

Two classes of UAS are used to model increased capability for Frontex Central Mediterranean Operations. The first class of UAS capability resembles Northrup Grumman's MQ-58 Hunter drone. Hunter drones are Land-Based UAS (LBU) that take off from a land-based runway. They have an approximate $34ft$ wing span. Their typical cruise speed is $60 - 80 knots$ with a flight time of 21 hours. The land based UAS take off from an airstrip on Lampedusa. The LBUs loiter in the Area of Operations for 21 hours before returning to Lampedusa for refueling. The LBU's sensor capabilities are based on the Hunter drone EO/IR specification. Sensor modeling is simplified to an estimated $13nmi$ detection radius to keep the modeling effort with the scope of this study [35].

The second class of UASs is the Ship-Based UAS (SBU) class. This class is modeled after Boeing Insitu's MQ-27A ScanEagle. The ScanEagle with a wing span of $10ft$ can be launched from a catapult on a ship. It has a loiter time of 20 hours with a cruise speed of $50 - 60knots$. As the SBU reaches its max loiter time, it returns to its home OPV for refueling and then redeployment after refueling. The SBU's sensor capabilities are based on the ScanEagle's EO/IR specification, with a $10nmi$ detection radius [36].

The operational construct and the roles each UAS fill is very different. The LBUs patrol the area of interest much like the surface vessels. They utilize the typical ladder pattern and can cover a much larger area than the surface vessels. The LBUs also dynamically change their search pattern based on the amount of same class UAS currently searching. LBUs can leave the search pattern for both refueling and tracking targets. The SBUs, during their search phase, circle their launching vessels to act as an extension to the operations of the boat.

Communication capabilities are modeled to flow freely between all friendly assets in the area of operations. The LBU typically have satellite communications and are within radio range of surface vessels. The SBU are usually within range to the OPV during loiter to communicate. Thus, the communication is assumed to have unlimited range for the current mission, but will be investigated further in the future.

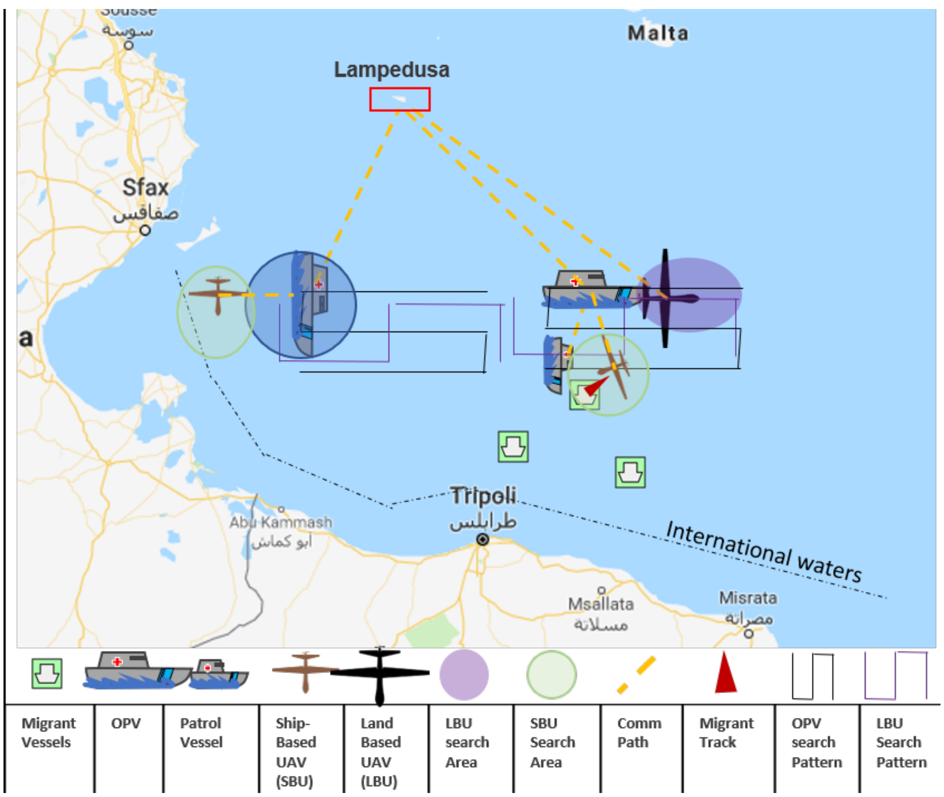

Figure 11. Operational Overview.

The most important capability of the UAS is to track migrants until a surface vessel can come to rescue the migrants.This logic is much more simplified than the surface vessels. If a UAS detects a migrant, it is its responsibility to track the migrant until a surface vessel arrives for rescue. In the event a UAS finds another migrant, a second UAS will be dispatched to the area to aid in tracking. If a UAS needs to stop tracking to refuel, another UAS with enough fuel to provide some amount of tracking will be called into the area to pick up the track. If no UAS is available to track a migrant vessel, the vessel track is lost and must be rediscovered before the migrants can be rescued.

Table 3. UAS Class

UAS Type	Model	Wing Span Ft	Cruise Speed Knots	Endurance Hrs	Sensor Payload	Detection Range nmi
LBU	MQ-58 Hunter	34	70	21	Flir StarSAFIRE	13
SBU	MQ-27A ScanEagle	10	60	20	Vidar Sensor	10

D. Decision Support

A decision support tool is created in the form of a dashboard, which interfaces with the rest of the trade-off environment as shown in Figure 4. The dashboard takes an input the data of each one of the simulation runs, where each simulation consists of a different UAS/boat fleet mix and size, as well as the operational scenario (migration flow). Then, it presents different visualization alternatives that, based on statistical analysis tools, allow the user to explore trends in the simulations. Furthermore, there is a need for the the decision maker to be able to provide input into the performance metrics' weights. The dashboard was built containing 6 different modules, arranged as tabs. These are as follows:

1) **Instructions:** description on how to utilize the dashboard and take the full advantage of its capabilities.
2) **Overall System Performance:** shows a scatter plot that shows fleet composition (number of UAS/boats and types) against average detection/rescue times and percentage detection/rescues. It also contains a filter that allows the user to either change the fleet composition or to filter out the cases that do not meet certain criteria. Colors are used to show the performance of a baseline case to also aid the user in assessing the goodness of the current results. This tab is shown in Figure 12.

