NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

EVALUATION OF COURSES OF ACTION SIMULATION TOOL

by

Kevin F. Riley

June 2023

Thesis Advisor:	Johannes O. Royset
Second Reader:	David Sidoti, Naval Research Laboratory - Monterey

Approved for public release. Distribution is unlimited.

THIS PAGE INTENTIONALLY LEFT BLANK

REPORT DOCUMENTATION PAGE				*Form Approved OMB No. 0704-0188*
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instruction, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188) Washington, DC 20503.				
1. AGENCY USE ONLY ***(Leave blank)***	**2. REPORT DATE** June 2023	**3. REPORT TYPE AND DATES COVERED** Master's thesis		
4. TITLE AND SUBTITLE EVALUATION OF COURSES OF ACTION SIMULATION TOOL				**5. FUNDING NUMBERS**
6. AUTHOR(S) Kevin F. Riley				
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943-5000				**8. PERFORMING ORGANIZATION REPORT NUMBER**
9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES) N/A				**10. SPONSORING / MONITORING AGENCY REPORT NUMBER**
11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government.				
12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release. Distribution is unlimited.				**12b. DISTRIBUTION CODE** A

13. ABSTRACT (maximum 200 words)

Maritime counter-drug operations and related activities constitute a high-priority national security mission because drug-trafficking involves criminals, a source of financing for illicit activities, and penetration of the U.S. border. Currently, Joint Interagency Task Force South is successful in executing this mission. Due to the wide area of coverage by a limited number of assets, there is a need for integration of intelligence, meteorology and oceanography information, as well as effective surveillance to detect and identify drug traffickers in order to gain situational awareness and effectively allocate resources for maritime operations. As a result, the U.S. Naval Research Laboratory is developing a system for dynamic resource management in counter-smuggling operations, named the Courses of Action Simulation Tool (COAST). This analysis assesses how well the present modeling framework and the associated decision support tool perform by developing an alternative optimization model, implemented in Pyomo, and comparing its recommendation to those of the existing tool. We present a mixed-integer linear program and assess that the results from COAST are within an average of 22% and 16% of our optimal solution of expected number of smugglers detected in single- and two-target scenarios, respectively.

14. SUBJECT TERMS JIATF-S, detection, interdiction, decision-support, counter-drug, CD, counter transnational organized crime, CTOC			**15. NUMBER OF PAGES** 79
			16. PRICE CODE
17. SECURITY CLASSIFICATION OF REPORT Unclassified	**18. SECURITY CLASSIFICATION OF THIS PAGE** Unclassified	**19. SECURITY CLASSIFICATION OF ABSTRACT** Unclassified	**20. LIMITATION OF ABSTRACT** UU

NSN 7540-01-280-5500 Standard Form 298 (Rev. 2-89) Prescribed by ANSI Std. 239-18

THIS PAGE INTENTIONALLY LEFT BLANK

Approved for public release. Distribution is unlimited.

EVALUATION OF COURSES OF ACTION SIMULATION TOOL

Kevin F. Riley
Commander, United States Navy
BSCSE, Marquette University, 2002
MA, Naval War College, 2018

Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN OPERATIONS RESEARCH

from the

NAVAL POSTGRADUATE SCHOOL
June 2023

Approved by: Johannes O. Royset
Advisor

David Sidoti
Second Reader

W. Matthew Carlyle
Chair, Department of Operations Research

THIS PAGE INTENTIONALLY LEFT BLANK

ABSTRACT

Maritime counter-drug operations and related activities constitute a high-priority national security mission because drug-trafficking involves criminals, a source of financing for illicit activities, and penetration of the U.S. border. Currently, Joint Interagency Task Force South is successful in executing this mission. Due to the wide area of coverage by a limited number of assets, there is a need for integration of intelligence, meteorology and oceanography information, as well as effective surveillance to detect and identify drug traffickers in order to gain situational awareness and effectively allocate resources for maritime operations. As a result, the U.S. Naval Research Laboratory is developing a system for dynamic resource management in counter-smuggling operations, named the Courses of Action Simulation Tool (COAST). This analysis assesses how well the present modeling framework and the associated decision support tool perform by developing an alternative optimization model, implemented in Pyomo, and comparing its recommendation to those of the existing tool. We present a mixed-integer linear program and assess that the results from COAST are within an average of 22% and 16% of our optimal solution of expected number of smugglers detected in single- and two-target scenarios, respectively.

THIS PAGE INTENTIONALLY LEFT BLANK

Table of Contents

THIS PAGE INTENTIONALLY LEFT BLANK

List of Figures

List of Tables

THIS PAGE INTENTIONALLY LEFT BLANK

List of Acronyms and Abbreviations

ADP	approximate dynamic programming
AOR	area of responsibility
CARIB	Caribbean
CD	Counter Drug
COAST	Courses of Action Simulation Tool
DOD	Department of Defense
DSS	Decision Support System
EPAC	East Pacific
GAO	Government Accountability Office
JIATF-S	Joint Interagency Task Force South
MILP	mixed-integer linear program
MINLP	mixed-integer nonlinear program
NRL	Naval Research Laboratory
PoA	Probability of Activity
SAP	Searcher Allocation Problem
SOM	Searcher Optimization Model
TACON	tactical control
TCO	Transnational Criminal Organization

THIS PAGE INTENTIONALLY LEFT BLANK

Executive Summary

We consider the task of Joint Interagency Task Force South mission planners assigning surveillance aircraft to multiple drug smuggling vessels, or targets, operating somewhere in the East Pacific Ocean and Caribbean Sea. The targets are spread out across a maritime environment spanning 42 million square-miles, effectively limiting the total number a single surveillance aircraft is able to detect within their allotted flight time. A mission planner's determination of which targets to pursue depends on many factors, one being the reliability of the target location, which diminishes over time and varies with the availability of and confidence in intelligence. Other factors include smuggler range to interdiction vessels, follow-on flight events, weather, ship schedules, and country-specific laws regulating intercepts. We define the issue of *determining how best to allocate surveillance aircraft* as the Searcher Allocation Problem (SAP).

This thesis is motivated and developed in close collaboration with the U.S. Naval Research Laboratory, the U.S. Navy's corporate research laboratory and main research and development component under the Office of Naval Research. NRL's answer to SAP is Courses of Action Simulation Tool (COAST), a modeling framework that addresses the many planning factors and decision support system that improves planner's ability to allocate resources. COAST uses a heuristic to determine which cells to allocate to a searching aircraft. We provide a validation tool for evaluating the quality of COAST recommendations.

In this thesis, we formulate a mixed-integer linear program for comparison against COAST's heuristic for searcher allocation. The model, referred to as Searcher Optimization Model (SOM), determines optimality bounds by using the expected number of detections in place of the probability of detection. The objective function maximizes the sum of this expectation. We use a constraint to impose a maximum range of motion on the searching aircraft. SOM uses COAST input data with over 1,000 lines of code consisting of data collection in Excel, pre- and post-processing in Python, and model implementation in Pyomo.

Experiment scenarios center both on computational and operational results SOM produces. The computational results reveal that we can limit SOM solve time by employing the CPLEX solver in Pyomo. We use two settings, both of which include five tests of an

increasing number of variables and constraints. The most straining setting shows with over 215,000 variables and 215,000 constraints, CPLEX has a faster solve time (134 seconds) compared to CBC and Gurobi. In comparison to the longest solve time, CPLEX solves 57 times faster than CBC. Operational results show that COAST recommendations are within an average of 22% and 16% of our optimal solution of expected number of smugglers detected in a single and two target scenario, respectively.

Acknowledgments

I would like to thank my advisor, Professor Johannes Royset, for his mentorship, guidance, and expertise throughout this process. I would like to thank my second reader, Dr. David Sidoti, for helping me through this entire process. For their support and advice along the way, I would like to thank my study group DBSG. I would also like to thank Professor Emily Craparo, who generously offered her time and expertise despite that fact that she was not on my committee. Finally, I would like to thank the NPS Operations Research professors for their devotion and commitment to teaching me, my fellow students in the program, and the naval enterprise writ large.

THIS PAGE INTENTIONALLY LEFT BLANK

CHAPTER 1:
Introduction

Every one of the military's 11 functional and geographic combatant commanders has a role and set of missions that contribute, in a fundamental way, to U.S. national security. Considering the significance of their missions and the fact that military spending makes up the largest percentage of the federal budget, commanders are not guaranteed to receive all the resources they need to effectively carry out those missions. This is especially true for the combatant commanders with comparatively low priority missions. It is in these missions where the task of optimally allocating limited resources is most vital.

The Chief of Naval Research, Rear Admiral Lorin Selby, has four priorities, one of which is "New Vision, Faster Results," a focus on the problem of conducting Counter Drug (CD) operations in the U.S. SOUTHCOM area of responsibility (AOR) (Office of Naval Research 2023). Naval Research Laboratory (NRL), the U.S. Navy's corporate research laboratory and main research and development component under the Office of Naval Research is developing a Decision Support System (DSS) called Courses of Action Simulation Tool (COAST) that will help U.S. SOUTHCOM's Joint Interagency Task Force South (JIATF-S) planners to optimally allocate their limited number of surveillance aircraft and interdiction vessels during CD operations (Zhang et al. 2020).

In this thesis, we evaluate the quality of COAST recommendations by developing an alternative optimization model for asset allocation. This model, referred to as Searcher Optimization Model (SOM), prescribes an optimal asset allocation that maximizes the expected number of detections of illicit traffic. SOM is solved to optimality and thus furnishes a means to benchmark the COAST recommendations.

1.1 Searcher Allocation Problem

Consider a JIATF-S mission planner's task of assigning a surveillance aircraft to multiple drug smuggling vessels operating somewhere in the East Pacific (EPAC) Ocean and Caribbean (CARIB) Sea. The smugglers, henceforth referred to as targets, are spread out across a maritime environment spanning 42 million square-miles, effectively limiting the total number of targets a single surveillance aircraft is able to surveil within their allotted flight time. We define the issue of *determining how best to allocate surveillance aircraft* as the Searcher Allocation Problem (SAP).

The determination of which targets to pursue for a surveillance aircraft, henceforth referred to as a searcher, depends on several factors, one being the reliability of the target's location. The certainty in each target location will vary with the availability of and confidence in law enforcement intelligence. This certainty will likely diminish as the time increases between contact reporting and the searcher's initial detection.

Another determining factor for where to assign searchers is the target's estimated range to interdicting ships. If the range is small, there is an opportunity to transition detection by the searcher into an intercept by the interdicting ship where a seizure of illicit drugs can be conducted. Beyond target location accuracy and associated range to intercepts, a mission planner tasked with assigning searchers to targets must consider many other factors including follow-on flight events, weather, ship schedules, and a host of country-specific laws regulating intercepts.

Currently, mission planners manually address SAP without the aid of computers, resulting in a time-intensive process that is difficult to determine efficient allocation of assets. NRL seeks to improve JIATF-S asset allocation by developing COAST to provide decision support to the mission planning process by ingesting various planning factors and proposing multiple allocation plans. The recommendations are generated in a fraction of the time it takes planners to develop a course of action and provides them with an additional ability to compare multiple plans. This thesis aims to assess the quality of those recommendations.

While COAST provides approximate solutions to SAP for both surveillance aircraft and interdicting ships, this thesis focuses on validating the quality of solutions as it pertains to aircraft. We accomplish this by developing SOM which prescribes an optimal plan for SAP. Optimality is achieved by formulating SOM as a mixed-integer linear program (MILP), where we focus on finding the expected number of detections of targets. This approach is in contrast to COAST which applies approximate dynamic programming (ADP) to SAP, resulting in a heuristic algorithm with some guarantees about optimality under specific circumstances. A comparison of the solutions prescribed by both models allows us to effectively measure the decision quality of COAST.

1.2 Literature Review

While SAP is fundamentally a search problem, it contains aspects of many other problems like traveling salesman, vehicle routing, orienteering, and maximum coverage. Even though the context around SAP is to counter drugs, the model being evaluated is a part of a decision support system where best practices for evaluation are not limited to specific industries (i.e., Department of Defense (DOD), Medical). In this section, we present Works associated with these efforts as well as others related to this research.

Search theory fundamentals created by Koopman (1946) were motivated on the ideal that no U.S. military service could bear the expense of less than optimal efficiency. Determining that efficiency requires dedicated analysis and for the problem of search an understanding of all its parts. One part involves the characteristics of the sensor used during detection, which ultimately drives probability of detection. Another aspect of search problems deals with the route the searcher takes as well as how they move along that route. The last part of the problem of detection deals with determining the minimum number of resources required to achieve the objective.

Charnes and Cooper (1958) expound on the last aspect, the efficient allocation of forces, in order to facilitate discussions of more general operations research problems. They formulate the issue of determining efficient allocation of search forces as a convex optimization problem. COAST adopts this method to determine the required surveillance effort in a discretized geographic area (Zhang et al. 2020).

Blachman and Proschan (1959) builds on the groundwork of Koopman, expanding his discussion beyond just the discrete case. Blachman and Proshan look at the problem realizing the target may not always be present at the beginning of the search effort. Using periodic search schedules, they determined the most effective search pattern given the target's probability of arrival.

Pollock (1964) furthers search theory by acknowledging what Koopman does not consider, the associated cost of false detections. Pollock views the search problem as an optimization of sequential search and detection decision problems. Using this approach, he can identify an optimal search strategy—a set of systems he defines as the union of sensors and decision rules—by the one that minimizes the overall cost of search.

Benkoski et al. (1991) summarizes the previous four and a half decades of search theory to provide an accessible, comprehensive body of work on the problem. The survey is limited to search planning, asset allocation, considerations of uncertainty, low fidelity target probability, and one-sided searches. Sections of interest to this thesis, outlining key studies, included stationary and moving targets as well as the constrained searcher.

Almost 30 years later, Raap et al. (2019) provides a literature review dedicated to optimizing searches for moving targets. They limit their scope to searches in discrete time, search planning involving predictions vice just observations, and one-sided searches. The results are a summary of 30 works dealing with path-constrained searches and 14 focused on motion-constrained searches. Both efforts include discussions on the heuristics for a single search asset and the methods to employ for multiple searchers. A table of the summary lists critical characteristics of every approach, facilitating comparisons and supporting easy reference for analysts and operators.

Moser (1990) contributes to optimal resource allocation analysis by addressing the problem of effectively employing Marine Corps Tactical Aerial Reconnaissance vehicles. He solves a multi-player orienteering problem with time windows, an approach that combines vehicle routing and scheduling problems, traveling salesman problems, and orienteering problems.

Pfeiff (2009) introduces an operational mission-planning aid that determines the optimal mix and placement of cooperative platforms executing a detection and classification mission against Self Propelled Semi-Submersibles (SPSS). He solves the maximization of successfully detecting an SPSS, assumed to be an intelligent attacker, by employing a defender-attacker optimization model. The defender controls a collection of JIATF-S tasked search platforms across multiple services and whose sensors span sub-surface, suface, and air domains. His solution is a mixed-strategy for the defender and a minimum-risk route for the attacker.

Sato and Royset (2010) develop a specialized branch-and-bound method for solving a time-constrained search problem and resource-constrained search problem, both with the objective of finding the optimal path of a single searcher that maximizes their probability of detecting a moving target. Sato and Royset use Lagrangian relaxation and network expansion to develop a new bounding technique for the optimal probability of detection. In contrast, this thesis determines optimality bounds by using the expected number of detections in place of the probability of detection.

Royset and Sato (2010) address excessive computation times for optimizations of real-world situations involving multiple cooperating searchers looking for one or more moving targets. They formulate a convex mixed-integer nonlinear program (MINLP) that minimizes non-detection across time in the case of a single target and minimizes non-detection of the target with the highest non-detection probability in the case of multiple targets (Royset and Sato 2010). What was considered to be operationally unacceptable solve times are significantly reduced with a scalable cutting-plane approach and in special cases with a single target, a linearization of MINLP.

Pietz (2013) builds on this general idea by adding resource dependent rewards to exploit resource trade-offs. He applies the combination of vehicle routing, traveling salesman, and maximum collection problems to the issue of countering drug smuggling and determining an optimal search plan under various conditions (Pietz 2013). Those conditions include complex and uncertain target motion, multiple searchers, multiple searchers coordinating with multiple interdictors, and multiple mission execution cycles.

