IISE Transactions

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/uiie21

Coupling agent-based simulation and spatial optimization models to understand spatially complex and co-evolutionary behavior of cocaine trafficking networks and counterdrug interdiction

Nicholas R. Magliocca, Ashleigh N. Price, Penelope C. Mitchell, Kevin M. Curtin, Matthew Hudnall & Kendra McSweeney

Coupling agent-based simulation and spatial optimization models to understand spatially complex and co-evolutionary behavior of cocaine trafficking networks and counterdrug interdiction

Nicholas R. Magliocca[a]*, Ashleigh N. Price[a], Penelope C. Mitchell[a], Kevin M. Curtin[a], Matthew Hudnall[b], and Kendra McSweeney[c]

[a]*Department of Geography, University of Alabama, Tuscaloosa, Alabama, USA;* [b]*Department of Information Systems, Statistics and Management Science and Institute of Data Analytics, University of Alabama, Tuscaloosa, Alabama, USA;* [c]*Department of Geography, The Ohio State University, Columbus, Ohio, USA*

Abstract

Despite more than 40 years of counterdrug interdiction efforts in the Western Hemisphere, cocaine trafficking, or 'narco-trafficking', networks continue to evolve and increase their global reach. Counterdrug interdiction continues to fall short of performance targets due to the adaptability of narco-trafficking networks and spatially complex constraints on interdiction operations (e.g., resources, jurisdictional). Due to these dynamics, current modeling approaches offer limited strategic insights into time-varying, spatially optimal allocation of counterdrug interdiction assets. This study presents coupled agent-based and spatial optimization models to investigate the co-evolution of counterdrug interdiction deployment and narco-trafficking networks' adaptive responses. Increased spatially optimized interdiction assets were found to increase seizure volumes. However, the value per seized shipment concurrently decreased and the number of active nodes increased or was unchanged. Narco-trafficking networks adaptively responded to increased interdiction pressure by spatially diversifying routes and dispersing shipment volumes. Thus, increased interdiction pressure had the unintended effect of expanding the spatial footprint of narco-trafficking networks. This coupled modeling approach enabled the study of narco-trafficking network evolution while being subjected to varying interdiction pressure as a spatially complex adaptive system. Capturing such co-evolution dynamics is essential for simulating traffickers' realistic adaptive responses to a wide range of interdiction scenarios.

Keywords: Central America; complex adaptive systems; operational environment; spatial dynamics.

1. Introduction

A 'wicked' problem is one that is challenging (or impossible) to solve because possible solutions present unavoidable social value tradeoffs that are difficult to judge objectively, and the problem is created by complex system dynamics that make unintended consequences nearly impossible to foresee (Liebman

1976, Rittel and Webber 1973). Many problems become 'wicked' because of the intractable challenges posed by spatial heterogeneity and feedbacks that render solutions effective in one locality ineffective and/or catalytic for problems in other spatially-linked locations. Consequently, a truly optimal strategy for responding to complex spatial systems may not exist, nor can the effectiveness of such a strategy be fully assessed until it is implemented (Berglund 2015, Liebman 1976). Transnational cocaine trafficking, or 'narco-trafficking', and associated counterdrug interdiction responses constitute a quintessential wicked problem. Narco-trafficking has severe, negative influences on public health and social stability (Devine et al. 2020, McSweeney et al. 2018), corruption and violence (Basu 2014, Dell 2015, Robles et al. 2013), environmental sustainability (McSweeney et al. 2014, Sesnie et al. 2017, Tellman et al. 2020, Wrathall et al. 2020), and global economic activity/trade (Boivin 2014, Hudson 2014, Robles et al. 2013). The scale and spatial extent of those impacts have continued to grow with more than 19,500 overdose deaths attributed to cocaine in 2020 (Centers for Disease Control and Prevention 2020), and a 'transit zone' that now spans from west of the Galapagos Islands in the Pacific Ocean, throughout the entirety of the Caribbean Sea, and to transatlantic smuggling to Europe (McSweeney 2020a). This persistent and widespread trafficking exists despite more than 40 years of a U.S. drug policy that invests heavily in counterdrug interdiction (Caulkins et al. 1993, McSweeney 2020b).

Several factors make counterdrug interdiction in the transit zone increasingly difficult, expensive, and ineffective . First, narco-trafficking networks are decentralized, highly flexible, and innovative (Dudley 2011, Magliocca et al. 2021), and as such are able to exploit a diversity of smuggling routes and modes greater than what counterdrug interdiction operations can currently match (Mcdermott et al. 2021, UNODC 2020, Williams and Godson 2002). Second, the large and increasing scale of cocaine trafficking operations provokes a concomitant increase in the scale of interdiction operations. The spatial and logistical growth of these operations increases the costs and decreases the effectiveness of interdiction due to the vast extent that must be policed (McSweeney 2020b). Finally, both drug traffickers and interdiction forces are unwilling or unable to expose their operational knowledge, motivations, and/or constraints on behavior. Limited information about the true locations and extent of drug trafficking operations challenges medium- to long-term counterdrug interdiction strategies and instead reinforces short-term, tactical interdiction decision-making that unintentionally triggers more widespread trafficking in response (Bright and Delaney, 2013; Caulkins, Crawford and Reuter, 1993; Magliocca *et al.*, 2019; McSweeney, 2020a; McSweeney *et al*., 2014)