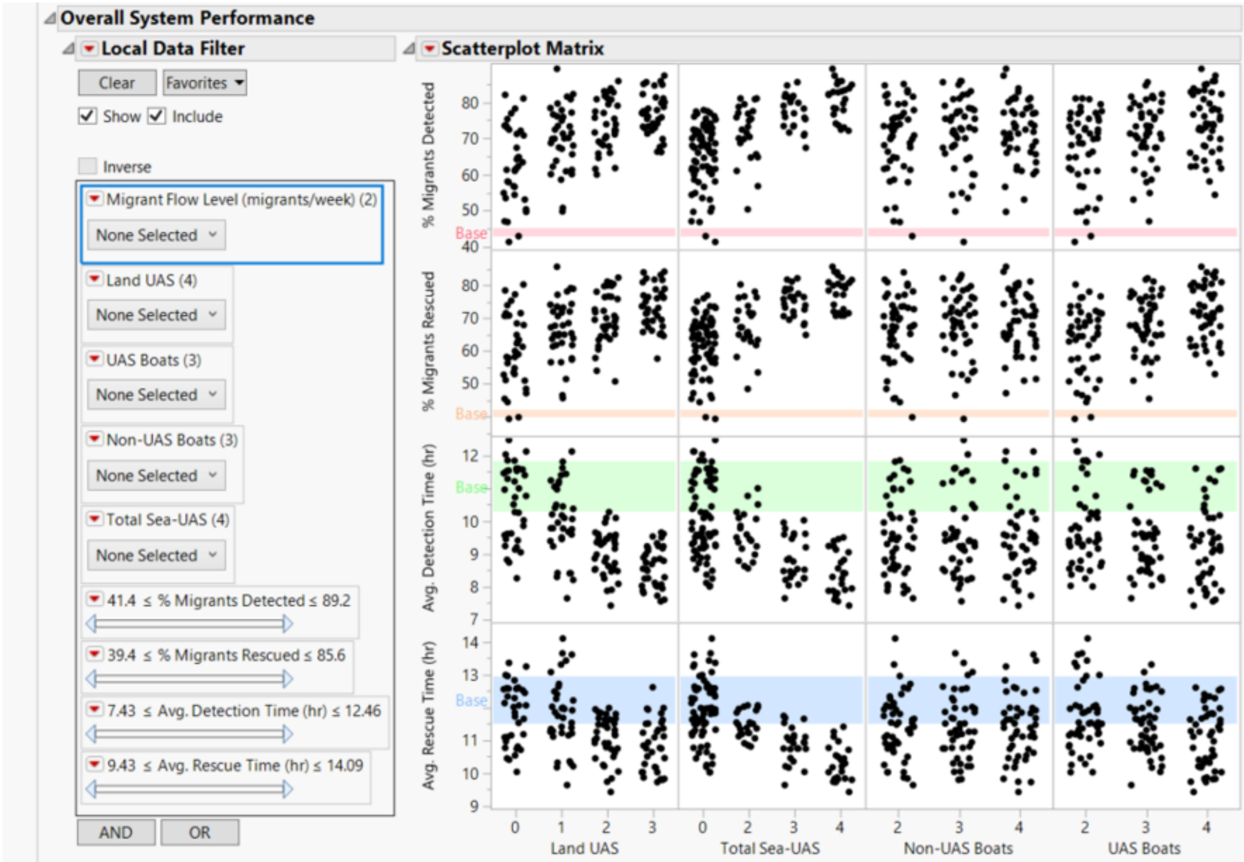

Figure 12. Overall System Performance Analysis.

3) **Sensitivity Analysis:** it features a prediction profiler where the impact of changing the fleet mix in the key performance metrics is observed by adding/removing a new asset while keeping everything else constant (upper part of Figure 13). It also shows the results from a predictor screening analysis that shows what variables in the fleet mix have the most effect in these key metrics.

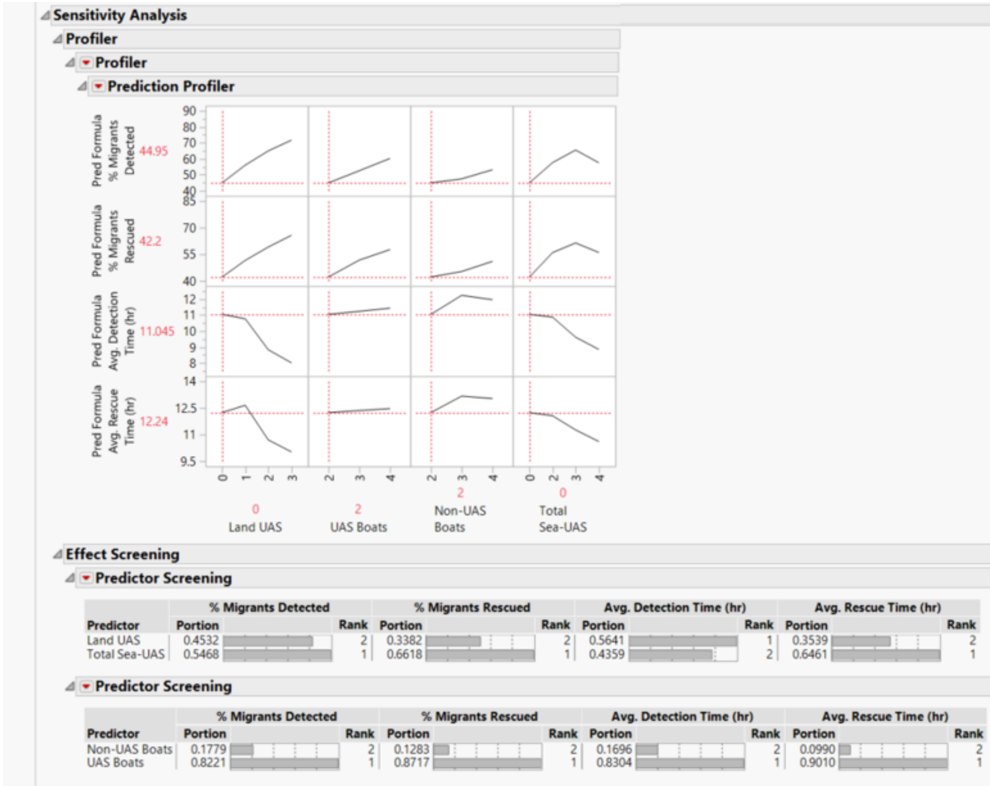

Figure 13. Sensitivity Analysis Tab.

4) **Cost vs. Performance:** this tab shows an analysis of how investing in UAS assets affects the SoS performance. It also includes a filter for the number and type of boats and some other simulation controls (migration flow level) to further aid the user in exploring trends.