Campos (2014) considers the smuggler search problem introduced by Pietz and designs a tool that aligns a target heat map with their optimization algorithm, improving the efficacy of both models as well as increasing the user-friendliness of the model. Campos' tool uses a Navy Research Lab developed probability model that captures weather effects on illicit drug movements as input to Pietz's multi-searcher optimization model (Campos 2014).

Kress et al. (2012) develop a stochastic dynamic program (DP) that optimizes the coordination of the airborne searcher—referred to as the *eye*—and the terrestrial interdicting asset—called the *fist*. They choose a greedy heuristic as their algorithm, in-place of a potentially solvable but intractable Backwards DP method. Relaxing the model provides an upper bound and thus allows them to assess the quality of that heuristic solution. In a similar manner, this thesis formulates a linear problem to compare its exact solution to the approximate one provided by COAST.

Pietz and Royset (2015) model an extension to the smuggler search problem presented in Pietz (2013) with the intent of maximizing the expected quantity of interdicted drugs. Given uncertainty surrounding target positions and a limited amount of search and interdiction assets, Pietz and Royset utilize special branch-and-bound algorithms to solve detect-and-interdict problems. Their work ultimately gives planners the ability to address low target probability situations and analysts the option to assess searcher and interdictor interactions.

Warner and Royset (2022) modeled satellite sensor optimization to solve an intelligence, surveillance, and reconnaissance resource allocation problem in the theater-level campaign model called Synthetic Theater Operations Research Model (STORM). They develop a mixed-integer linear program that optimally determines search plan and resolution for sensors achieving a 55% improvement in search coverage compared to STORM. We employ many of the same approaches to addressing and solving an allocation problem as expressed in Warner's work, notably determining an allocation problem and solving it using a SOM.

Griggs (1991) discusses investment justification and, in a similar approach as this thesis, the evaluation of a DSS, which he calls a necessary advantage in a financially burdened environment. He describes how tangible benefits of a DSS will include increased decision alternatives and sensitivity analysis between alternatives. Furthermore, DSS investment will likely be justified as these tangibles can only be compared to human performance. While the time of the publication of this research provides justification to this position, it no longer holds currently. The availability and performance of present-day open-source technology demands potential investments employ comparisons beyond just systems and humans.

Fayoumi (2018) describes DSSs as a data repository that organizations use to inform and coordinate decisions. They explore various ways to measure the effectiveness of DSSs and due to the associated complexity propose component based metrics. The fundamental elements of a DSS being the data, model, interface and knowledge base. Fayoumi provides example functions each element could support as well as associated metrics. This thesis focuses on the data component of COAST and use the metric of *decision quality* for evaluation.

Although Manar et al. (2017) focus on health care, the applicability of their approach to and methods for evaluating medical decision support systems is broad reaching. They separate the aspects of DSS evaluation into four bins: effect on work quality, effect on work processes, soundness of the supporting knowledge database, and technical requirements. Evaluation will only occur during the last three of the four development stages (i.e., inception, elaboration, construction, and transition) (Manar et al. 2017). Evaluating a DSS during elaboration and construction deals with user requirements, while the transition phase involves more testing and anomaly detection. Work beyond this thesis should keep in mind the development phase of evaluated models as well as the objectives for that phase.

This thesis adopts many of the terms and methods of analysis addressed in Stone et al. (2016). The target's location is provided as a *discrete prior* (see Section 2.1.1 of Stone et al. 2016), a probability arrangement over a set of cells which represents what we know and do not know about the target's location. Our searcher employs a *discrete-effort search plan* (see Section 3.3 of Stone et al. 2016), a spatio-tempo allocation "specifying the number of looks" in each cell at some time. Our searcher's movements between cells is best described as a *path-constrained search* (see Section 4 of Stone et al. 2016) where their movements are restricted to a set of cells defined by a separate function. Our searcher's *probability of detection* is the "expectation over the probability distribution" (see Section 3.1 of Stone et al. 2016). The gist of our model is to apply search effort to some cell at some time that maximizes the probability of detecting the target (Stone et al. 2016).

1.3 Thesis Organization

The next chapter concludes the data collection efforts as depicted at the top of Figure 1.1. The section begins with a review of the importance of the CD mission, the role and effort of JIATF-S, and how NRL will provide decision support to that effort.

In Chapter 3, we present data pre- and post-processing efforts along with a discussion on model construction, according to Figure 1.1. We introduce parsing actions that provide the model data as well as processing techniques that filter the same information. We formulate SOM as a mixed-integer linear program and describe the formulaic and computational approaches to solving it. SOM provides an exact optimal solution that can be used to evaluate the quality of COAST's approximate solution. We conclude the section with a discussion of post-processing actions required to set-up our evaluation.

In Chapter 4, we finalize COAST evaluation, the last block depicted in Figure 1.1. The section begins with an example case used to walk-through our computational approach. We discuss computational results and present operational comparisons between SOM and COAST.

We conclude with final remarks and recommendations for further research in Chapter 5.

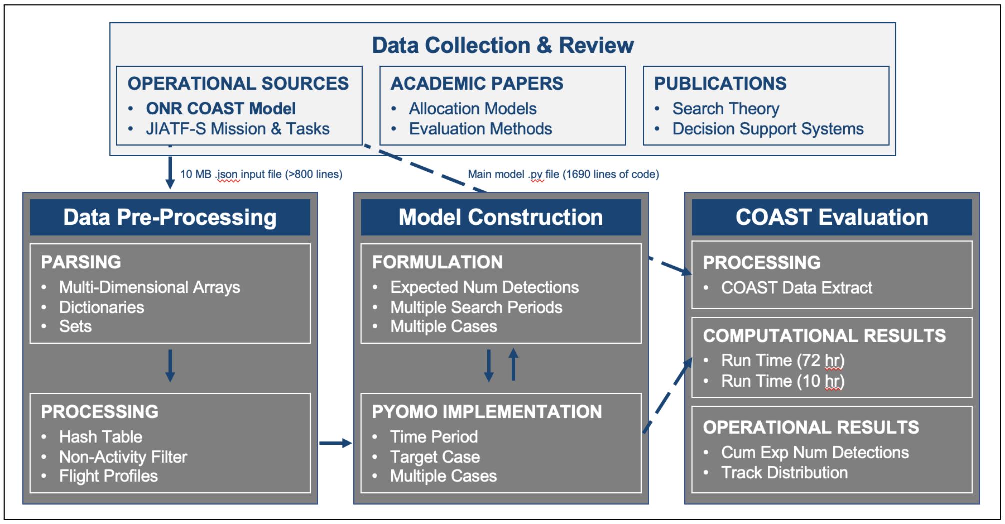

Figure 1.1. Method of Analytical Approach to Evaluating COAST

CHAPTER 2:
Background

This section provides significance to our research problem beyond just the desire to evaluate the allocation of limited resources. We provide background on illicit drug trafficking and how JIATF-S plans to counter this threat. We also discuss the decision support system NRL is developing to support JIATF-S.

2.1 Drug Problem Overview

A *drug* can be considered any material ingested for the purpose of affecting the organization or operation of the body. This does not include food, a tool, or a part of a tool (Drug 2023). While there are legal and illicit drugs in the world, the trafficking of illicit drugs — primarily by Mexican Transnational Criminal Organizations (TCOs) — into the U.S. is what fuels the drug epidemic, endangering all Americans (Drug Enforcement Administration 2020).

Ever since President Nixon's call for a federal response to drug-related crimes, America has been embroiled in a "war on drugs" (National Public Radio 2007). The National Center for Health Statistics reports that overdose deaths have increased over the past 20 years. Figure 2.1 shows a 14% rise between 2020 and 2021, where more than 106,000 deaths from overdose occurred in 2021 (Spencer et al. 2022).

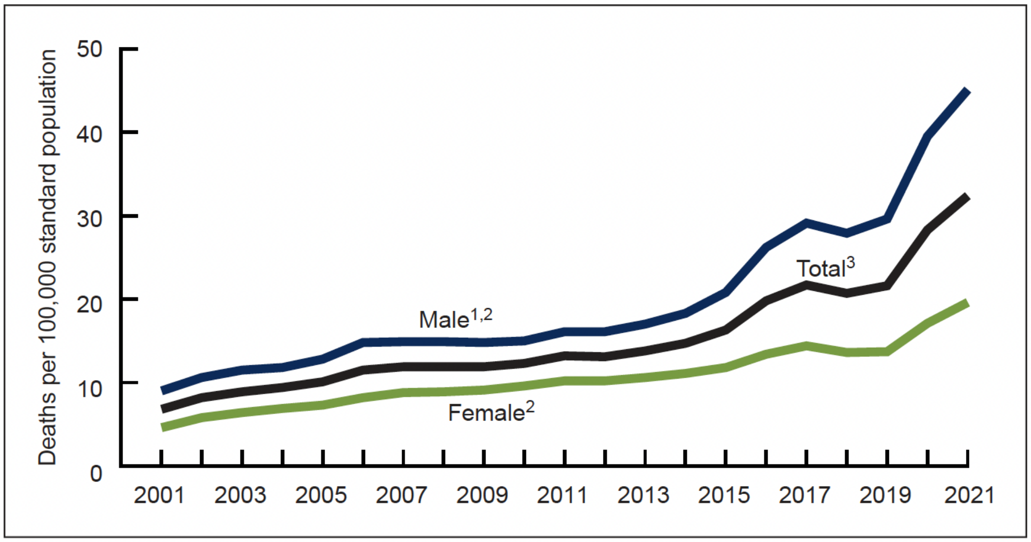

Figure 2.1. Age-adjusted rate of drug overdose deaths, by sex: United States, 2001–2021. Source: Spencer et al. (2022).

Illicit drugs also have a significant economic cost on the country. The U.S. Department of Justice's National Drug Intelligence Center reports "in 2007, the cost of illicit drug use totaled more than $193 billion" (US Department of Justice 2011). The *Drug and Alcohol Dependence Journal* estimated the total cost for opioid use disorder and related overdoses to be more than $1 trillion in 2017 (Florence et al. 2021).

In addition to the deaths and economic costs, drugs impact many other aspects of society, including health, public safety, environment, productivity, and governance (United Nations: International Narcotics Control Board 2013). Some may be familiar with one federal response to drugs, called the Controlled Substance Act. If the title is unfamiliar, the act of categorizing drugs according to *schedules* "based upon the substance's medical use, potential for abuse, and safety or dependence liability" may be more recognizable (Drug Enforcement Agency 2023).

2.1.1 U.S. Response to the Drug Problem

Other government responses include enforcing strict penalties for possession, use, or distribution of drugs, as well as the formation of the Office of National Drug Control Policy, an agency in the Executive Branch that coordinates the nation's drug policy (The White

House 2023). While awareness of some U.S. domestic policies may be commonplace, efforts abroad tend to be lesser known.

Mexican TCOs command the wholesale distribution of cocaine within the U.S.; but with 91% of the cocaine in the U.S. market originating from Colombia, it is Colombian TCOs that are responsible for the production and supply. They work with Mexican, Central American, and Caribbean TCOs to smuggle multi-ton quantities of cocaine primarily via maritime routes in the EPAC and CARIB, depicted in Figure 2.2.

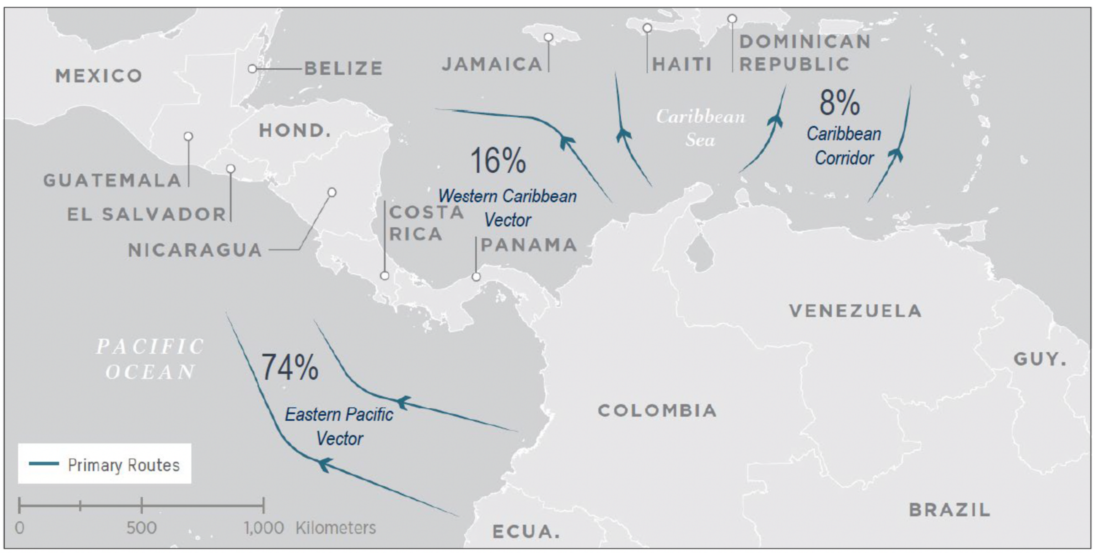

Figure 2.2. Cocaine Movement to Mexico, Central America, and the Caribbean, Calendar Year 2019. Source: Drug Enforcement Administration (2020).

In 1989, the National Defense Authorization Act directed the President "to designate a single lead agency for detection and monitoring of aerial and maritime transit of illegal drugs into the United States" (Library of Congress 2023). According to Government Accountability Office (GAO) analyst, Nathan Anderson, that same year the DOD created joint task forces to align military CD operations with local and federal law enforcement agencies; ultimately, these forces would become what is now U.S. SOUTHCOM's JIATF-S and U.S. INDO-PACOM's JIATF-W (Anderson 2019).

In a 2017 testimony to the Senate Armed Services Committee, then Admiral Kurt Tidd

(Commander, U.S. Southern Command) said that "On average, one metric ton of cocaine will kill 10 Americans every year and harm hundreds more," and that "last year, we watched almost 450 tons pass freely toward our country" (Selinger 2017). The inability to interdict 75% of known drug shipments is partly due to SOUTHCOM being the "least resourced major command" (US Senate Committee on Armed Services 2018). It is also due to TCOs recouping profits in excess of $300 billion, 10 times larger than all of the militaries in the region combined (Congress 2022). United States and partner nations remain outnumbered in people, assets, and resources for what amounts to a significant threat to national security.

2.2 JIATF-S

To fully understand the comparative analysis between SOM and COAST, we present an overview of the JIATF-S mission, metrics, and targeting process.

JIATF-S is U.S. SOUTHCOM's special task force for CD operations. Their mission is to "in conjunction with Partner Nations, leverage all-domain capabilities to target, detect and monitor illicit drug trafficking in the air and maritime domains, within the Joint Operating Area, facilitating interdiction and apprehension to reduce the flow of drugs and degrade and dismantle TCOs" (Joint Interagency Task Force South 2023a). JIATF-S AOR depicted in Figure 2.3, spans 42-million square miles (Munsing and Lamb 2011).