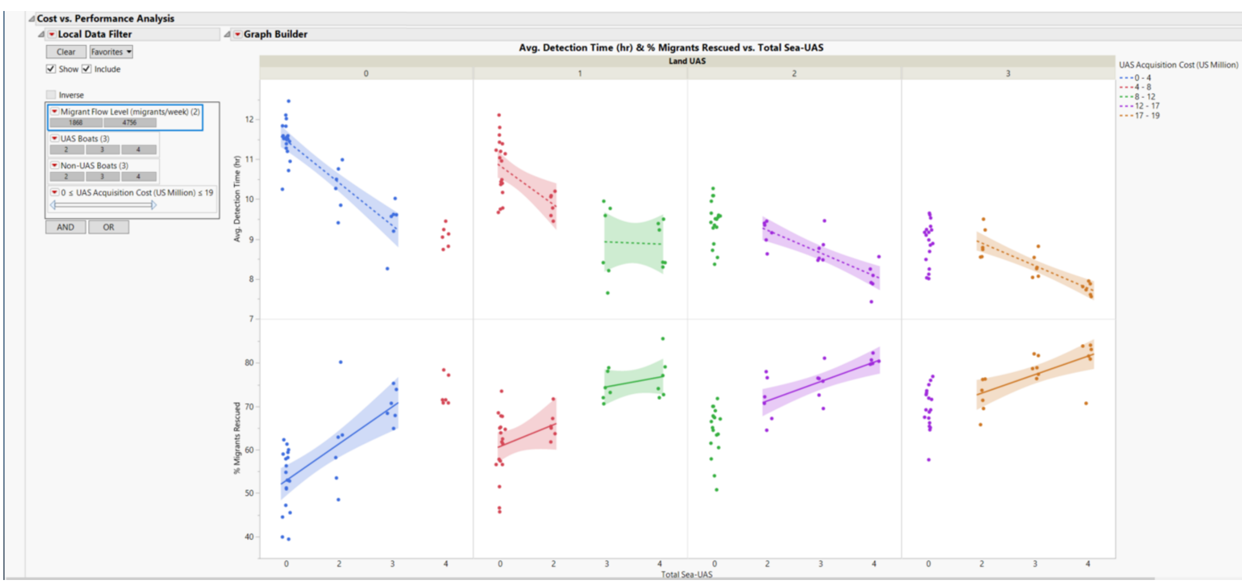

Figure 14. Cost vs. Performance Tab Results.

5) **Case Comparison:** this tab gives the user the ability to compare the differences that changing UAS or boats fleet has in the system performance. It features two graphs (one on top of the other) to treat each case separately

and facilitate visualizing the data (see Figure 15).

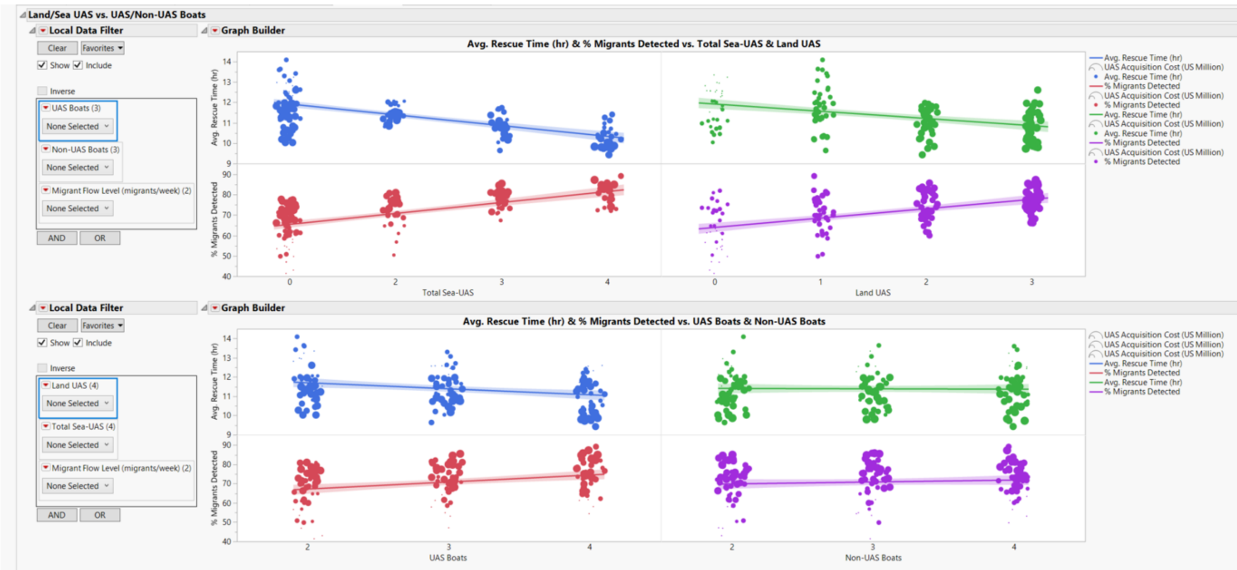

Figure 15. Case Comparison Tab.

6) **Ranking of Alternatives:** it features the results from the OEC analysis. Three different scenarios were coded in to show: 1) a scenario where the interest is in maximize the number of rescues and detections regardless of all other metrics 2) a case where cost is a restriction and therefore it is to be minimized, and 3) a scenario where all key metrics are regarded as equally important. The results from each OEC scenario are visualized as a scatter plot, allowing the user to select those cases with the best improvements.

Overall Evaluation Criteria

Scenario 1 | Scenario 2 | Scenario 3

Moderate Migration Flow	Inputs						Outputs					
Case Number	Land UAS	Sea-UAS	UAS Boats	Non-UAS Boats	% Detected	% Rescued	Detection Time (hr)	Rescue Time (hr)	Stdev Detection Time (hr)	Stdev Rescue Time (hr)	UAS Acquisition Cost ($ Million)	Operating Cost ($/hr)
51	2	3	3	4	81.1	81.1	9.46	11.38	3.39	3.35	19.00	10,200
65	3	2	2	3	81.0	76.3	9.23	11.36	3.49	3.54	17.00	28,850
68	3	3	3	3	85.5	82.1	8.54	10.75	3.03	3.31	17.00	29,400
High Migration Flow	**Inputs**						**Outputs**					
Case Number	Land UAS	Sea-UAS	UAS Boats	Non-UAS Boats	% Detected	% Rescued	Detection Time (hr)	Rescue Time (hr)	Stdev Detection Time (hr)	Stdev Rescue Time (hr)	UAS Acquisition Cost ($ Million)	Operating Cost ($/hr)
129	3	0	2	4	74.1	69.2	9.53	12.61	3.83	3.85	15.00	34,500
128	3	0	2	3	75.4	71.6	9.23	11.96	3.99	4.08	15.00	28,250
144	3	4	4	4	87.3	84.1	7.61	9.83	3.14	3.24	19.00	36,200