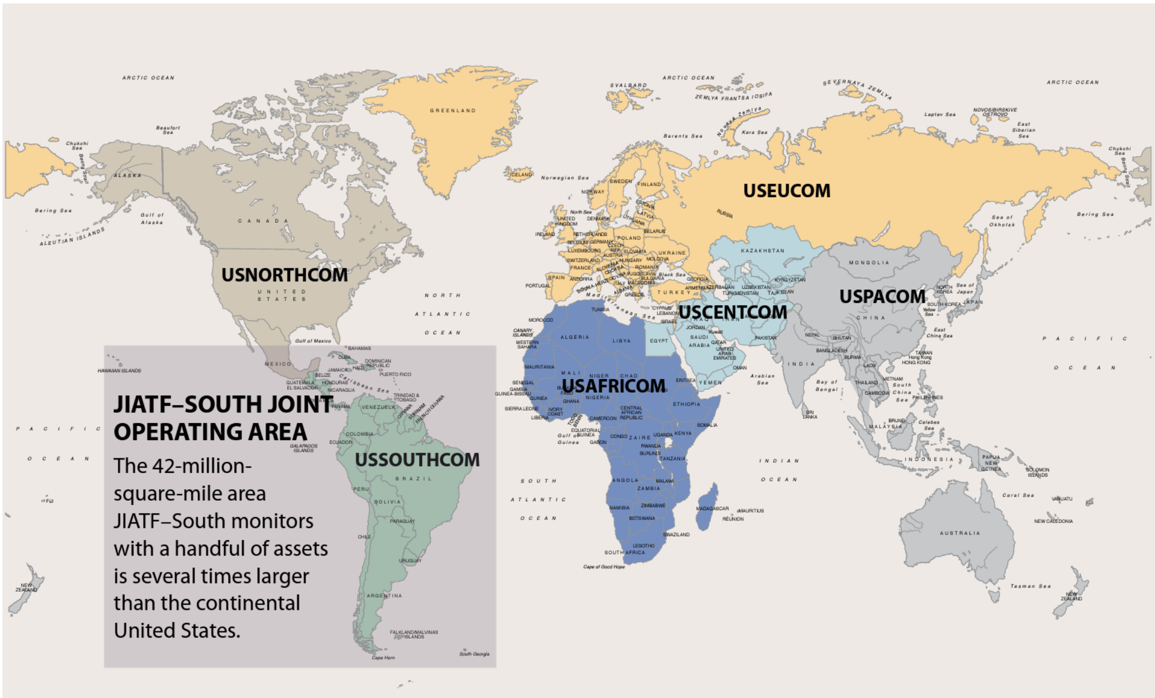

Figure 2.3. Map of Joint Interagency Task Force South's Geographical Joint Operating Area. Source: Munsing and Lamb (2011).

JIATF-S maintains focus on the interdiction of bulk cocaine smuggled via maritime vessels and are allocated ships and aircraft from DOD, DHS, and foreign partners to execute their mission (Anderson 2019). An annual report to the DOD Deputy Assistant Secretary of Defense for Counternarcotics and Global Threats captures their key performance measures of "(1) total maritime smuggling events, (2) targeted smuggling events, (3) detected smuggling events, and (4) seized or disrupted smuggling events" (Anderson 2019, p. 19).

The J3 Directorate of JIATF-S directs and controls current operations involving maritime and air assets of which they have tactical control (TACON) over (Joint Interagency Task Force South 2023b). The directorate consists of operational planners called targeteers who are responsible for developing and executing courses of action for surveillance aircraft. The day prior to a mission, they review all available data related to law enforcement intelligence, area weather, ship and aircraft operational and maintenance requirements, and a host of other information. This review supports determining where and to what smuggling event an asset is dedicated. On the day of the mission, targeteers hand asset assignment recommendations over to the battle watch captain to review, update as intelligence allows, and execute.

2.3 COAST

The U.S. Navy has been showing increasing interest in employing mixed-initiative frameworks for human-machine interfaces as well as becoming experts in dominating information for a dynamic battle-space. As such, NRL is developing an architecture for optimizing interdiction and surveillance asset management, named COAST (Zhang et al. 2020, p. 3,4). This decision support system addresses the demand for information fusion in its intent to support planners in determining which areas have the highest probability of smuggling activity (Zhang et al. 2020). Using planner-specified parameters, it provides a moving horizon estimation for managing surveillance and interdiction resources as well as suggest plans that can be analyzed and modified to support additional resource allocation needs (Zhang et al. 2020, p. 6).

JIATF-S's operational problem can be decomposed into two allocation subproblems, one for surveillance aircraft and one for interdiction ships. The surveillance aircraft problem, referred to as SAP and focused on in this thesis, begins with determining how best to employ a limited number of assets over a wide area to locate a target whose position is not well known—a concept addressed in the study of search theory (Zhang et al. 2020).

The basis for their resource allocation is a spatiotemporal probability surface, Probability of Activity (PoA), over numerous time periods (Zhang et al. 2020). This PoA, shown in Figure 2.4, constitutes the pertinent intelligence with respect to allocating assets and consists of "meteorology and oceanography information with actionable intelligence with regard to uncertain smuggler departure point(s), departure times, waypoint(s), destination(s), and their behavior on the ocean" (Zhang et al. 2020). Numerically, the PoA is the joint probability of the random events that a target's case has trustworthy intelligence and that the target of that case exists at some location and time (Zhang et al. 2020). As such, this probabilistic number referring to the likelihood of a smuggler's presence is indexed by its position, time, and target case. The same probability surface and method for indexing will be used as input for SOM.

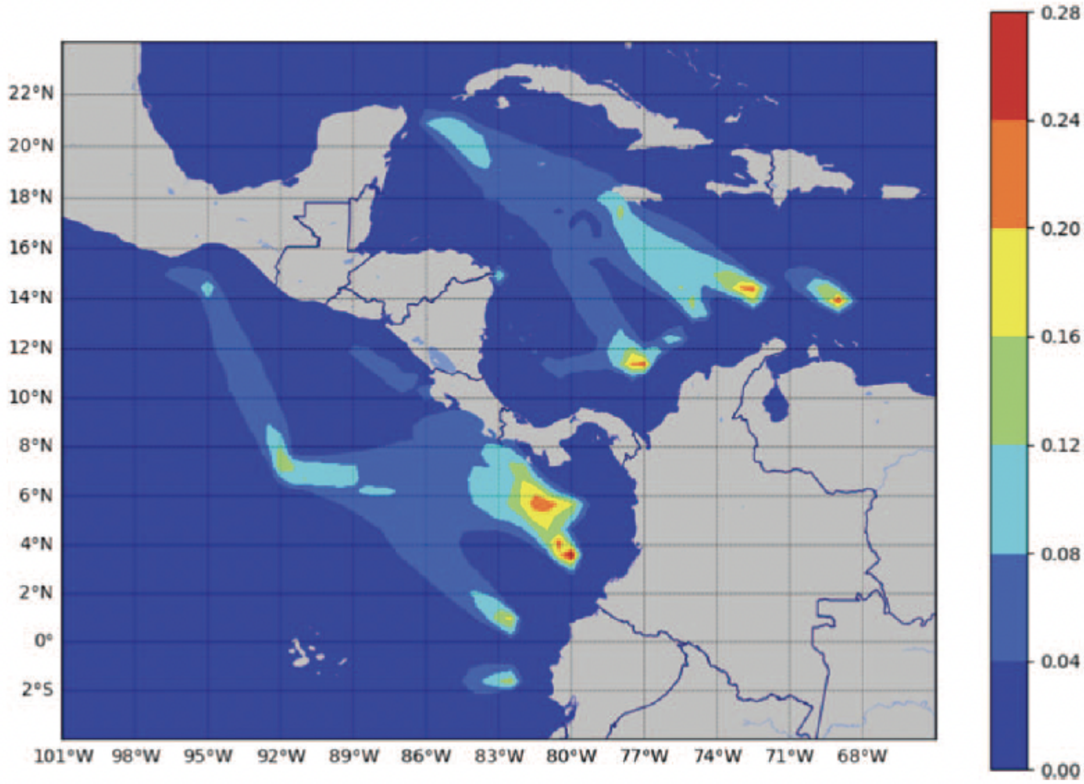

Figure 2.4. PoA surface PoA(q, k, j) summed over all k. Source: Zhang et al. (2020).

COAST calculates an optimal search effort by first ranking all positive PoA cells in descending order. Given an asset's available effort to search for the target, a critical probability is determined by averaging the difference between subsequent PoA cells and that effort available. The number of cells searched is reduced by only searching cells with a PoA greater than this critical probability.

COAST also calculates a probability of successful detection "which is the product of the PoA surface and the [probability of detection]," a lower bound probability for the searcher (Zhang et al. 2020). This probability of detection is provided by a basic random search formula and uses predetermined asset parameters (e.g., sweep width, search speed).

Several algorithms for allocating maritime surveillance assets are developed for performance comparisons. An exhaustive branch-and-cut method enumerates all feasible combinations.

Two greedy branch-and-cut algorithms generate a successful probability of detection based asset schedule. Two multi-step lookahead approximate dynamic programming algorithms acquire approximate asset assignments, differing only in how they compute asset allocation. All of these algorithms employ a heuristic to solve the nonlinear problem of allocating assets and thus provides an approximation. We contrast this approximation against SOM in the following chapters.

CHAPTER 3:
Model

The operational planner's desire is to be able to task a searcher to visit all cells in a search area, maximizing the chance of detecting targets. This is unattainable as the magnitude of the search area is too large in relation to the area a searcher can cover, given their limited flight duration. Instead, a planner must choose which cells a searcher should visit and at what time that search should commence.

In this section, we formulate the mixed-integer optimization model SOM for allocating cells for a searcher to look into. We describe initial processing efforts, how they feed into model development, and post-processing requirements to setup for model evaluation.

3.1 SOM Formulation

A feature of SOM is its handling of searchable space. We constrain the set of cells a searcher can occupy based on where it last was and where it will be next. This attribute represents the fact that a searcher's path over ground is continuous and thus the searchable space must be connected across time periods. The set of time T, which consists of time periods t, is provided by COAST or assumed to be the duration of the scenario. SOM takes the following form.

Indices and Sets

$c, c' \in C$	Cells ($\sim 7,000$)
$t \in T$	Time periods (~ 72)
$k \in K$	Search assets (~ 2)
$t \in T_k$	Time periods searcher k is not available
$g \in G$	Target cases (~ 9)
$N(c)$	Set of cells adjacent to c

Data

$p^g_{c,t}$	Probability that target g in cell c at time t
$q^k_{c,t}$	Probability that searcher k detects a target in cell c at time t given the target is in cell c at time t

Decision Variables

$X^k_{c,t}$	1 if searcher k in cell c at time t, 0 otherwise

Objective Function

$$\text{maximize} \quad \sum_{g\in G}\sum_{k\in K}\sum_{t\in T}\sum_{c\in C} p^g_{c,t}\cdot X^k_{c,t}\cdot q^k_{c,t} \tag{3.1}$$

Constraints

$$\text{s.t.} \quad \sum_{c'\in N(c)} X^k_{c',t-1} \geq X^k_{c,t} \qquad \forall c\in C, \forall t\in T\setminus\{1\}, \forall k\in K \tag{3.2}$$

$$\sum_{c\in C} X^k_{c,t} \leq 1 \qquad \forall t\in T, \forall k\in K \tag{3.3}$$

$$\sum_{k\in K} X^k_{c,t} \leq 1 \qquad \forall c\in C, \forall t\in T \tag{3.4}$$

$$X^k_{c,t} = 0 \qquad \forall c\in C, \forall t\in T_k, \forall k\in K \tag{3.5}$$

3.1.1 Discussion

The objective function seeks to maximize the expected number of detections and is a linear function of three terms. The first term is a parameter that indicates the probability of a smuggling event. It is produced by a PoA map that integrates multiple sources of information. The PoA map is also used by COAST. The second term in the objective function is the decision variable and represents which cells should be searched and which should be avoided. The last term is a parameter calculated using the random search formula

$$\text{Probability of Detection} = 1 - e^{-vwt/A}.$$

It is calculated using a homogeneous searcher's sensor (e.g., P-3C APS-137 radar), whose sweep width w varies based on a case's target type (e.g., merchant vessel, fishing vessel). The other parameters remain fixed across all cases. The velocity v of the searcher is 150 knots. The time t the searcher spends in a cell searching is 1 hour. The size of a search area A is 30x30 nautical miles (900 square miles).

We use constraint (3.2) to limit the number of cells a searcher can move across between time periods. Considering search speed v and the size of a search area A, the maximum number of cells a searcher can move across in a time period t is 5 cells ($\leq$ 150 [nm]). Each cell c, considered during optimization, uses the previous and next cell from the set of cells $N(c)$.

Anytime a searcher flies, it occupies some cell within the search area. Constraint (3.3) specifies that a searcher can be in at most one cell, across all cells and in every time period. In scenarios where there are multiple searchers, constraint (3.4) prevents searchers from occupying the same cell at the same time.

3.2 Data Collection and Processing

We use Pyomo, an open-source software package for optimizing models in Python, to solve SOM (Bynum et al. 2021). The following is a discussion of the data collected and processed for this optimization.

3.2.1 Data Collection

The input file shared by both COAST and SOM is a 10 MB .json file with over 800 lines. It contains 11 pairs of keys and their associated multi-nested values, all of which provide specifications for the scenario including details about the searcher, target and its PoA map.

Before the input file is processed by COAST, the default parameters are overwritten according to user defined arguments describing the number of cases and assets. Manipulating the input in this fashion allows us to generate different scenarios for COAST as well as SOM.

Once the COAST model runs, it creates a .csv file that the model uses as additional input representing the performance of COAST in this scenario.

3.2.2 Initial Data Processing

Two data structures are the focus of initial data processing. Since SOM seeks to maximize the expected probability of detection across all cells C for all time T, those sets are the focal point. The need for pre-processing is a result of the size of the decision space. The initial search area is composed of an 83x91 cell grid, containing 7,553 cells. Over a 72-hour time period, the model optimizes over more than 540,000 variables and constraints. Even though this linear problem is not difficult to solve, it is quite costly in terms of model solve time. Additionally, providing bounds and a more accurate evaluation for the solution drive the need to alter the set of times used during optimization.

Figure 3.1 shows target probability at times 12, 18, and 30. The amount of space the target probability takes up in each grid is very small. In contrast, the amount of space in the grid never occupied by the target is significant. Many of the cells c in the set of cells C can be removed without affecting decisions on optimizing searcher placement, which we refer to as filtering for non-activity. Any cell containing a zero probability of target activity for the entirety of that target's case (i.e., across 72 hours) is filtered for non-activity and thus not considered by SOM. Scenarios with multiple targets will require filtered cells to have non-activity across all target cases g for all time periods t. This one data-processing technique has the largest effect on the reduction of model solve time.

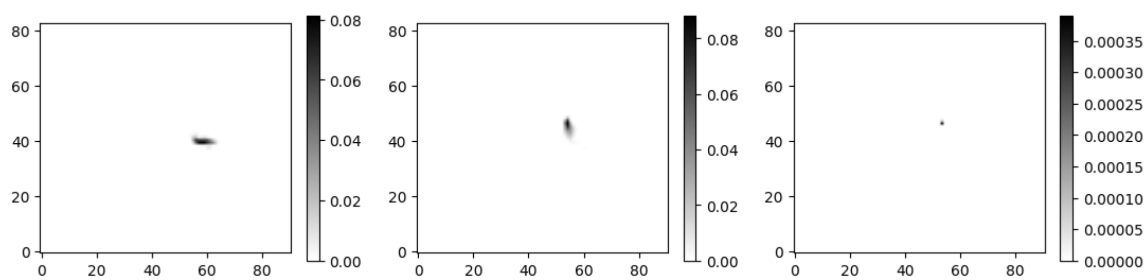

Figure 3.1. Example Target Surface PoA at Hours 12, 18, and 30.

Towards the end of this research, the desire arose to create three versions of SOM, differentiating only by the amount of searcher scheduled flight time. This provides an upper and lower bound for expected detections, as well as an optimal solution. The model acting as an upper bound, called SOM72, represents searchers scheduled to fly for 72 hours, the entirety of the scenario. SOM72 produces a number of expected detections that will never be equalled or exceeded by COAST or any of the remaining models created.

The other models were specifically dependent on the flight time output from COAST. That time was used to generate two sets of time T for each model. The first of which, referred to as SOM10, uses the starting flight time by COAST for a 10-on, 14-off flight profile. That is, the searcher would fly for 10 hours and then be unavailable for another 14 hours, repeating the cycle until the end of the scenario. SOM10 would potentially act as a lower bound for scenarios with multiple targets and multiple searchers.

The last model is called SOMCst, referred to henceforth as SOM, uses the same set of flight times produced by COAST. SOM differs only in the cells it directs the searchers to fly in and is the preferred model to compare with COAST. Figure 3.2 shows the flight times for all of the models mentioned as well as COAST. The scenario here represents one target and one searcher.

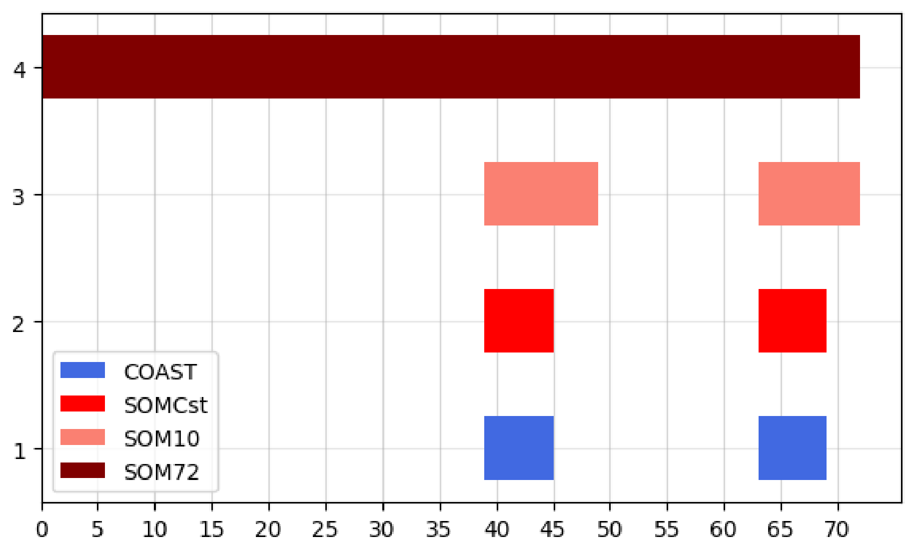

Figure 3.2. Basic Scenario Flight Schedule for All Models.

THIS PAGE INTENTIONALLY LEFT BLANK

CHAPTER 4: Results

In this section, we use a base case as an example to present our approach to solving SOM. We discuss both the computational and operational results SOM produces. The computational results address concerns about lengthy run times resulting from the number of variables and constraints passed to SOM. We identify the most effective solver from a list of solvers. Operational results focus on comparing SOM and COAST solutions for the number of expected detections. Other comparative metrics of interest are the number and position of cells each model allocates for search. The results from COAST were obtained using the surveillance optimization endpoint packaged with COAST alpha version 0.8a.

4.1 Example Scenario

Our base case involves one target operating in the western portion of the CARIB. The evolution of this target's probability of activity over time is depicted in Figure 4.1. This PoA map captures what is known and estimated about the target's location. We use the PoA map to visually assess if the solutions provided by COAST and SOM are reasonable. The cells on this map coinciding with the darker areas have higher probabilities of target activity and thus we would expect both models to allocate search efforts there. We would also expect the distribution of search cells to mirror the shape of the target's probabilistic distribution. In this case, we should see an even distribution of search cells in a short linear pattern oriented northwest to southeast. For this base case, and often in real-world scenarios, the number of assets available to search for the target is limited to one.

4.1.1 Interpretation of COAST Results

COAST provides details as to how the searcher should be employed. For each mission (term used to refer to a target-searcher pairing), COAST provides the mission start time, end time, recommended set of cells to search, and the amount of time to spend searching in each cell. We interpret this data in four different ways, using the cell search order and the amount of search time as conditions. Table 4.1 lists the names of these interpretations as well as the expected number of detections for each. The interpretation with the largest number of expected detections will be used for evaluation against SOM.

Table 4.1. Example COAST interpretations.

Interpretation	# of Expected Detections
Equal Spacing Greedy Order	0.6909
Equal Spacing Default Order	0.6909
COAST Spacing Greedy Order	0.7004
COAST Spacing Default Order	0.7004

The first two interpretations discard the amount of search time COAST allocates for each cell. Instead, we determine the amount of search time for a mission by dividing the total search time of that mission (i.e., mission start to end) by the number of cells allocated to be searched for that mission. This results in an equal amount of search time for each of the cells recommended by COAST for search.

The difference between the first two interpretations is how we determine the search order. The first interpretation, *Equal Spacing Greedy Order*, determines cell search order by first figuring out which cell, out of the set of searchable cells, has the highest probability of target presence at a time equal to mission start time. Once we determine that cell, we remove it from the set of searchable cells. We establish the next time period by advancing the initial time by the equally spaced search time recently determined. This greedy heuristic is in contrast to the second interpretation, *Equal Spacing Default Order*, where we determine search order according to the indexed order of the cells as provided by the COAST output.

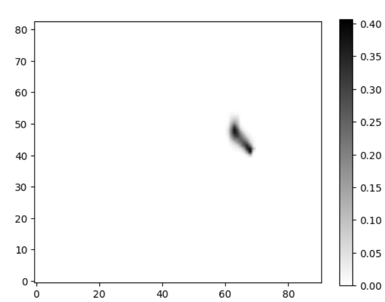

Figure 4.1. Example probability of target activity (PoA map).

In this example, the default search order is the same as the greedy heuristic.

In the last two interpretations in Table 4.1, we use the amount of search time allocated to each cell as dictated by the COAST output. These interpretations differ in how we assign the cell search order. *COAST Spacing Greedy Order* uses the greedy heuristic described above to find the cells with the highest probability of target activity at the current time. The last interpretation, *COAST Spacing Default Order*, uses the indexing order of the cells provided by COAST to dictate search sequence. As was mentioned previously, in this example, the default search order is the same as the greedy heuristic.

We calculate the number of expected detections for each interpretation in Table 4.1 similar to how we formulate our objective (3.1). We find the searcher probability of detection $q_{c,t'}$ by using the amount of search time t' allocated for a cell c. The probability of target activity $p_{c,t}$ in cell c is provided by the PoA map associated with time t. The sum of these products over all the searchable cells $\sum_{t \in T} \sum_{c \in C} p^g_{c,t} \cdot q^k_{c,t}$ yields the expected number of detections. In this example, *COAST Spacing Greedy Order* has the first largest value of 0.7004 and thus will be used for evaluation later.

4.1.2 Determination of SOM Results

Once we generate and interpret the COAST output, we use the mission's determined flight schedule to inform the set of times which SOM and SOM10 will use during optimization. SOM72 does not require any input from COAST as it optimizes over the duration of the entire scenario. SOM10 optimizes over a 10-on, 14-off flight profile, initiating at the mission start time, in this example 39 hours. SOM uses the exact same flight hours COAST produces for the mission. All the flight times used in this example are seen in Figure 4.2.

The resultant expected number of detections for all models is included in Table 4.2, as well as the maximum expected number of detections calculated for SOM72, SOM, and SOM10. We determine this maximum value by finding the cell c out of all cells C with the largest probability of target activity $p_{c,t}$ available for each time period t. This calculation is considered unconstrained as the distance between cells in adjacent time periods is unlimited. At time t_1, the determined cell could be in position (0,0), the bottom left portion of the grid. In the next time period, t_2, the determined cell could be in position (83,91), the top right portion of the grid, an equivalent 123 cells or 3,690 nm away. In contrast, the number

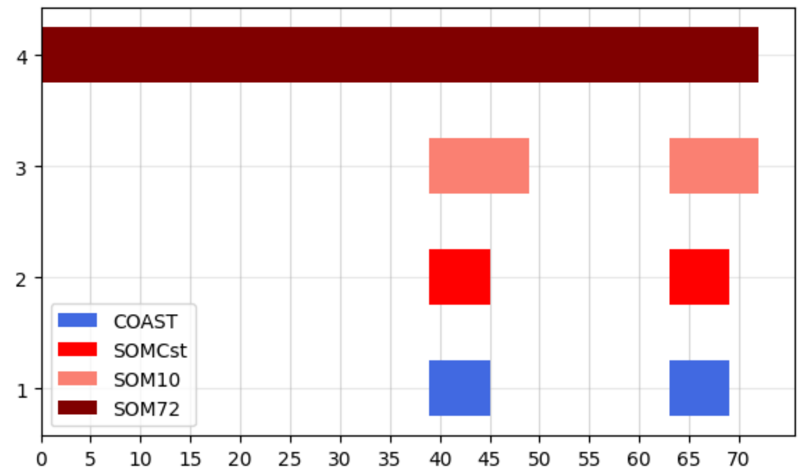

Figure 4.2. Example - Flight Schedule.

of expected detections for SOM72, SOM, and SOM10 is constrained to 5 cells or 150 nm between consecutive time periods.

Table 4.2. Example model performance results.

Model	# of Expected Detections	Maximum # of Expected Detections
SOM72	2.3487	2.3487
SOM	0.9091	0.9091
SOM10	1.4001	1.4001
COAST	0.7004	

Table 4.2 reveals no differences between the expected number of detections and their associated maximum values, which we would expect there to be. In this example, the target is moving at 10 kts, a distance of one-third of a cell, between consecutive time periods. Additionally, the PoA map in Figure 4.1 shows the target activity distributed along a short, linear fashion over the entire 72 hours with a probability of activity evenly distributed throughout. In contrast, the searcher is traveling at 150 kts and can move 5 cells between time periods.

The speed difference between searcher and target as well as the orientation of the target's movement and its maximum range make it easy for SOM to assign the searcher to cells coincident with the highest probability of target activity. In situations like this, SOM should produce a number of expected detections near or at the maximum value. We would expect, as the number of targets increases and/or target activity is distributed more widely, that SOM would be unable to allocate the searcher to cells coinciding with the maximum probability. It is in these conditions we would see large differences in the expected and maximum expected number of detections.

We also see in Table 4.2 that SOM72 acts as an upper bound to COAST, while SOM10 is not the lower bound we wanted. The large number of expected detections is attributed to SOM10 modeling a searcher flying for 19 hours, seven hours more than the flight duration of COAST. With a larger amount of flight time, SOM10 should have a higher number of expected detections. The model we are primarily interested in using to evaluate COAST, SOM, is 0.26 percent above the number of expected detections of COAST. More detail is provided in Figure 4.3, revealing that SOM achieved 0.9 expected detections while operating from two positions over the course of 12 hours. In comparison, COAST had their searcher look in 15 different cells for the same amount of time to obtain a slightly smaller number of expected detections, 0.7.

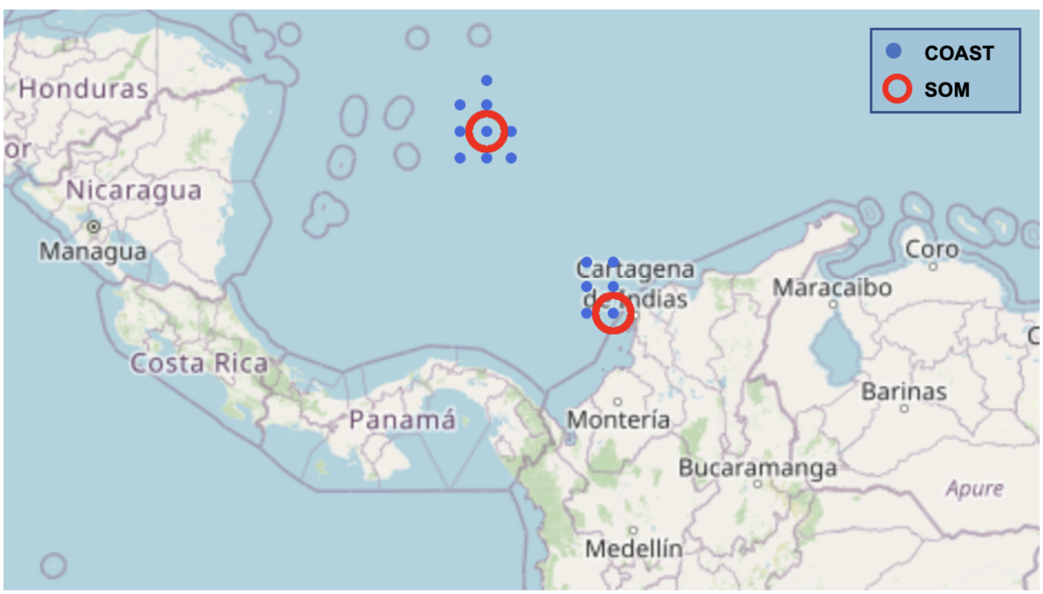

Figure 4.3. Example - Distribution of Search Cells.

The proximity of COAST and SOM values indicate that the expected number of detections estimated by COAST is near the expected number of detections exactly calculated by SOM. Comparisons like this validate the heuristic solutions produced by COAST. We apply the computational steps explained in this example to two experiments covering multiple scenarios for one and two targets.

4.2 Computational Results

The decision space SOM optimizes over includes an 83x91 cell grid for each hour in a target's case. Over the 72 hours of a single target case, the decision space will grow to include hundreds of thousands of cells. Since model solve times scale with the number of variables and constraints it optimizes over, it is important we reduce the decision space before we conduct operational experiments requiring batch runs of multiple scenarios. After the decision space has been reduced, the factor most affecting model solve time is the solver.

Using a laptop with 16 GB RAM and a 2 GHz Quad-Core processor running macOS Ventura on a 13-inch MacBook Pro, we examine the effects of increasing variables and constraints on CBC, CPLEX, and Gurobi solvers. We conduct two sets of tests consisting of four cases each. One set of tests represent a persistent, 72-hour flight profile. The other set of tests represent an intermittent flight profile similar to a 12-on, 12-off flight schedule. Each set consists of five, iteratively scaled tests used to identify the solver with the shortest run times. The five tests are:

1. One time period
2. One target case (i.e., 72 time periods) - unconstrained
3. One target case - constrained
4. All four target cases - unconstrained
5. All cases - constrained

Whether or not a test is constrained refers to the implementation of our constraint (3.2), referred to as the neighborhood constraint. This limits the searcher's range of movement between time periods. Unconstrained cases do not have the neighborhood constraint, allowing the searcher to go anywhere within the search area, simplifying computation greatly.

Results in Tables 4.3 and 4.4 show similar performances between all solvers for both persistent and intermittent flight profiles when the optimization is unconstrained. Once the neighborhood constraint is applied, limiting searcher movement to five cells between time periods, CBC performance reduces significantly compared to the other solvers.

Table 4.3. Runtime summary for persistent flight profile.

	Scenario	Variables	Constraints	CBC	CPLEX	Gurobi
Unconstrained	1 period	747	1	0.2	0.1	0.4
	1 case	53784	72	9.3	8.5	7.2
	4 cases	215136	288	26.6	24.3	22.5
Constrained	1 case	53784	53856	251.3	126.8	150.8
	4 cases	215136	215424	7633.9	134.7	172.3

Table 4.4. Runtime summary for intermittent flight profile.

	Scenario	Variables	Constraints	CBC	CPLEX	Gurobi
Unconstrained	1 period	747	1	0.2	0.2	0.4
	1 case	$\leq$ 26,892	$\leq$ 36	4.6	4.8	3.4
	4 cases	$\leq$ 107,568	$\leq$ 144	11.6	12.2	11.9
Constrained	1 case	$\leq$ 26,892	$\leq$ 26,928	104.9	63.5	67.7
	4 cases	$\leq$ 107,568	$\leq$ 107,712	112.8	73.8	78.9

In the persistent flight profile constrained test with one case, CBC run time is approximately twice as long as the other solvers. When the number of tests increases to four cases, CBC computation time grows to more than 40-times the other solvers. The performance between CPLEX and Gurobi is relatively the same across all tests and flight profiles. We will use CPLEX as the solver for SOM.

4.3 Operational Results

The last section of this chapter consists of two experiments. In the experiment 1, we evaluate the quality of a COAST solution under the conditions of one target and one searcher.

Experiment 2 uses two targets and one searcher. In order to motivate these experiments, we describe a simulated setting developed to be representative of real-world issues encountered by planners. Table 4.5 includes target characteristics for this simulation. Figure 4.4 depicts the expected routes for the targets.

Table 4.5. Smuggler details for all cases.

Case	CASE ID	Vessel Type	Speed (kts)	Payload (kg)	Departure Uncertainty (hours)
1	GF1	GO FAST	10	1000	72
2	SP1	SPSS[a]	10	5000	72
3	GF2	GO FAST	10	1500	72
4	MV1	MV[b]	10	2000	72
5	GF3	GO FAST	10	1000	72
6	GF4	GO FAST	10	1000	72
7	SP2	SPSS[a]	10	2500	72
8	SP3	SPSS[a]	10	5000	72
9	GF5	GO FAST	10	2000	72

[a]Self-propelled semisubmersible
[b]Merchant vessel

There are five P-3C aircraft available for supporting counter-drug search and detect missions. Two are deployed out of Daniel Oduber Quirós International Airport, Costa Rica. The remaining three are individually deployed out of Tocumen International Airport, Panama; Pista de Aterrizaje Base Aérea San Isidro, Dominican Republic; and El Salvador International Airport, El Salvador. Each can provide an on-station search speed (V) of 150 kts resulting in an endurance of 10 hrs (T). Maintenance efforts and crew rest requirements restrict consecutive flights of one aircraft to no less than 14 hours. Mission specifics require support over a 72-hour period in search of six targets of interest operating throughout the East Pacific and Western Caribbean. The expected sweep width (W) against all targets is 15 nm.