Decision-making Scenarios

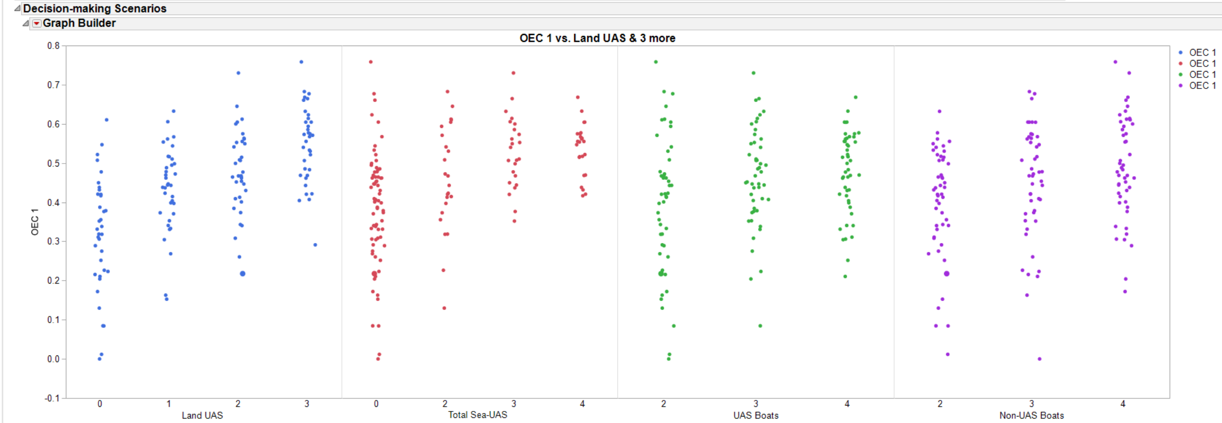

Figure 16. OEC Results Visualization.

VII. Analysis

A. Design of Experiments

A DoE, seen in Table 4, was created to setup the necessary cases to be ran in Janus. A range of land-based UAS, ship-based UAS per OPV, OPV, and patrol boats are combined together for the simulation runs. Each of these cases is repeated for both moderate and crisis flow levels. These cases multiply out to be 144 total cases.

Many stochastic effects occur within the simulations such as the migrant departure location, the time a migrant boat capsizes, UAS maintenance downtown, and migrant movement from the weather. Multiple runs must be done for each case to account for this, so 10 reruns were done for each of the 144 cases. This was done using Janus's built-in Batch-Mode process.

Table 4. Variable ranges for the Design of Experiments

Land-based UAS	Ship-based UAS per OPV	Offshore Patrol Vessels	Patrol Boats	Migrant Flow Level
0	0	2	2	Moderate
1	1	3	3	Crisis
2		4	4	
3				

B. Baseline Evaluation

An initial investigation was completed before running the larger set of cases to test the tool and get a notional concept of the impact. The results from the baseline case can be seen in Figures 17 and 18 and the UAS enhanced case in 19 and 20.

The baseline case can be seen at two periods of the simulation, one which features all five surface vessels in the distributed grid pattern and one which features one surface vessel returning home while the remaining four re-distribute themselves to cover the search area. This is an example of the dynamic search pattern that the UAS swarm and surface vessel can perform. A key point to notice is that in Figure 18 there is still a single migrant boat which has not been detected and appears to be floating away from the search area. It can be seen that later in the simulation the migrant boat will actually return into the search space because of the ocean current shift, but will still not be detected because of the surface vessels making rescues and having to redistribute across the remaining area. This is an example of the types of failures that occur during with only the surface vessels.

Two periods of the enhanced case can also be seen in Figure 19 and 20. The five surface vessels operate the same as in the baseline case, and three land-based UAS fly above in the same search area. The UAS operate in the same dynamic grid pattern coordination as the patrol vessels, with the two available UAS filling in the space of the busy UAS. The other UAS is tracking a migrant boat towards the right side of the images. Once the UAS tracks down the migrant boat it loiters around it until the surface vessel arrives, which can be seen in Figure 19. Later in the simulation the surface vessel does indeed make the rescue and then returns to base, while the UAS returns to the search area and redistributes the swarm. This detection and rescue is a perfect example of the benefit of the UAS systems, as the UAS was able to make a detection in an area that a surface vessel either wouldn't have made or would have made much later, meaning the rescue could have not been made in time.

The results from the two cases show that the addition of the three land-based UAS increase the number of detections by up to 30%. This is largely due to the larger detection radius, the more consistent presence, and the faster movement speeds of the UAS. The following section discusses more details of the results from the DoE.

C. Overall Evaluation Criterion

The dashboard was used to answer the research question regarding the top performing fleet overall and in a cost-limited scenario. Figure 22 shows the top cases by OEC and Figure 23 shows the top cases from the cost-limited scenario of $5 Million acquisition and $20,000 /hr operating cost. All times are in hours. These results were found by using the Dashboard's OEC data filter. The weighting scenario selected for calculation of the OEC is seen in Table 5 This scenario focused on rescue % and time, with a low weighting on cost.

Figure 17. Janus Simulation of baseline case before redistribution.

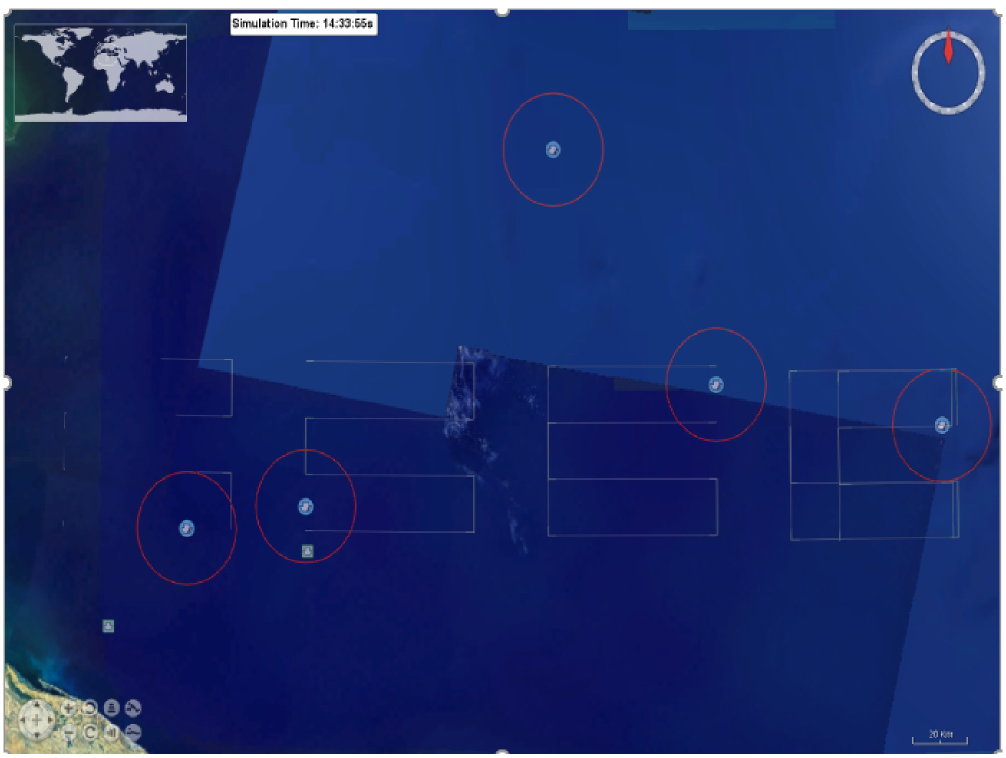

Figure 18. Janus simulation of baseline case after redistribution.