The first target (GF1) is a go-fast boat (GO FAST)—a small, stealthy, high-speed vessel

Figure 4.4. Smuggler Routes for Cases. Source: Zhang et al. (2020).

used by smugglers to evade detection and if necessary, out-run interdiction. It is assessed to depart Arboletes, Colombia, around 0044Z (0544 local time) headed for Puerto Cabezas, Nicaragua. The intended route is along the east coast of Panama and Costa Rica at a speed of 10 kts, likely to evade detection and blend in with maritime traffic. The expected payload is 1000 kg of cocaine.

The second target (SP1) is a self-propelled semi-submersible (SPSS)—a custom built craft almost invisible to radar. It has the same destination, departure location, and departure time as GF1, with the only difference being the direct route it is taking, likely attributable to its stealth. It is expected to be traveling at 10 kts, carrying a 5000 kg load of cocaine.

The third target (GF2) is a GO FAST assessed to be departing Cabo de La Vela, Colombia, in the morning, carrying 1500 kg of cocaine, destined for Tulum, Mexico. It is expected to take a direct route, traveling at 10 kts.

The fourth target (MV1) is a merchant vessel (MV), expected to depart Cartagena, Colombia, in the morning with 2000 kg of cocaine. It is assessed that it will employ some deception in what looks to be a route to Jamaica. Once within visual sight of Jamaica, it will likely change course towards its true destination, Cusuna, Honduras. Expected speed is 10 kts.

The fifth target (GF3) is a GO FAST also departing Cartagena, Colombia, in the morning. It is assessed to be headed for Tulum, Mexico, with 1000 kg of cocaine. The route will likely be direct and at a speed of 10 kts.

The sixth target (GF4) is a GO FAST departing Valdez, Ecuador, bound for Port Chiapas, Mexico, carrying 1000 kg of cocaine. The uncertainty for departure of all these targets are 72 hours.

We calculate the expected number of detections a searcher will have against a target and compare this value between SOM and COAST. We will not use the difference between expected detections because this value alone does not communicate proximity well. To account for how close COAST is to SOM, and thus assess the quality of COAST's solution, we divide their absolute difference by their average, as in

$$\% \text{ Difference} = \frac{\text{SOM} - \text{COAST}}{\frac{\text{SOM}+\text{COAST}}{2}}.$$

Our metric for evaluating COAST will be *percent difference*, as this determines how far off the approximate COAST solution is from the optimal solution calculated by SOM.

4.3.1 Experiment 1: One Searcher vs. One Target

To evaluate the quality of COAST solutions, we select the first six cases from Table 4.5 to represent targets in our single-target, single-searcher experiment. The number of expected detections we calculate for each model in scenario 1 (GF1) are listed in Table 4.6. We note that the expected number of detections can exceed the number of targets because each target might be detected multiple times throughout a scenario.

Table 4.6. Exp 1. Scenario 1 (GF1) model performance results.

Model	# of Expected Detections	Maximum # of Expected Detections
SOM72	1.1355	1.1355
SOM	0.3214	0.3214
SOM10	0.6949	0.6949
COAST	0.3326	

The percent difference for scenario 1 is

$$\%\text{ Difference} = \frac{|0.3214 - 0.3326|}{\frac{0.3214+0.3326}{2}} = 3.4407\%.$$

While the value 3.4% is relatively small—indicating it is close to SOM's solution—the number of expected detections exceeds SOM's and requires discussing. The interpretation of COAST we select for evaluation, due to it possessing the highest number of expected detections, is *COAST Spacing Greedy Order*. Using Table 4.7 to compare how SOM and COAST represents the first hour of search reveals the difference in the number of looks. For a one hour snapshot, SOM employs looks as a binary decision, either the searcher looks in a cell or it does not. In contrast, COAST uses fractional looks.

Table 4.7. Exp 1. Scenario 1 overview of hour 7.

Time	CELL	POA	Duration (hrs)	POD	EXP
7	(39, 63)	0.1438	0.4656	0.4412	0.0634
7.4656	(39, 62)	0.1144	0.3705	0.3707	0.0424
7.836	(39, 64)	0.0783	0.2537	0.2717	0.0213
COAST Number of Expected Detections in hour 7					**0.12709**
7	(39, 63)	0.1438	1	0.7135	0.1026
SOM Number of Expected Detections in hour 7					**0.10256**

During the 7th hour of scenario 1, COAST allocates 0.46 hr in cell (39,63), 0.37 hr in cell (39,62), and the remainder of the hour in cell (39,64). The increased fidelity to task searchers down to the minute results in 0.1271 expected detections, 0.0245 more than SOM.

Figure 4.5 (left) shows the location of GF1 evolving over time as described by the PoA map. The L-shaped PoA has a maximum probability of activity less than 0.2 and when superimposed on the map in Figure 4.5 (right) is located just north of Panama. Solutions from COAST and SOM indeed recommend searching in that area as shown in the right-portion of the figure. The blue dots are the cells COAST recommends to search. The red circles are the cells SOM recommends to search. We see that COAST allocates 16 unique cells to be searched and SOM allocates four, two of which are unique cells.

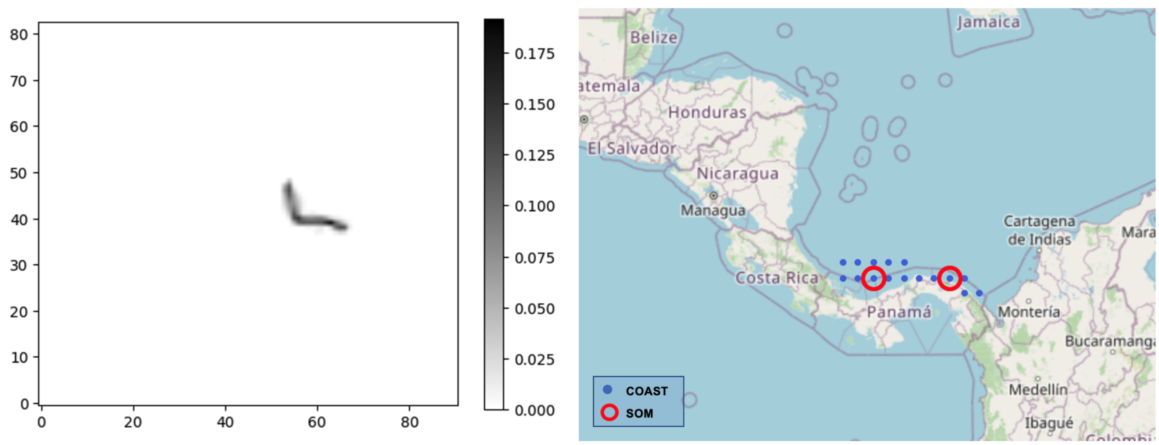

Figure 4.5. Scenario 1 target, GF1, PoA map (left). Geographic positions of COAST and SOM recommendations for cells to search (right).

In scenario 2, we see from comparing SP1's location and linear PoA in Figure 4.6 (left) to the map in the right-portion of the figure that both SOM and COAST provide valid search plans. Both models recommend searching along a northwest-southeast linear orientation between Nicaragua and Colombia. Also, both models produce solutions grouped near Colombia and in a linear form approaching Nicaragua. This cell placement coincides with the ends of SP1's PoA, where probability of target activity is highest, approximately 0.35. Figure 4.6 (right) shows SOM allocating eight cells to be searched, four of them unique and split between the two countries. COAST assigns 19 cells to be searched, all unique, with the majority grouped in a line towards Nicaragua. SOM exceeds COAST in the number of expected detections obtained by 0.0272, resulting in a percent difference of 5.7.

At this point in the experiment, there is no obvious reason why the number of expected detections for SOM would be greater than COAST. The only notable difference between scenarios is the ratio of the number of searched cells between models. In scenario 1, COAST searched four times as many cells than SOM. In this scenario, that ratio is reduced to approximately two.

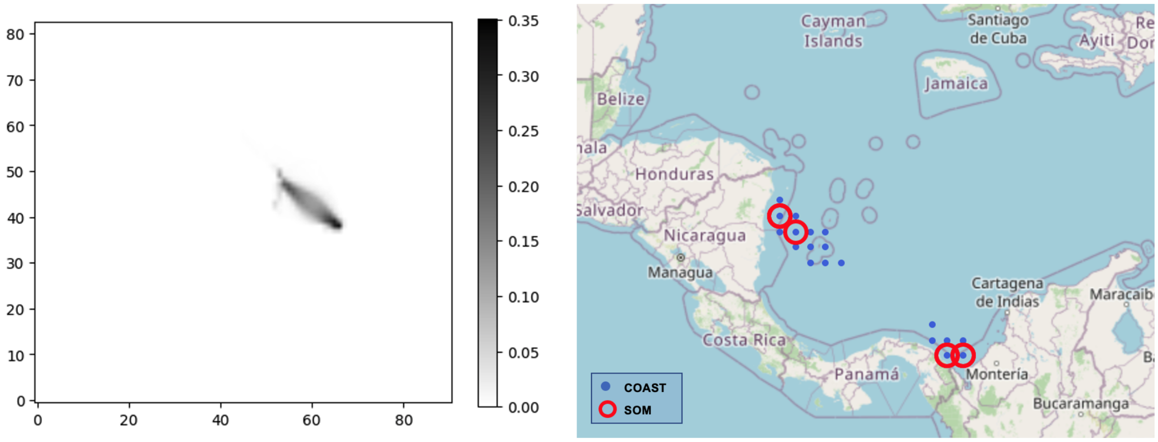

Figure 4.6. Scenario 2 target, SP1, PoA map (left). Geographic positions of COAST and SOM recommendations for cells to search (right).

In scenario 3, GF2 presents as a northwest-southeast oriented, linear PoA positioned near the top-right of the graph, as depicted in Figure 4.7 (left). A point representing a probability of activity greater than 0.4 appears just below the center of the linear portion of the PoA. GF2's PoA appears on the map in Figure 4.7 (right) as a line between Quintana Roo, Mexico (north of Belize) and the northern tip of Colombia. The PoA point of high probability positioned below the center of this line is located on the map near Nicaragua. Solutions from COAST in fact, recommends searching that area, allocating 22 cells, 15 unique, for search. SOM, on the other hand, produces solutions recommending search just along the southeast portion of the PoA, near Colombia, and at the PoA point of high probability, near Nicaragua. SOM recommends allocating 11 cells, two unique, for search.

In this scenario, SOM exceeds COAST in expected detections by 0.0802, resulting in a comparatively large difference of 56.3%, relative to the differences in scenarios 1 (3.4%) and 2 (5.7%). We find that the ratio of recommended searched cells between COAST and SOM is relatively low in scenario, 2. Using the ratios in the other two scenarios as data points, the value of this ratio does indeed correlate with SOM having a higher number of expected detections.

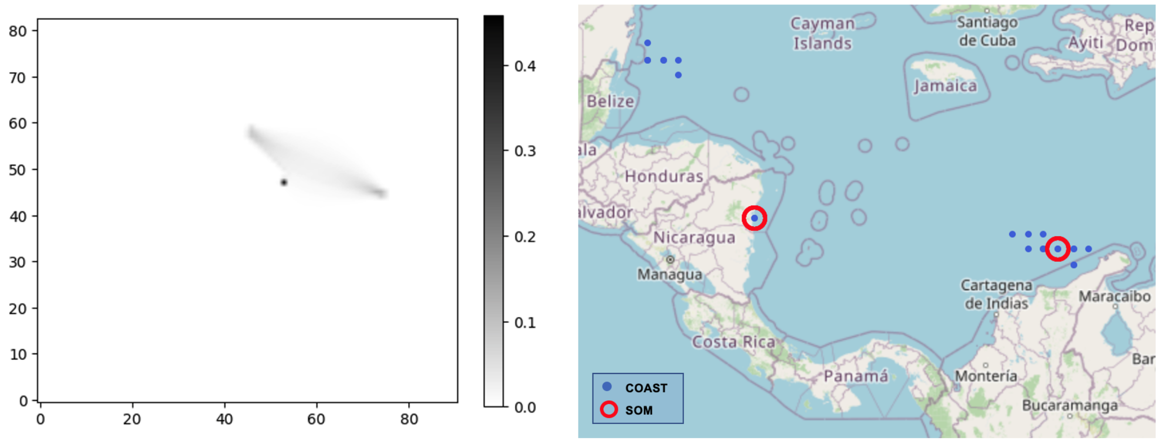

Figure 4.7. Scenario 3 target, GF2, PoA map (left). Geographic positions of COAST and SOM recommendations for cells to search (right).

For scenario 4, the PoA map describing MV1's evolution over time in Figure 4.8 (left) presents as a short, linear grouping oriented northwest-southeast. The short, linear PoA is positioned roughly between Jamaica and Colombia and has a maximum probability of activity of approximately 0.4.

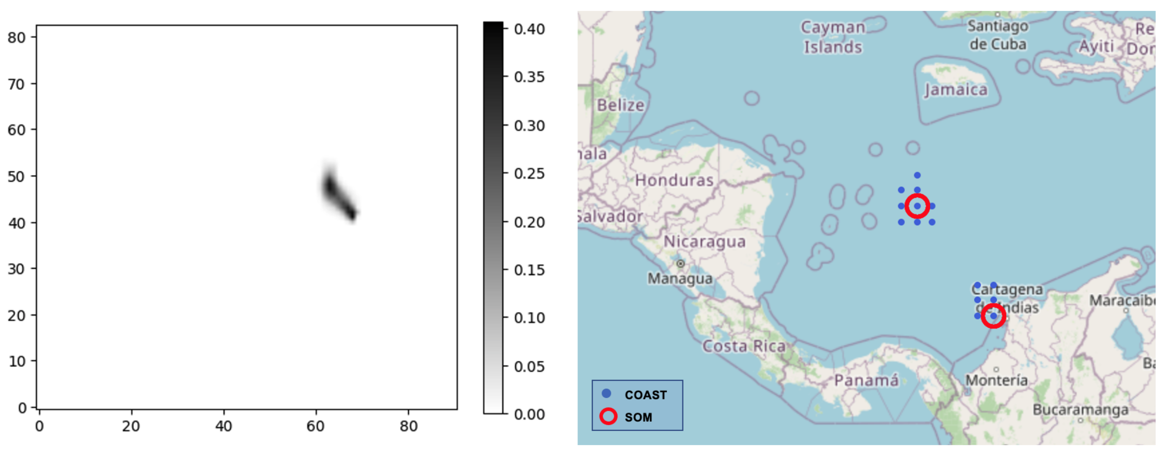

Figure 4.8. Scenario 4 target, MV1, PoA map (left). Geographic positions of COAST and SOM recommendations for cells to search (right).

Figure 4.8 (right) shows how solutions produced from COAST and SOM recommend allocating search cells in that area, concentrating efforts along the ends of the PoA where probability is highest. We see that COAST allocates 15 cells to be searched, all unique and evenly split between the ends of the PoA. Likewise, SOM evenly splits coverage between the ends of the PoA, allocating 12 cells to be searched, 2 of which are unique. SOM exceeds COAST in expected detections by 0.2087, resulting in a difference of 25.9%. Checking the ratio of searched cells, we find a low value of 1.25, correlating with the fact that SOM has a higher number of expected detections than COAST.

In scenario 5, the PoA map representing GF3, and depicted in Figure 4.9 (left), shows a linear evolution oriented northwest-southeast with a point of probability located below the center of the line. The linear-shaped PoA is located north of Panama, oriented between Mexico and Colombia. The point located below the center of PoA line is located near Nicaragua. This PoA appears similar to the PoA in scenario 3 except for the amounts of probability of target activity. The maximum probabilities in this scenario of approximately 0.25 are half the amount of probabilities in scenario 3, approximately 0.5.

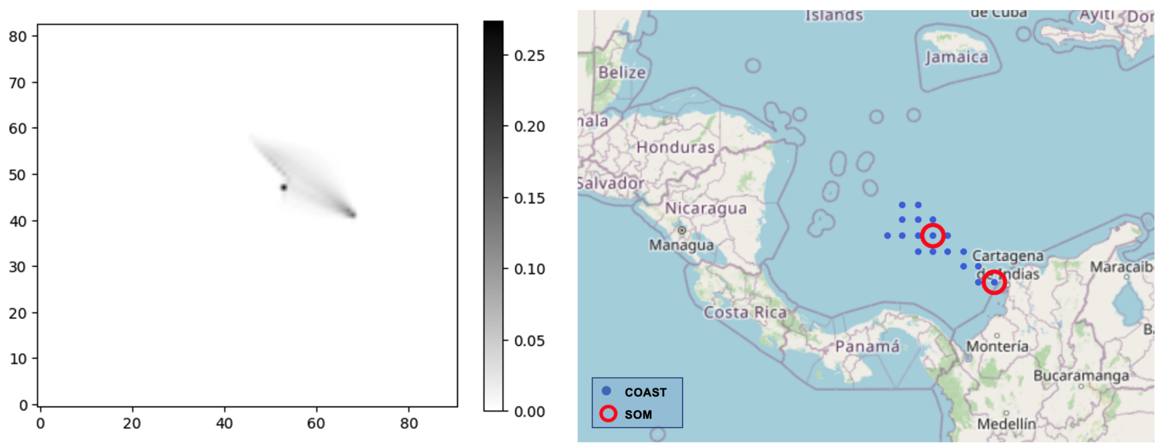

Figure 4.9. Scenario 5 target, GF3, PoA map (left). Geographic positions of COAST and SOM recommendations for cells to search (right).

We see the smaller probability in this scenario translate to a reduction in certainty, resulting in solutions from COAST and SOM recommending search just along the southeast potion of the PoA, extending northeast from Colombia. This is in contrast to what we saw in scenario 3, where the solutions from both models recommended search cells near the point below the center of the PoA, near Nicaragua. Figure 4.9 (right), shows COAST allocating 18 cells, all unique, to search while SOM recommends allocating four cells, two unique, for search. The ratio of searched cells is 4.5, comparatively high in relation to the ratios found in the other scenarios. This high ratio is correlated with COAST having a larger number of expected detections and indeed we find COAST exceeding SOM by 0.0337 expected detections for a 17.1% difference.

In scenario 6, we see the PoA representing GF4's evolution over time depicted in Figure 4.10 (left). We see that the maximum probability of activity is approximately 0.12 and the PoA is shaped as an inverted L pointing downwards. The down-facing, inverted L-shaped PoA is located south of Panama and along the west coast of Colombia. From Figure 4.10 (left), we see that solutions from COAST and SOM indeed recommend searching the area along the west coast of Colombia. As depicted, COAST recommends allocating for search 8 cells, all unique and directed southerly aligned with the foot of the PoA, along the west coast of Colombia. SOM recommends searching only two cells, one unique, positioned at the heal of the PoA. The ratio of searched cells in this scenario is 4, which we correlate to COAST having a larger number of expected detections and that is indeed the case. COAST exceeds SOM in the number of expected detections by 0.0266, resulting in a difference of 22.9%.

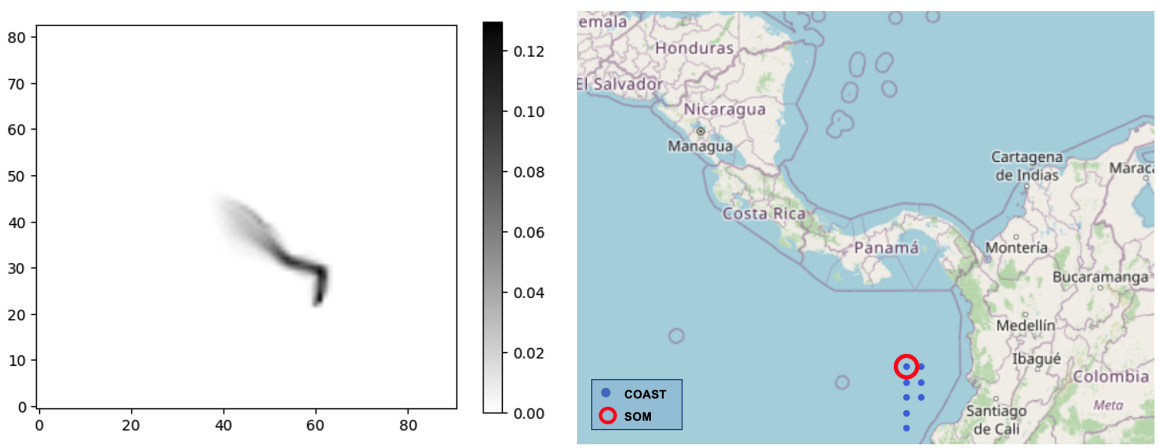

Figure 4.10. Scenario 6 target, GF4, PoA map (left). Geographic positions of COAST and SOM recommendations for cells to search (right).

The average difference in the number of expected detections of targets across all scenarios is 21.91% with a standard of deviation of 19.11%. This average includes instances where SOM and COAST have the most expected detections. The large standard of deviation relative to the mean indicates the observations are very spread out and thus, the average alone may not be a good evaluator of the quality of a COAST solution.

Out of the six scenarios, three include instances where the number of expected detections for COAST are less than SOM. Figure 4.11 shows a graph of these scenarios along with a line for the average percent difference and dashed lines representing ± 1 standard deviation. Two of the three scenarios fall within one standard deviation of the average percent difference. The remaining outlier, scenario 1, is approximatley 1% outside of one standard deviation of the mean.

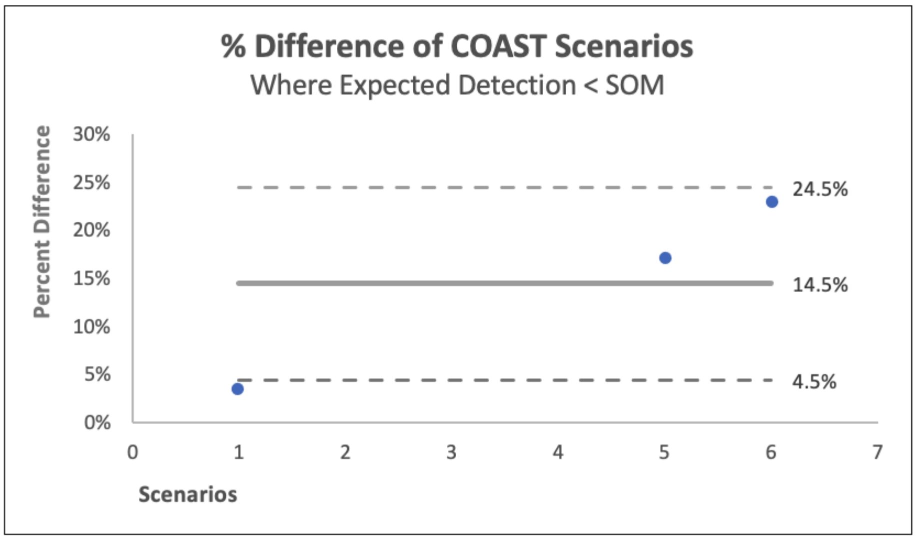

Figure 4.11. Graph of Percent Differences for Scenarios 1, 5, and 6.

4.3.2 Experiment 2: One Searcher vs. Two Targets

Experiment 1 represents a situation where the number of searchers were equal to the number of targets; however, this is not always the case in real life. Often, planners will have multiple targets and not enough search assets to employ, forcing a determination of priority. In this experiment, we present a set of scenarios where there are two targets for one searcher to find. All other conditions discussed in the previous section will be used here. Given there are six targets, the number of scenarios we examine in the conduct of the research total the non-repeating pairwise combination, $\binom{6}{2} = 15$. We present a discussion of six of those scenarios.

The models we employ in the example at the beginning of this chapter remain the same except for SOM10, now referred to as SOM06. The reason for this change is we now use six hours, vice 10, for the on-station period. This change accounts for a nominal two hour transit to and from the recommended search areas. This profile is more realistic than having a 10 hour on-station with no transit times as search areas are often located far away from detachment locations.

In this experiment, we include SOM06 in parts of our evaluation in order to compare the choices of allocated cell positions. With two targets, and the fact that SOM and COAST share the same flight profile, they may both fail to produce solutions for cell recommendations that solutions by SOM06 includes. We attribute this dynamic to the fact that SOM06 may have, in aggregate, a longer period on-station compared to COAST and SOM. SOM06 is formulated to continue flying throughout the duration of the scenario, initiating search at the same time as SOM and COAST. SOM and COAST, however, may not continue to fly throughout the duration of the scenario, thus impacting the number and location of cells each model allocates to be searched.

GF1 and SP1 make up the targets for scenario 1. The number of expected detections determined from each model are included in Table 4.8. We see that SOM exceeds COAST in the expected number of detections by 0.0014, resulting in a difference of 0.19%.

Table 4.8. Exp 2. Scenario 1 (GF1 and SP1) model performance results.

Model	# of Expected Detections	Maximum # of Expected Detections
SOM72	2.85092	3.09869
SOM	0.72715	0.72715
SOM06	1.07665	1.07665
COAST	0.72576	

Figure 4.12 (left) shows how the location of GF1 and SP1 evolves over time as described by the PoA map. The triangular-shaped PoA is located north of Costa Rica and Panama with a base extending linearly from Nicaragua to Colombia. The maximum probability of target activity for this PoA is approximately 0.5 and is found at the vertices of the triangular-shape, near Nicaragua, Panama, and Colombia. Solutions from COAST, SOM, and SOM06 indeed recommend searching in that area, as shown in the Figure 4.12 (right).

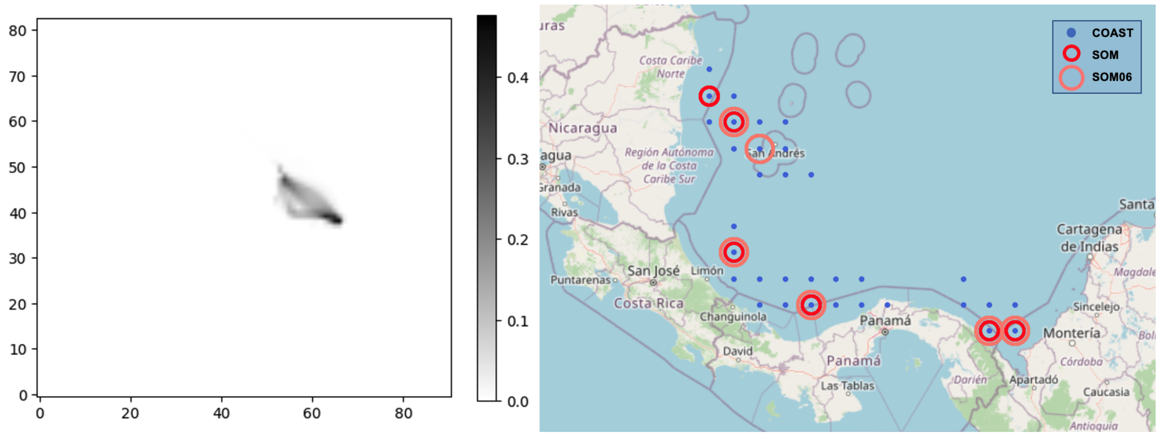

Figure 4.12. Scenario 1 targets, GF1 and SP1, PoA map (left). Geographic positions of COAST, SOM, and SOM06 recommendations for cells to search (right).

The recommended cells to be searched, as produced by COAST, are depicted as blue dots in Figure 4.12 (right). The red circles represent the solutions produced by SOM and the salmon colored, larger circles represent the solutions produced by SOM06. We see that SOM allocates 24 cells, six unique, to search while COAST allocates 33, all unique, resulting in a ratio of allocated search cells of 1.375. As in experiment 1, we find here that a small ratio of allocated search cells correlates with SOM having more expected detections than COAST.

As a point of comparison, SOM06 has 0.3495 more expected detections than SOM, which can be attributed to the additional 6 hours of flying represented by SOM06 as well as the larger number of cells allocated to be searched (36, six of which are unique).

The targets in scenario 2 are GF1 and GF2. From Table 4.9 we determine that the difference in the number of expected detections between SOM and COAST is 0.0308 with a resultant difference of 7.26%.

The evolution over time of the location of targets GF1 and GF2, as depicted in the PoA map in Figure 4.13 (left), describes a v-shape beneath a line oriented northwest to southeast. This shape outlines the coast of Nicaragua, Costa Rica, and Panama. Additionally, the PoA extends northwest, in a linear fashion positioned from Colombia towards Mexico.

Table 4.9. Exp 2. Scenario 2 (GF1 and GF2) model performance results.

Model	# of Expected Detections	Maximum # of Expected Detections
SOM72	1.938	2.2006
SOM	0.4392	0.4604
SOM06	0.6754	0.707
COAST	0.4084	

We find that the maximum probability of target activity, listed in the PoA map Figure 4.13 (left), is approximately 0.5 and appears at the northwest corner of the v-shaped PoA, near Nicaragua. We see less probability of activity along the remainder of the v-shaped PoA, extending out towards Panama. Even smaller probabilities are found along the linear-shaped PoA, extending northwest from Colombia.

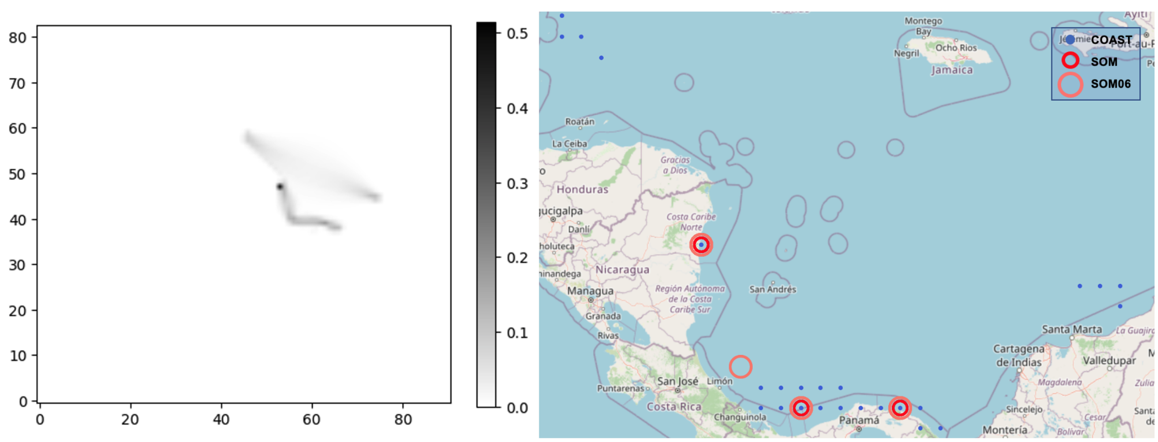

Figure 4.13. Scenario 2 targets, GF1 and GF2, PoA map (left). Geographic positions of COAST, SOM, and SOM06 recommendations for cells to search (right).

We see from Figure 4.13 (right) that, in fact, COAST, SOM, and SOM06 recommend searching near Nicaragua and along the Isthmus of Panama, coincident with the v-shaped PoA. SOM allocates 20 cells, three unique, to search in this area. SOM06, flying an additional 8 hours over SOM, allocates 36 cells, four unique, to search the same area. Only solutions produced by COAST recommend allocating cells to search along the ends of the linear-shaped PoA extending northwest from Colombia. COAST allocates about a third of its recommended cells to search along this line, with the remaining two-thirds of allocated cells to be positioned similarly as in the solutions produced by SOM and SOM06. Comparing the number of allocated cells to be searched by SOM and COAST, we see that SOM exceeding COAST in the number of expected detections is correlated with a low allocation ratio of 1.35.

SP1 and GF2 are the targets for scenario 3 and the expected number of detections obtained by all models conducting a search are included in Table 4.10. We find that the difference between the number of expected detections from SOM and COAST is 0.0278, resulting in a difference of 5.59%.

Table 4.10. Exp 2. Scenario 3 (SP1 and GF2) model performance results.