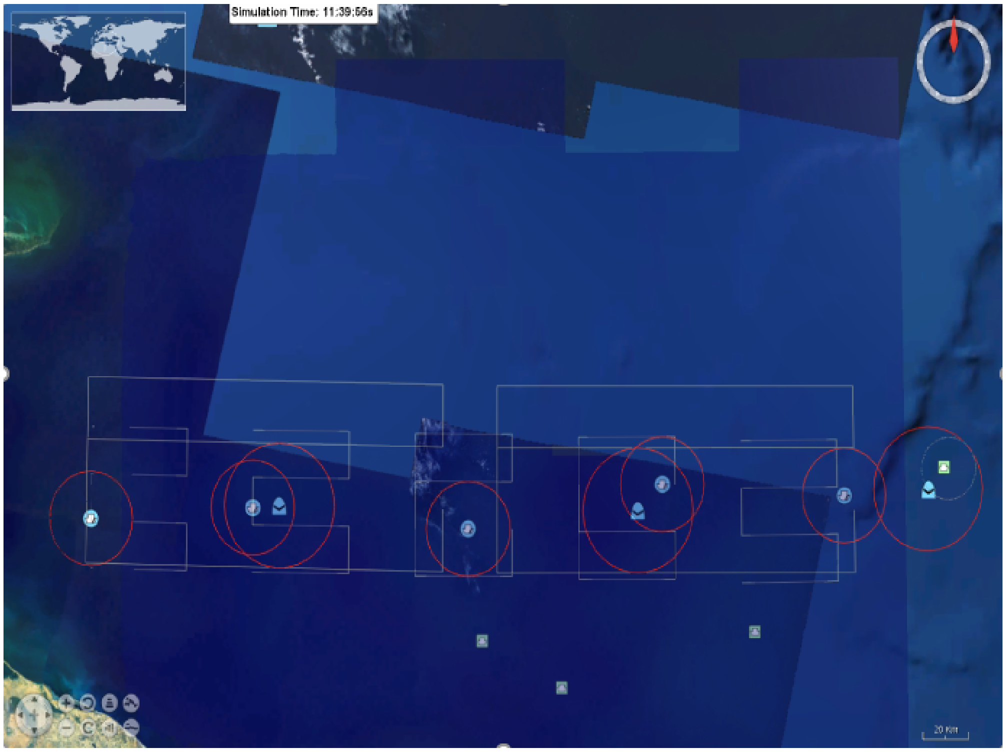

Figure 19. Janus Simulation for the case featuring three UAS before redistribution.

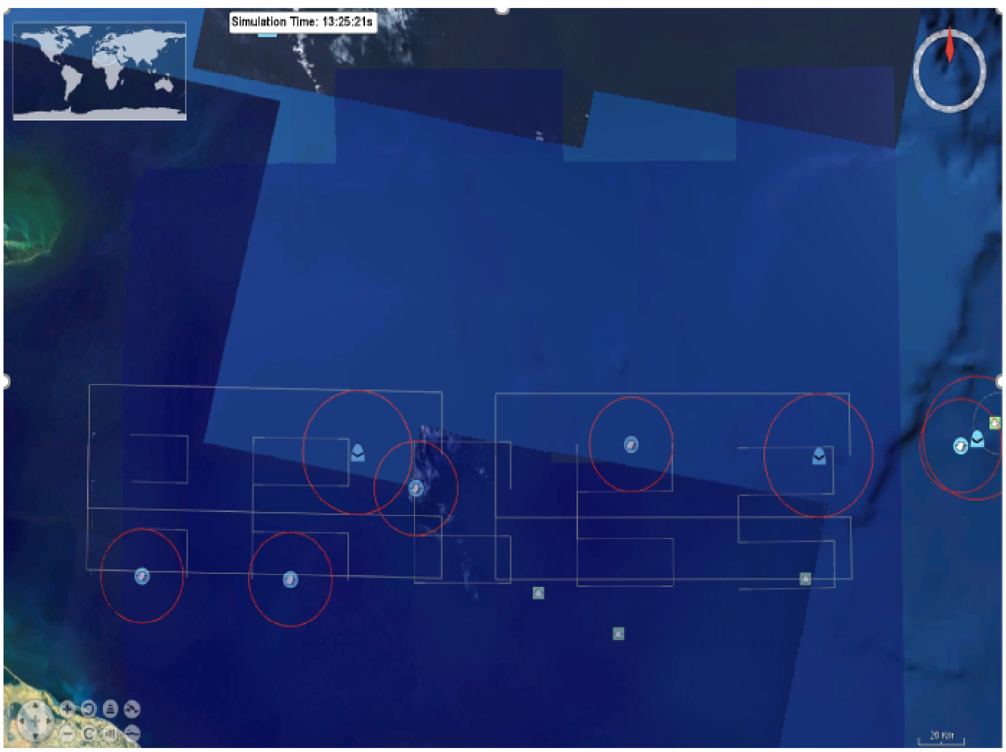

Figure 20. Janus Simulation for the case featuring three UAS after redistribution.

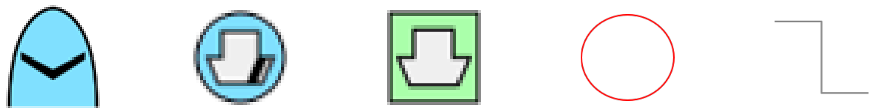

Figure 21. Legend of Mil-Std Icons in the simulation environment: UAS, Surface Vessel, Migrant Boat, Detection Radius, Waypoint Path.

The top cases are compared to the baseline case which can be seen in 6 and 7. The baseline case features two OPV and two patrol boats, and no UAS. It is assumed to have zero acquisition cost since the surface vessels are already available. Surface vessel operating costs are accounted for although. The key thing to notice on the baseline case is the % rescued at 47% and the time to detect at 11.84 hrs.

A direct comparison of the baseline case with the top performers can be seen in Figure 24. The % of detections and rescued are shown to almost double for all the top cases. In addition, the results of the top overall largest improvement by OEC show that the top case features the use of three land-based UAS and 4 ship-based UAS. While the cost is much higher than the other cases, the reason this case has the highest OEC is because of the dramatically reduced values for standard deviation of detection and rescue times. This indicates one key conclusion, that land-based UAS are key to providing consistent monitoring.

The results of the cost-limited case shows that the top performers feature the use of two ship-based UAS and no land-based UAS. This is largely because of the lower cost of the ship-based UAS. Another detail that can be seen is that the % detected and rescued for the top performing case is over 15% higher than the second best case. This occurs with the addition of only a single patrol boat. The key conclusion here is that sometimes the critical addition to the overall fleet is a surface vessel.

Table 5. Weighting Scenario used for OEC.

% Detected	% Rescued	Time to Detection	Time to Rescue	Std. Dev. Time to Detect	Std. Dev. Time to Rescue	Acq. Cost	O&S Cost
0.15	0.20	0.15	0.20	0.10	0.10	0.05	0.05

Table 6. Baseline Case for Comparison.

OEC	Land-based UAS	Ship-based UAS	Offshore Patrol Vessels	Patrol Boats	% Detected	% Rescued	Acq. Cost ($ Million)	O&S Cost ($/hr)
1.00	0	0	2	2	46.9	44.5	0	13000

Table 7. Baseline Case for Comparison (cont'd).

OEC	Land-based UAS	Ship-based UAS	Offshore Patrol Vessels	Patrol Boats	Avg. Time Detect	Avg. Time Rescue	Std. Dev. Detect	Std. Dev. Rescue
1.00	0	0	2	2	11.84	12.95	3.41	3.43

D. Tradespace Sensitivity Studies

The dashboard is also used to look at the sensitivities. The effect on the variability of the response of each asset can be calculated to determine which assets play the most important role to increasing rescues or reducing rescue time. As seen in Figure 13, the asset which effects % of migrants rescued the most is the ship-based UAS. This makes it more clear why the ship-based UAS ended up in many of the top cases by OEC. Especially since the ship-based UAS is 1/3 the cost of land-based UAS.

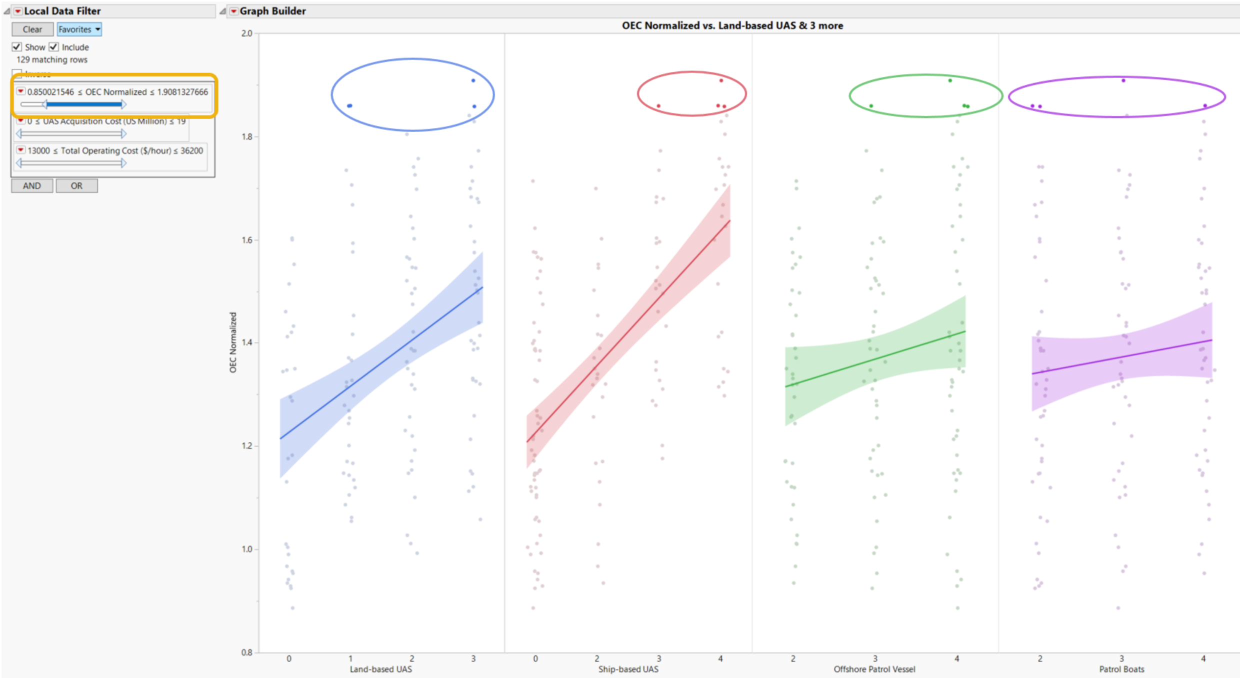

Figure 22. Top Performers Overall by OEC in Dashboard.

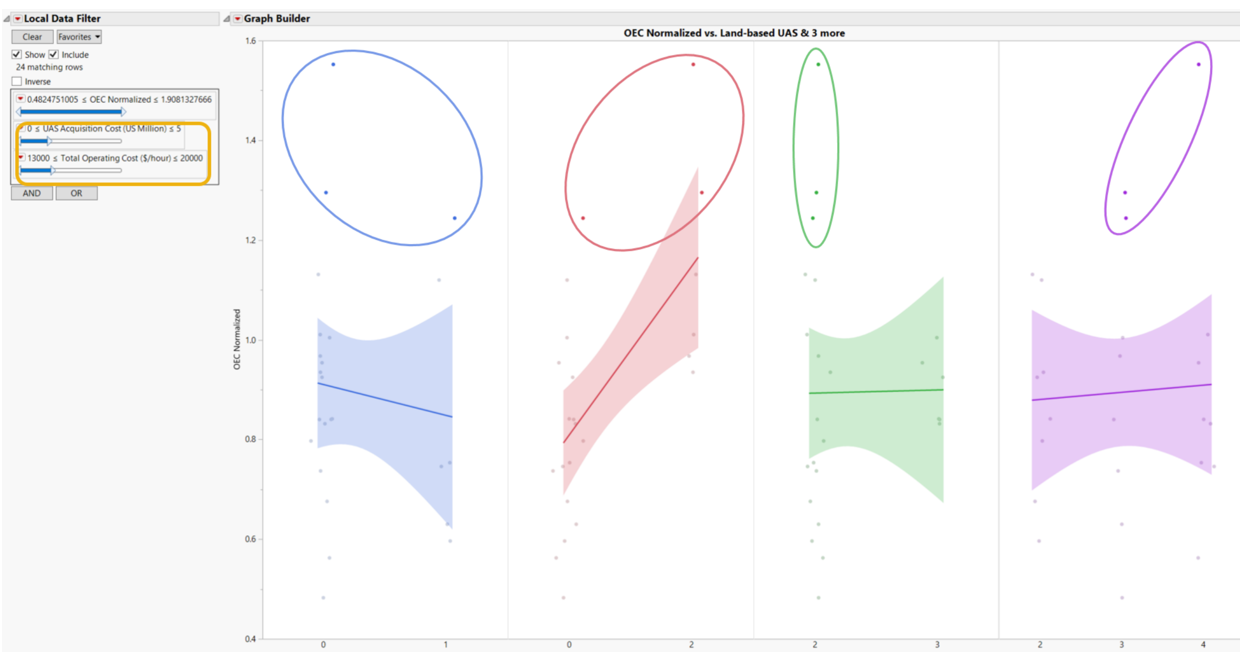

Figure 23. Top Performers of Cost-Limited Scenario by OEC in Dashboard.