Model	# of Expected Detections	Maximum # of Expected Detections
SOM72	2.1218	3.0284
SOM	0.5106	0.6765
SOM06	0.7302	0.9743
COAST	0.4828	

The PoA map describing SP1 and GF2 location evolution over time, as depicted in 4.14 (left), is shaped as a pair of different length parallel lines located along the coast of Colombia and extending northwest. The shorter, linear-shaped PoA depicted on the bottom extends from the border of Panama and Colombia and proceeds towards Nicaragua. It has a maximum probability of target activity near 0.5. The longer, linear-shaped PoA depicted on the top extends from the northern tip of Colombia, towards Mexico. The probability of target activity in this PoA is much smaller compared to the linear-shaped PoA to the south.

Solutions from COAST, SOM, and SOM06, as shown in Figure 4.14 (right) provide recommendations for cells to search that coincide with these areas. We see that 24 cells, five of which are unique, are allocated by SOM. There is an even distribution of the number of cells recommended for search, split between both ends of the shorter line-shaped PoA, near Nicaragua and Panama, and the southeast tip of the longer, line-shaped PoA, near North Colombia.

We also see, in Figure 4.14 (right), COAST allocating 28 cells, all unique, in the same area. Likewise, SOM06 allocates 36 cells to be searched, seven unique, in that area. We find that the ratio of allocated cells between COAST and SOM is 1.17, correlating to what we see in Table 4.10, that SOM has a larger number of expected detections than COAST.

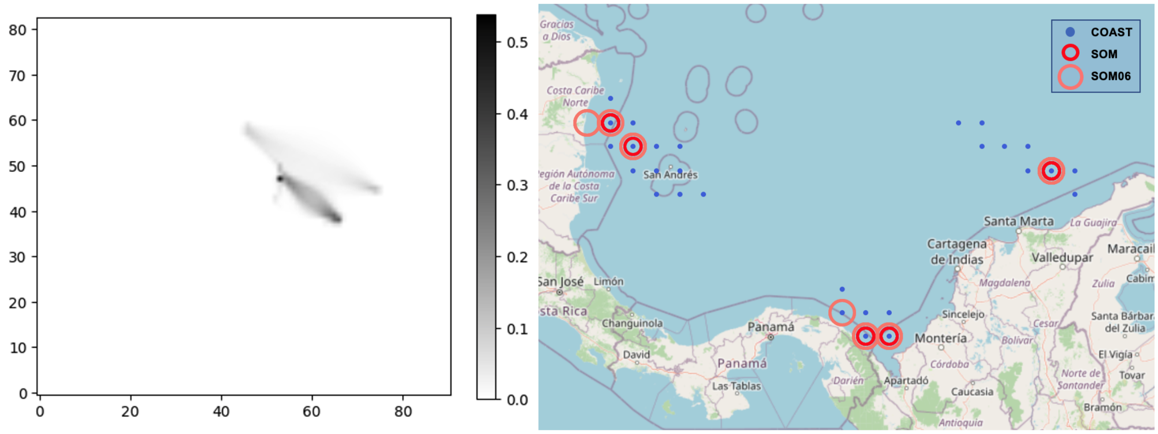

Figure 4.14. Scenario 3 targets, SP1 and GF2, PoA map (left). Geographic positions of COAST, SOM, and SOM06 recommendations for cells to search (right).

In scenario 4, we find a PoA map, pictured in Figure 4.15 (left), that describes SP1 and MV1 over time as a pair of different length parallel lines located along the coast of Colombia and extending northwest. The shorter, linear-shaped PoA, depicted in the left-portion of the figure on the top, extends from Colombia to just north of Panama. It has a maximum probability of target activity near 0.4. The longer, linear-shaped PoA depicted in the left-portion of the figure on the bottom, extends from the border of Panama and Colombia and proceeds northwest towards Nicaragua. It has a maximum probability of target activity near 0.4, but only along the ends of the PoA.

As pictured in Figure 4.15 (right), the solutions provided by COAST, SOM, and SOM06 all recommend searching along the border of Panama and Colombia, an area that coincides with the bottom of the longer, linear-shaped PoA. Only solutions produced by COAST recommend also searching along the top of this linear-shaped PoA, near Nicaragua. COAST recommends allocating 19 cells, all unique, to this search effort. In contrast, solutions produced by SOM and SOM06 recommend allocating additional search cells to areas coincident with the top end of the linear-shaped PoA depicted on top in the left-portion of the figure; areas located north of Panama and equidistant from Nicaragua and Colombia. SOM recommends allocating 16 cells to be searched, four of which are unique. The resulting ratio of allocated cells between COAST and SOM is 1.19, correlating with our findings that SOM exceeds COAST by 0.1606 expected detections for a difference of 29.6%. Only SOM06 recommends searching near Cartagena, Colombia. SOM06 models a searcher flying an additional 4 hours over SOM and COAST, allocating a total of 24 cells to be searched, six of them unique.

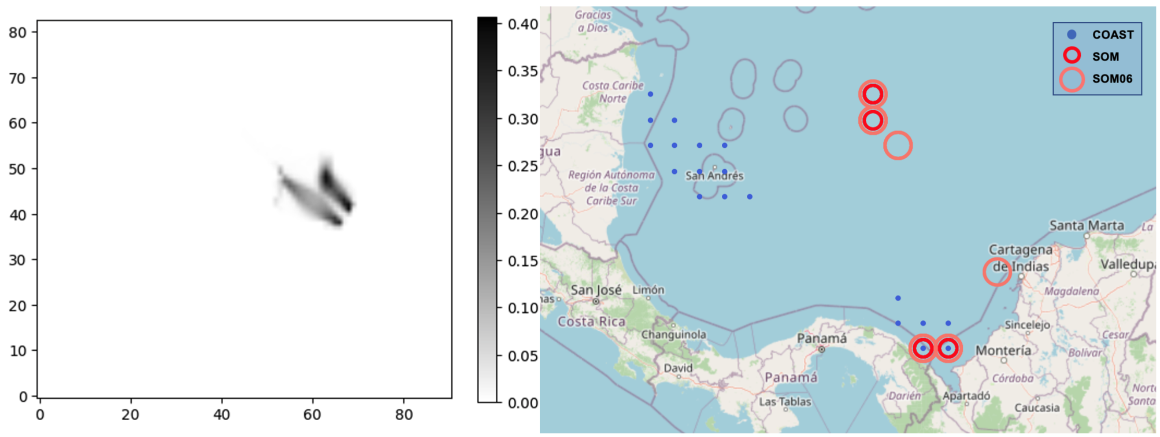

Figure 4.15. Scenario 4 targets, SP1 and MV1, PoA map (left). Geographic positions of COAST, SOM, and SOM06 recommendations for cells to search (right).

In scenario 5, Figure 4.16 (left) shows how the locations of GF2 and MV1 evolves over time as pictured by the PoA map. The triangle-shaped PoA has its base along the coast of Colombia and its vertex approaching Mexico. The maximum probability of target activity for the PoA is approximately 0.5 and can be found at a point in the PoA below the center of the triangle, located equidistant between Panama and Jamaica. Solutions from COAST, SOM, and SOM06 recommend searching in that area, as shown in right-portion of the figure. We see that COAST allocates 29 cells to be searched, all unique. SOM allocates 28 cells to be searched, four of which are unique. We find that the ratio of allocated cells to search is small, 1.03, which correlates with the fact that SOM has more expected detections than COAST, which is in fact what we see. The difference in the number of expected detections is 0.096. The difference between the models is 14.1%. SOM06 models a searcher flying an additional 4 hours over SOM and COAST, allocating a total of 36 cells to be searched, four of them unique.

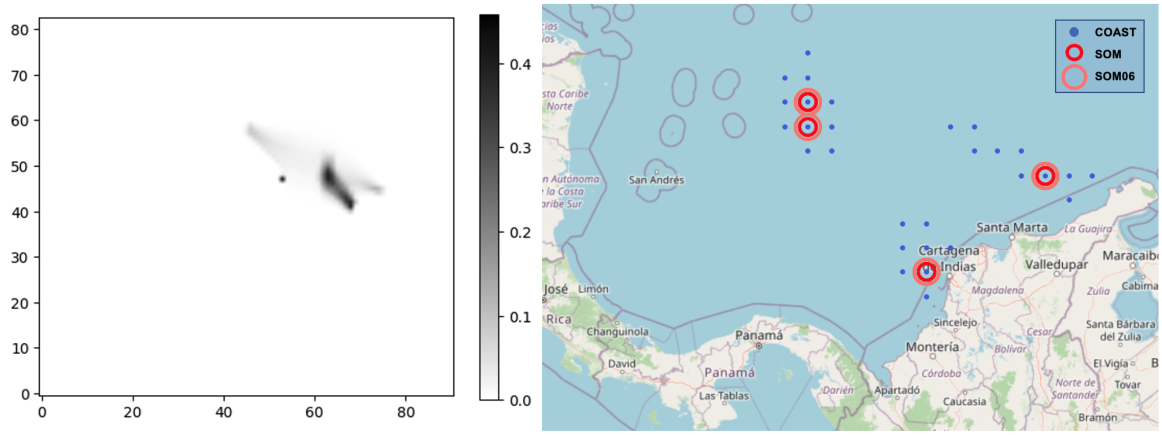

Figure 4.16. Scenario 5 targets, GF1 and MV1, PoA map (left). Geographic positions of COAST, SOM, and SOM06 recommendations for cells to search (right).

Figure 4.17 (left) depicts the PoA map that describes how targets GF3 and GF4 evolve over time. One linear-shaped PoA is oriented northwest-southeast, from Panama to Mexico, with a point of probability located below the center of the line, near Nicaragua. The other PoA, depicted on the bottom of the left-portion figure, is shaped as an inverted L pointing downward. The down-facing, inverted L-shaped PoA is located south of Panama and along the west coast of Colombia.

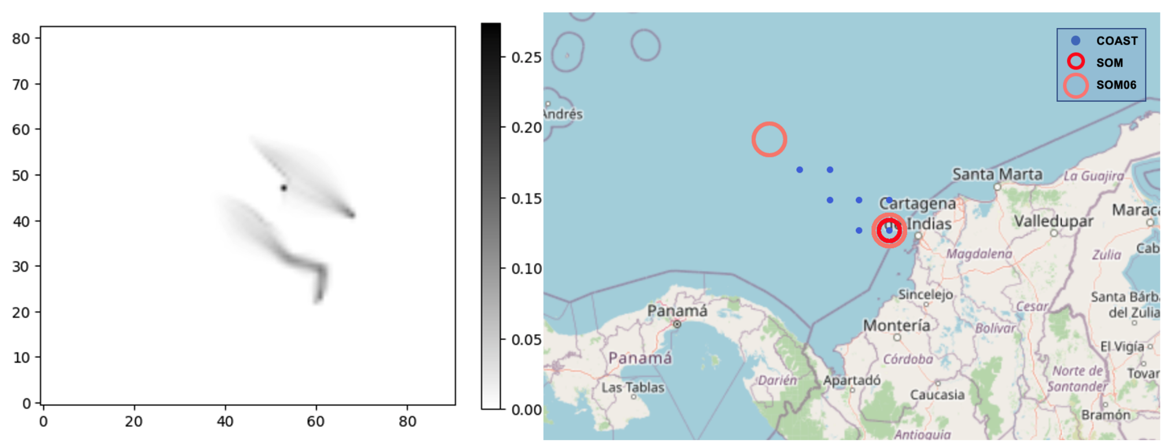

Figure 4.17. Scenario 6 targets, GF3 and GF4, PoA map (left). Geographic positions of COAST, SOM, and SOM06 recommendations for cells to search (right).

Solutions from COAST, SOM, and SOM06 recommend searching near Colombia, ignoring the portion of PoA located south of Panama. We see, from Figure 4.17 (right), that COAST recommends allocating seven cells to be searched, all unique, while SOM recommends allocating eight cells to be searched, one of which is unique. The resulting ratio between allocated cells to search is 0.87, correlating with SOM having a larger number of expected detections, which it has. SOM has 0.23 expected detections and COAST has 0.15 detections, resulting in a difference of 42.8%. SOM06 models a searcher flying an additional 2 hours over SOM and COAST, allocating a total of 12 cells to be searched, two of them unique.

Tables 4.11, 4.12, and 4.13 show the expected detections for all models and scenarios in experiment 2. The average difference across all 15 scenarios is 16.3% with a standard deviation of 13.5%. As with experiment 1, the average percent difference does not look like a metric by which to evaluate the quality of solutions produced by COAST. Instead, we will continue relying on comparisons made in specific scenarios.

Only scenarios 4, 5, and 12 provide examples where the number of expected detections for COAST exceeds SOM. The respective ratios of searched cells for those scenarios are 2.13, 2.67, and 1.75. In experiment 1, we saw a cell allocation ratio > 4 correlated with COAST exceeding SOM. In experiment 2, we see a cell allocation ratio ≥ 1.75 correlated with COAST having a relatively larger number of expected detections.

Table 4.11. Exp 2. Model performance summary (scenarios 1–5).

Scenario	1	2	3	4	5
SOM72	2.851	1.938	3.365	1.965	1.836
SOM	0.727	0.439	1.144	0.501	0.419
SOM06	1.077	0.675	0.816	0.759	0.730
COAST	0.726	0.408	1.023	0.546	0.460

Table 4.12. Exp 2. Model performance summary (scenarios 6–10).

Scenario	6	7	8	9	10
SOM72	2.122	2.966	2.474	2.067	2.495
SOM	0.511	0.623	0.507	0.495	0.731
SOM06	0.730	0.878	0.751	0.761	0.914
COAST	0.483	0.462	0.462	0.462	0.635

Table 4.13. Exp 2. Model performance summary (scenarios 10–15).

Scenario	11	12	13	14	15
SOM72	1.712	1.232	2.520	2.349	1.185
SOM	0.296	0.167	0.921	0.909	0.226
SOM06	0.424	0.395	0.921	0.909	0.316
COAST	0.195	0.176	0.700	0.700	0.147

4.3.3 Relation between Allocation Ratio and Expected Detections

We next explore the relationship of the ratio of allocated cells to a determination of SOM or COAST having a higher number of expected detections The ratio of cells allocated to a search is the independent variable, also referred to here as the predictor. The difference in the number of expected detections between SOM and COAST is the dependent variable, also referred to here as the response.

We investigate the statistical relationship between the variables by first graphing a scatter plot, depicted in Figure 4.18. COAST expected detections were subtracted from SOM's amount, resulting in negative values in situations where COAST exceeded SOM. Those points are colored in red on the graph. In the scenarios above, we saw there is a negative relationship between the variables. As the allocation ratio increases, the difference becomes more negative, indicating that COAST has more expected detections. Visually, the scatter plot confirms these observations, revealing a linear relationship. A trend line is plotted for reference.

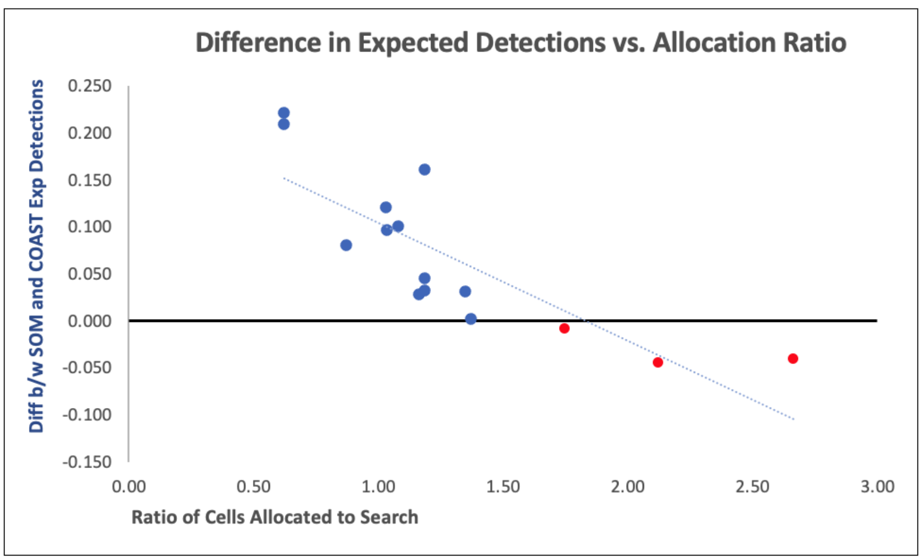

Figure 4.18. Graph of SOM and COAST Difference in Expected Detections.