Table 8. Results for Overall Largest Improvement by OEC.

OEC	Land-based UAS	Ship-based UAS	Offshore Patrol Vessels	Patrol Boats	% Detected	% Rescued	Acq. Cost ($ Million)	O&S Cost ($/hr)
1.91	3	4	4	3	84.8	81.6	19	35950
1.86	1	4	4	4	89.2	85.6	9	30200
1.86	1	3	3	2	81.5	78.1	8	23150

Table 9. Results for Overall Largest Improvement by OEC (cont'd).

OEC	Land-based UAS	Ship-based UAS	Offshore Patrol Vessels	Patrol Boats	Avg. Time Detect	Avg. Time Rescue	Std. Dev. Detect	Std. Dev. Rescue
1.91	3	4	4	3	7.95	9.80	2.81	2.63
1.86	1	4	4	4	8.30	10.18	3.28	3.15
1.86	1	3	3	2	7.65	9.64	3.22	3.27

Table 10. Top Performers by OEC in Cost-Limited Scenario.

OEC	Land-based UAS	Ship-based UAS	Offshore Patrol Vessels	Patrol Boats	% Detected	% Rescued	Acq. Cost ($ Million)	O&S Cost ($/hr)
1.55	0	2	2	4	81.0	80.2	2	14100
1.30	0	2	2	3	64.7	62.9	2	13850
1.24	1	0	2	3	72.4	67.7	5	16250

Table 11. Top Performers by OEC in Cost-Limited Scenario (cont'd).

OEC	Land-based UAS	Ship-based UAS	Offshore Patrol Vessels	Patrol Boats	Avg. Time Detect	Avg. Time Rescue	Std. Dev. Detect	Std. Dev. Rescue
1.55	0	2	2	4	9.85	11.18	3.75	3.38
1.30	0	2	2	3	9.41	10.81	3.81	3.51
1.24	1	0	2	3	10.40	11.85	3.66	3.34

VIII. Conclusion

In summary, this effort shows that agent-based simulations can be used to model complex system of systems interactions and effects on mission success. In particular, the ASDL developed Java-based Janus SDK provides a flexible tool for the investigation of system of system level effectiveness. This methodology is shown through the case study focused around the crisis of migrants crossing the Mediterranean which continues to be an issue, Technological solutions were investigated with one potential solution being the utilization of UAS in coordinated swarms, or fleets, alongside surface vessels. In our case study, Frontex data was used to model migrant patterns and trends which were used in our simulation to compare baseline operations to enhanced cases which featured various combinations of UAS and surface vessel agents. The completed tradeoff environment features a JMP dashboard dubbed SEAMASTER that allows users to investigate according to cost and performance to find the top cases. In general, the observed effect of the addition of UAS is an improvement in detection and rescue rate and time. The SBU provides the greatest impact based on its ability to extend the surface vessels detection radius at a lower cost than the LBU.

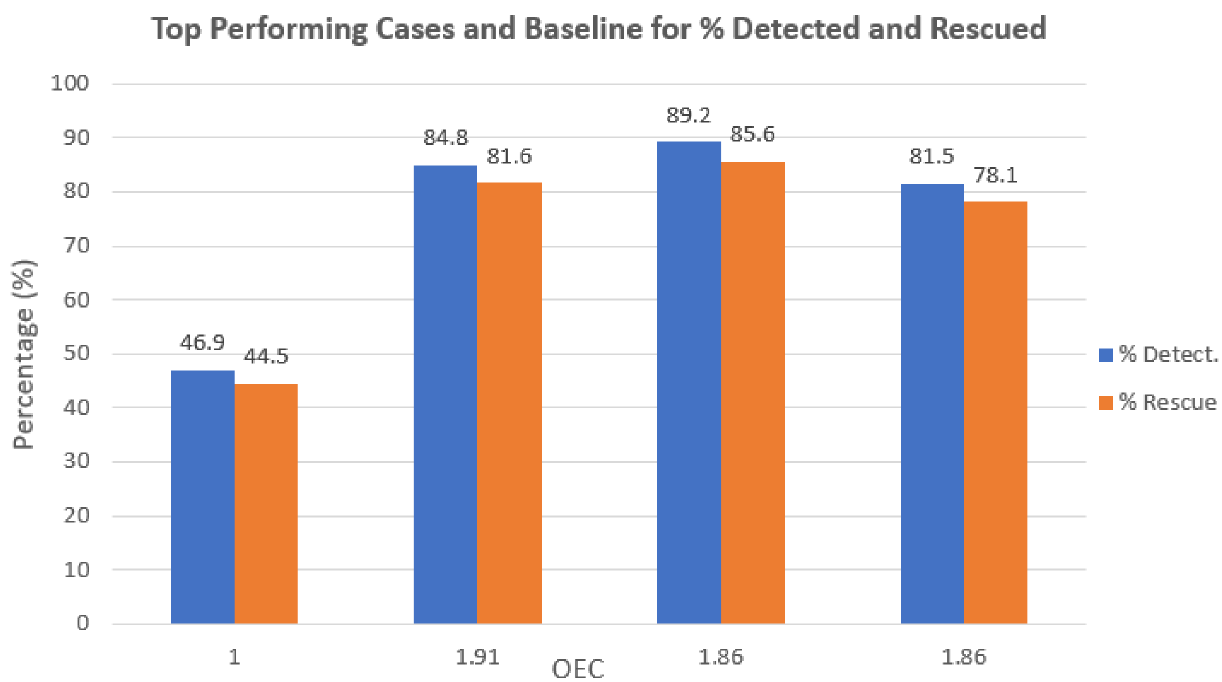

Figure 24. Comparison of the baseline with the top performers for detection and rescue percentage.

IX. Future Work

There are many avenues for future work that would improve the fidelity of the analysis and the sophistication of questions which may be answered through the use of this methodology. For one, while this effort involved some heuristics to distribute assets over a search area and intelligently allocate the nearest available tracker or rescuer, these processes could be optimized using more sophisticated techniques. The fidelity of the model could be increased in several important areas. Modeling communications equipment would enable trade studies in this key area to be conducted. Sensor subsystems are another area that was simplified to the absolute minimum model for this effort and which could greatly benefit from improved fidelity. This would allow for trade studies on which sensors perform best, and, if modeling sensor power requirements, will introduce a link to vehicle size. In this case, more complex vehicle performance models would be become necessary. Finally, the same agent-based approach could be applied to answer similar questions about related scenarios such as security of a smaller area, like a corporate or college campus, or border patrol operations in other regions around the world.

X. Acknowledgments

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References

[1] Frontex, "Risk Analysis for 2016," 2016.

[2] Frontex, "Risk Analysis for 2017," 2017.

[3] Frontex, "Risk Analysis for 2015," 2015.

[4] Malakooti, A., and Davin, E., "Migration Trends Across the Mediterranean: Connecting the Dots," 2015.

[5] EMSA, "Contracts for demonstrating state-of-the-art remotely piloted aircraft systems (RPAS) services in support of the execution of coast guard functions," , 2016.

[6] Klimkowska, A., I, L., and K, C., "Possibilities of UAS for Maritime Monitoring," *International Archives of the Photogrammetry, Remote Sensing, and Spatial Information Sciences*, 2016.

[7] Price, I., "Evolving Self-Organized Behavior for Homogeneous and Heterogenous UAV or UCAV Swarms," Master's thesis, Air Force Institute of Technology, Wright-Patterson AFB, Dayton, Ohio, 2004.

[8] Cortes, J., Martinez, S., and F, B., "Spatially-Distributed Coverage Optimization and Control with Limited-Range Interactions," *ESAIM: Control, Optimization, and Calculus of Variations*, 2005.

[9] Lerman, K., Martinoli, A., and Galstyan, A., "A Review of Probabilistic Macroscopic Models for Swarm Robotic Systems," *Swarm Robotics Work Symposium*, 2004.

[10] Reynolds, C., "Flocks, Herds, and Schools: A Distributed Behavioral Model," *SIGGRAPH*, 1987.

[11] Polycarpou, M., and Yang, Y., "Cooperative Control of Distributed Multi-Agent Systems," *Swarm Robotics Work Symposium*, 2004.

[12] Heng, L., and Gao, G., "Navigating Robot Swarms Using Collective Intelligence Learned from Golden Shiner Fish," *Collective Intelligence*, 2014.

[13] Olfati-Saber, R., "Flocking for Multi-Agent Dynamic Systems: Algorithms and Theory," *IEEE Transactions on Automatic Control*, 2018.

[14] Jun, M., and D'Andrea, R., *Cooperative Controls: Models, Applications, and Algorithms*, Springer-Science+Business Media, 2003, Chap. Path Planning for Unmanned Aerial Vehicles in Uncertain and Adversarial Environments.

[15] Delima, P., and Pack, D., "Maximizing Search Coverage Using Future Path Projection for Cooperative Multiple UAVs with Limited Communication Ranges," , 2009.

[16] Hirshorn, S., "NASA Systems Engineering Handbook," 2007.

[17] Council, N. R., "Pre-Milestone A and Early-Phase Systems Engineering: A Retrospective Review and Benefits for Future Air Force Systems Acquisition," 2008.

[18] Mavris, D., "Introduction to System of Systems Engineering Principles," 2018.

[19] Skinner, S., Urdahl, S., Harrington, T., Balchanos, M., and Mavris, D., "UAV Swarms for Migration Flow Monitoring and Search and Rescue Mission Support," *AIAA Scitech*, 2018.

[20] "MQ-4C Triton," , 2018. URL `http://www.northropgrumman.com/Capabilities/Triton/Pages/default.aspx`.

[21] Directorate, E. S., *MQ-4C Triton Unmanned Aircraft System (MQ-4C Triton)*, Selected Acquisition Report (SAR), Vol. RCS: DD-AT(QA)823-373, 2016. URL `http://www.esd.whs.mil/Portals/54/Documents/FOID/ReadingRoom/Selected_Acquisition_Reports/16-F-0402_DOC_71_MQ-4CTriton_DEC_2015_SAR.pdf`.

[22] Mavris, D., and Delaurentis, D., "An integrated approach to military aircraft selection and concept evaluation," *AIAA Aircraft Engineering, Technology, and Operations Congress*, 1995. doi:10.2514/6.1995-3921.

[23] ACAPS, "Humanitarian Overview: An Analysis of Key Crises into 2018," 2017.

[24] Campbell, Z., "Europe's Plan to Close its Sea Borders Relies on Libya's Coast Guard Doing its Dirty Work, Abusing Migrants," , 2017. URL `https://theintercept.com/2017/11/25/libya-coast-guard-europe-refugees/`, accessed: 2018-01-30.

[25] Kirkpatric, D., "Europe Wanted Migrants Stopped. Now Some Are Being Sold as Slaves," , 2017. URL `https://www.nytimes.com/2017/11/30/world/africa/slave-market-libya-european-migrants.html`, accessed: 2018-01-30.

[26] "FRAN Quarterly," 2017.

[27] "WindSat/Coriolis Measurements Data Products," `https://manati.star.nesdis.noaa.gov/products/WindSAT.php`, 2010. Accessed: 2018-03.

[28] "OSCAR third degree resolution ocean surface currents," `https://podaac.jpl.nasa.gov/dataset/OSCAR_L4_OC_third-deg`, 2015. Accessed: 2018-03.

[29] Luke, I., and et al, *National Search and Rescue Manual, Vol I: National Search and Rescue System*, Joint Chiefs of Staff, Washington, D.C. 20318-0200, February 1991.

[30] "Panoply netCDF, HDF and GRIB Data Viewer," , March 2018. URL `https://www.giss.nasa.gov/tools/panoply/`, accessed: 2018-03.

[31] "Africa-Frontex Intelligence Community Joint Report 2016," 2017.

[32] Lukas, V., "Migration Phenomena Towards EU: Joint Operations in the Central and Eastern Mediterranean Sea," 2016.

[33] "Luigo Dattilo Vessel Details," , 2018. URL `http://www.northropgrumman.com/Capabilities/MQ5BHunter/Pages/default.aspx`, accessed 2018-03.

[34] Luke, I., and et al, "Caribbean Mass Migration Operations: MOOTW with the US Coast Guard in the Lead," Tech. rep., Naval War College, 686 Cushing Rd, Newport, RI 02841, May 1998.

[35] "MQ5B Hunter," , 2018. URL `http://www.northropgrumman.com/Capabilities/MQ5BHunter/Pages/default.aspx`, accessed: 2018-02.

[36] "Scaneagle Unmanned Aerial Vehicle," , 2018. URL `https://www.boeing.com/history/products/scaneagle-unmanned-aerial-vehicle.page`, accessed: 2018-02.