We next conduct regression analysis, output shown in Figure 4.19, to model the relationship between the predictor and the response. The *Multiple R* value represents the correlation coefficient. The value of -0.8183, indicates strong negative correlation between the response and the predictor variable, as was seen in the observations and scatter plot.

Regression Statistics	
Multiple R	0.818354229
R Square	0.669703645
Adjusted R Square	0.644296233
Standard Error	0.322404789
Observations	15

ANOVA

	df	SS	MS	F	Significance F
Regression	1	2.739839994	2.739839994	26.35859355	0.000191946
Residual	13	1.351283021	0.103944848		
Total	14	4.091123016			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	1.650437033	0.109541763	15.06673797	1.30693E-09	1.413786443	1.887087624
Allocation Ratio	-5.334031257	1.038949503	-5.13406209	0.000191946	-7.578545198	-3.089517315

Figure 4.19. Regression Analysis of Allocation Ratio.

The percentage of total variation, as explained by the R^2 value of 0.6697, suggests that $\sim$ 67% of the response variable can be explained by the predictor. This goodness of fit is further confirmed by the *Significance F* value of 0.0002, suggesting the regression model as a whole is significant.

The p-value of 0.0002 indicates that the independent variable is statistically significant and thus a good predictor. In order to accept these findings, we must assure the four assumptions of regression are satisfied.

The linear relationship was shown in the scatter plot and confirmed by the correlation coefficient. All observations are independent from one another as they are each based on separate scenarios involving a model's determination of how best to allocate an asset to search for the scenario-specific targets. Figure 4.20 displays a graph of the predictor variable's residuals. Here, we see the variance of residuals is generally the same above the line as it is below. Furthermore, there are no discerning patterns, all of which indicating homoscedasticity.

Lastly, a visual assessment of both the P-P plot and Q-Q plot in Figure 4.21 shows images resembling straight lines suggesting no evidence to discount normality. Furthermore, a calculation for the Anderson-Darling Normality Test provides a p-value of 0.5629, exceeding

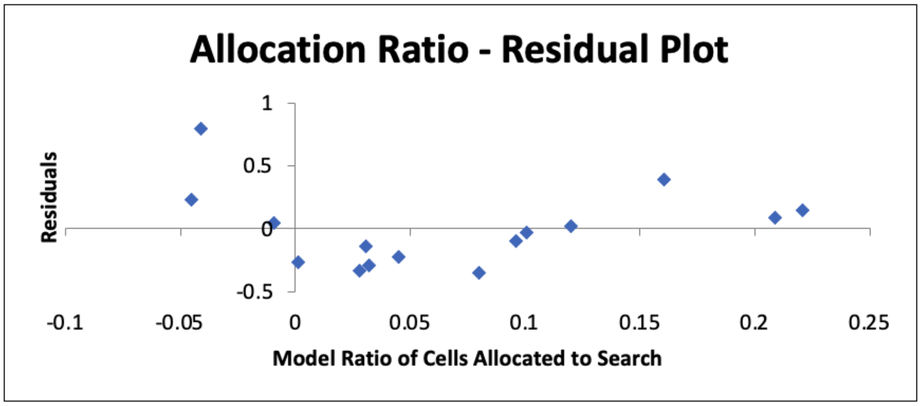

Figure 4.20. Graph of Residuals.

the critical value of 0.05. This also indicates there is no evidence to suggest non-normality.

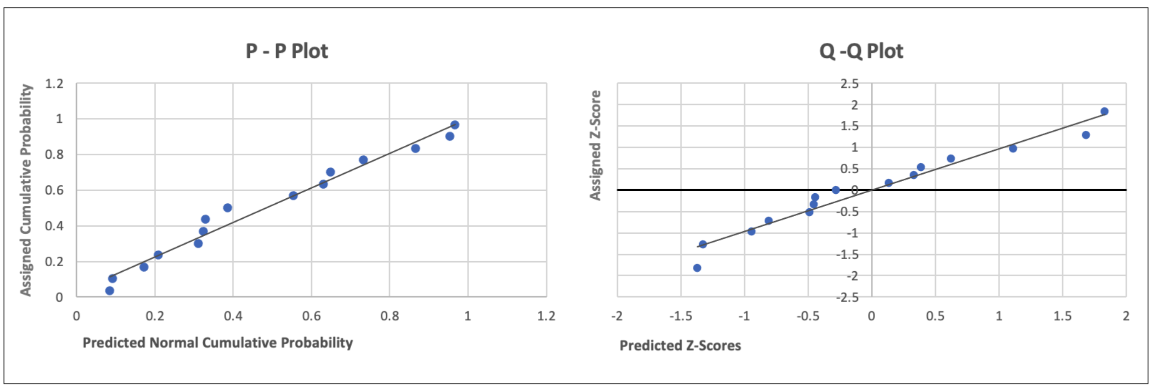

Figure 4.21. Graphs of P-P and Q-Q Plots.

It has been shown that all assumptions for regression analysis have been satisfied and that the ratio of allocated cells to search is a good predictor for whether or not COAST or SOM has a higher number of expected detections.

THIS PAGE INTENTIONALLY LEFT BLANK

CHAPTER 5: Conclusions

There is an on-going effort by NRL to develop a decision support system, COAST, to aid JIATF-S in their effort to optimally allocate resources for the purposes of stopping the flow of drugs to the United States. This research supports allocation problem by evaluating a proposed solution, specifically COAST's optimization model.

We present SOM as a method for evaluating complex, heuristic models, such as COAST. We show that formulating a mixed-integer linear program allows us to solve one aspect of SAP to optimality, specifically the expected number of detections. Using this value, we are able to validate the solution COAST derives for the same metric.

We conduct two experiments that replicate conditions found in real-world planning situations. Experiment 1 consists of six scenarios, each pairing one searcher against one target. Experiment 2 examines 15 scenarios where one searcher was tasked to find two targets. The average percent difference in the expected number of targets detected (21.9% in experiment 1 and 16.3% in experiment 2) calculated across all respective scenarios had a relatively high standard of deviation (19.1%, 13.5%). The large spread (greater than 80% of the mean value) suggests that the mean itself may not be useful in assessing the quality of model solution. Instead, validation would rely on the percent difference calculated in that specific scenario.

For 10 out of the 15 scenarios in experiment 2, COAST's heuristic solutions were within 15% of the solutions SOM solved to optimality. In contrast, experiment 1 shows three of the six scenarios in which COAST is within 18% of SOM. A drawback to using SOM was, although it solves to optimality, the complexity of SAP prevents it from being the optimal solution. The potentially intractable nature of the problem is what motivates the use of a heuristic in the first place.

In three out of the six scenarios in experiment 1, COAST has higher number of expected detections than SOM. In experiment 2, it is three out of 15 scenarios. In all scenarios, we observe that the ratio of allocated cells between the models is relatively high. In experiment

1, that meant the ratio is greater than four and in experiment 2, the ratio is greater than 1.75. This provides enough justification to warrant further analysis on the association between the two variables, exposing a strong linear relationship.

It was initially thought that the ability of COAST to assign multiple cells to search within an hour contributes to more expected detections. This is true in so much that it results in more cells to search during a mission. Only when there exists a large gap between the number of cells searched by a model do we see COAST having the most expected detections. When that difference gets smaller, SOM's optimal solution proves to be the highest value.

During the conduct of this research, we formulate a simple MILP to provide a means of evaluating the alpha-version of a heuristic algorithm. This simple MILP requires complex programming and there is still room to improve. Additionally, as COAST continues to mature and advance, the means of evaluating it must also advance. Several possible areas of future research follow:

1. Update and employ SOM in COAST's final validation and verification process.
2. Use SOM during the transition phase to JIATF-S to provide easy to understand solutions as benchmarks to solutions that COAST produces.
3. Determine additional simple metrics that can be used to evaluate more complex heuristics. The problems may be intractable, but if they can be divided into less complex portions, a large percentage of those portions could be solved to optimality.
4. Create a database of modular functions that can be used when evaluating a model. It is likely that code used to solve one aspect of a problem could be reused to solve another problem for the same model.

List of References

Anderson N (2019) Drug control - Certain DOD and DHS joint jask forces should enhance their performance measures to better assess counterdrug activities. GAO-19-441, https://www.gao.gov/assets/710/700456.pdf.

Benkoski SJ, Monticino MG, Weisinger JR (1991) A survey of the search theory literature. *Naval Research Logistics* 38(4):469–494, https://doi.org/10.1002/1520-6750(199108)38:4<469::AID-NAV3220380404>3.0.CO;2-E.

Blachman N, Proschan F (1959) Optimum search for objects having unknown arrival times. *Operations Research* 7(5):625–638, https://pubsonline.informs.org/doi/epdf/10.1287/opre.7.5.625.

Bynum ML, Hackebeil GA, Hart WE, Laird CD, Nicholson BL, Siirola JD, Watson JP, Woodruff DL (2021) *Pyomo–Optimization Modeling in Python*, volume 67 (Springer Science & Business Media), 3rd ed. edition.

Campos S (2014) An analysis of mathematical models to improve counter-drug smuggling operations. Master's thesis, Dept. of Operations Research, Naval Postgraduate School, Monterey, CA, https://calhoun.nps.edu/handle/10945/43885.

Charnes A, Cooper WW (1958) The theory of search: Optimum distribution of search effort. *Management Science* 5(1):44–50, https://www.jstor.org/stable/2626971.

Congress (2022) Statement of General Laura J. Richardson Commander, United States Southern Command before the 117th Congress House Armed Services Committee March 8, 2022. Washington, DC, https://www.southcom.mil/Portals/7/Documents/Posture%20Statements /SOUTHCOM%20Posture%20Final%202022.pdf.

Drug (2023) *Merriam-Webster*. Accessed January 13, 2023, https://www.merriam-webster.com/dictionary/drug.

Drug Enforcement Administration (2020) Drug enforcement administration national drug threat assessment. *Drug Enforcement Strategic Intelligence Section*, accessed January 12, 2023, https://www.dea.gov/sites/default/files/2021-02/DIR-008-21%202020%20National%20Drug%20Threat%20Assessment_WEB.pdf.

Drug Enforcement Agency (2023) Drug policy. Accessed January 12, 2023, https://www.dea.gov/drug-information/drug-policy.

Fayoumi AG (2018) Evaluating the effectiveness of decision support system: Findings and comparison. *International Journal of Advanced Computer Science and Applications* 9(10).

Florence C, Luo F, Rice K (2021) The economic burden of opioid use disorder and fatal opioid overdose in the United States, 2017. *Drug and Alcohol Dependence*, https://www.sciencedirect.com/science/article/abs/pii/S0376871620305159.

Griggs G (1991) Decision support systems: A framework for evaluation and justification. Master's thesis, Dept. of Information Sciences, Naval Postgraduate School, Monterey, CA, https://calhoun.nps.edu/handle/10945/26443.

Joint Interagency Task Force South (2023a) About us. Accessed January 12, 2023, https://www.jiatfs.southcom.mil/about-us/.

Joint Interagency Task Force South (2023b) Directorates. Accessed January 21, 2023, https://www.jiatfs.southcom.mil/About-Us/Directorates/.

Koopman BO (1946) Search and screening. Technical report, Columbia University New York, https://apps.dtic.mil/sti/pdfs/AD0214252.pdf.

Kress M, Royset JO, Rozen N (2012) The eye and the fist: Optimizing search and interdiction. *European Journal of Operational Research* 220(2):550–558, https://doi.org/10.1016/j.ejor.2012.02.016.

Library of Congress (2023) S.2355 - National defense authorization act for fiscal year 1989. Accessed January 12, 2023, https://www.congress.gov/bill/100th-congress/senate-bill/2355.

Manar J, Mouna B, Naima AM, Samy H, Zineb S, Mohammed B (2017) Evaluation of the decision support systems. *Journal of Communication and Computer* 14:129–136, https://www.researchgate.net/profile/Mohammed-Bennani-Othmani/publication/319014960_Evaluation_of_the_Decision_Support_Systems/links/5bfbca1192851ced67d80689/Evaluation-of-the-Decision-Support-Systems.pdf.

Moser H (1990) Scheduling and routing tactical aerial reconnaissance vehicles. Master's thesis, Dept. of Operations Research, Naval Postgraduate School, Monterey, CA, https://apps.dtic.mil/sti/pdfs/ADA239523.pdf.

Munsing E, Lamb CJ (2011) Joint Interagency Task Force-South: The best known, least understood interagency success. Technical Report 5, National Defense University Institute for National Strategic Studies, Washington, DC: USA, https://ndupress.ndu.edu/portals/68/documents/stratperspective/inss/strategic-perspectives-5.pdf.

National Public Radio (2007) Timeline: America's war on drugs. *NPR*, https://www.npr.org/templates/story/story.php?storyId=9252490.

Office of Naval Research (2023) Chief of naval research (CNR) priorities 2022. Accessed January 13, 2023, https://www.nre.navy.mil/our-research/priorities.

Pfeiff DM (2009) Optimizing employment of search platforms to counter self-propelled semi-submersibles. Master's thesis, Operations Research Department, Naval Postgraduate School, Monterey, CA, https://calhoun.nps.edu/handle/10945/4697.

Pietz J (2013) A generalized orienteering problem for optimal search and interdiction planning. Ph.D. thesis, Dept. of Operations Research, Naval Postgraduate School, Monterey, CA, https://calhoun.nps.edu/handle/10945/43885.

Pietz J, Royset JO (2015) Optimal search and interdiction planning. *Military Operations Research* 20(4):59–73, https://www.jstor.org/stable/24838653.

Pollock SM (1964) Sequential search and detection. Technical report, Massachusetts Institute of Technology Cambridge Operations Research Center, Cambridge, MA: USA, https://apps.dtic.mil/sti/pdfs/AD0601641.pdf.

Raap M, Preuß M, Meyer-Nieberg S (2019) Moving target search optimization–a literature review. *Computers & Operations Research* 105:132–140, https://doi.org/10.1016/j.cor.2019.01.004.

Royset JO, Sato H (2010) Route optimization for multiple searchers. *Naval Research Logistics (NRL)* 57(8):701–717, https://doi.org/10.1002/nav.20432.

Sato H, Royset JO (2010) Path optimization for the resource-constrained searcher. *Naval Research Logistics (NRL)* 57(5):422–440, https://doi.org/10.1002/nav.20411.

Selinger M (2017) Southcom says it needs more ships, aircraft to intercept drugs. *Defense Daily*, https://www.defensedaily.com/southcom-says-needs-ships-aircraft-intercept-drugs/navy-usmc/.

Spencer M, Miniño A, Warner M (2022) Drug overdose deaths in the United States, 2001–2021. *NCHS Data Brief*.

Stone LD, Royset JO, Washburn AR (2016) *Optimal Search for Moving Targets* (Switzerland: Springer).

The White House (2023) Office of national drug control policy. Accessed January 12, 2023, https://www.whitehouse.gov/ondcp/.

United Nations: International Narcotics Control Board (2013) Report of the international narcotics control board for 2013. *United Nations: International Narcotics Control Board*, Vienna, https://www.incb.org/incb/en/publications/annual-reports/annual-report-2013.html.

US Department of Justice (2011) The economic impact of illicit drug use on American society. https://www.justice.gov/archive/ndic/pubs44/44731/44731p.pdf.

US Senate Committee on Armed Services (2018) Hearing to consider the nominations of: General Robert B. Abrams, USA, for reappointment to the grade of general and to be Commander, United Nations Command, Combined Forces Command, and United States Forces Korea; and Vice Admiral Craig S. Faller, USN, to be admiral and Commander, United States Southern Command. Washington, DC, https://www.armed-services.senate.gov/imo/media/doc/18-59_09-25-18.pdf.

Warner SM, Royset JO (2022) Optimizing surveillance satellites for the synthetic theater operations research model. *arXiv preprint arXiv:2210.11370*, https://doi.org/10.48550/arXiv.2210.11370.

Zhang L, Sidoti D, Avvari GV, Ayala DFM, Mishra M, Kellmeyer DL, Hansen JA, Pattipati KR (2020) Context-aware dynamic asset allocation for maritime surveillance operations. *ISIF Journal of Advances in Information Fusion* 15(1), https://isif.org/journal/15/1.

Initial Distribution List

1. Defense Technical Information Center
   Ft. Belvoir, Virginia

2. Dudley Knox Library
   Naval Postgraduate School
   Monterey, California