The persistence of transnational cocaine trafficking, its array of negative societal impacts, and the expansive spatial nature of the problem demand analysis and understanding of the phenomenon as a complex spatial and adaptive system (Magliocca et al. 2019). A complex adaptive system emerges and maintains a coherent form over time, and adapts and self-organizes in response to interactions among its internal components and environment (Choi et al. 2001, Holland 1995). Complex adaptive systems become even more challenging to understand when causal dynamics and emergent behavior vary with spatial context and include long-distance spatial interactions (Manson 2001, O'Sullivan 2004). Since narco-traffickers' primary adaptive response to counterdrug interdiction is to change trafficking route locations (Magliocca et al. 2019), a spatial dynamics perspective must be integrated with a complex adaptive systems approach. However, understanding adaptive behaviors requires the study of system dynamics over time and space at the level of system components (i.e., trafficking nodes), which is a daunting task for a phenomenon as expansive and dynamic as the co-evolution of transnational cocaine trafficking and counterdrug interdiction.

Computational approaches are thus vital tools for understanding the spatial dynamics of interactions between drug traffickers and counterdrug interdiction forces as a complex adaptive system (Anzoom et al. 2021). Given their foundation in complex system science, agent-based models (ABMs) are a popular tool to simulate complex system-level behaviors that emerge from the distributed, adaptive interactions among system components (An et al. 2021, Elsawah et al. 2020, Schwarz et al. 2020). Many authors have noted the advantages of an agent-based approach for modeling supply networks, particularly the ability to simulate emergent supply chain configurations as a self-organizing phenomenon resulting from producersupplier interactions (e.g., Thomas Y Choi, Dooley and Rungtusanatham, 2001; Akanle and Zhang, 2008). Similarly, optimization methods have been the preferred choice for modeling counterdrug interdiction efforts and similar optimization. The counterdrug interdiction challenge, characterized by high need but low resources for intervention, warrants optimized deployment of the limited resources available. Combining these two modeling paradigms is an emerging frontier to dynamically simulate multi-scale, adaptive systems (Niamir et al. 2018, Widener et al. 2015).

However, the spatial expansion and complex nature of interdiction and trafficker interactions present empirical, conceptual, and methodological challenges for research. The large theater of operations with a concomitantly large number of potential interdiction locations drive spatial optimization problem instances toward the bounds of solution tractability, given the highly combinatorially complex nature of the optimization models (Resig et al. 2020). The clandestine and classified nature of drug trafficking and counterdrug interdiction operations, respectively, introduces substantial uncertainty into attempts by outsiders (i.e., researchers) to conceptualize and study trafficker and interdiction interactions as a system. Moreover, there is substantial information asymmetry between traffickers and interdiction forces (typically in favor of traffickers), which critically drives their spatial interactions in reality but is often reduced or ignored in most interdiction optimization modeling approaches (see *Literature Review* below). The work presented here advances the integration of spatial simulation and optimization paradigms through a novel coupling of a spatial optimization model for locating interdiction assets, based on realistic objectives and constraints on interdiction operations, with an agent-based model of adaptive narco-trafficker behavior. Integrating a spatial perspective on complex adaptive systems with the methodological tools of complexity science, geography, and operations research presents an opportunity to gain insight into the co-evolution of narco-trafficking and counterdrug interdiction interactions.

2. Literature Review

2.1 *Optimization approaches for counterdrug interdiction*

A large and growing body of operations research methods, and spatial optimization in particular, addresses aspects of interdiction. These models are intended to assist decision makers in spatially allocating their interdiction resources to improve or optimize the disruption of illicit activity. There is, however, a relatively broad view of what constitutes interdiction modelling and how the objectives and constraints of those models reflect actual counterdrug interdiction operations. Allocating counterdrug interdiction assets optimally relies not only on the location of known drug shipments, but on differentiating among potential targets, the types of interdiction resources available, and agency jurisdiction. Given the expansive spatial scope of drug trafficking and comparatively small amount of resources available to counterdrug forces, the objectives and constraints on counterdrug operations are readily modeled as a location allocation problem. In the context of interdiction, the objective is to optimally allocate counterdrug assets (i.e., force packages) among known trafficking locations to best disrupt the illicit activity. The demands associated with potential interdiction locations are typically known or estimated shipment volumes, and there can be multiple organizations and varying types of assets available to intercept shipments at the demand locations.

Determining the optimal location for interdiction operations is generally approached from either a network or spatial optimization perspective. Network interdiction models aim to modify the structure of and/or flow within the illicit network to cause maximum disruption to flow of illicit goods from the source to the sink. Methods that target network structure include removing arcs (i.e., connected components), reducing arc capacity, increasing the cost of transit, or by eliminating nodes connecting arcs within the network. Flow-oriented approaches attempt to minimize flow across a network (Altner et al. 2010, Malaviya et al. 2012), maximize the amount of flow captured or covered (e.g., Zeng, Hodgson and Castillo, 2009), or minimize the maximum flow; essentially making the worst-case trafficking scenario as good as possible (Cormican et al. 1998, Morton et al. 2007, Wood 1993). Still others seek to make the interdiction presence as efficient as possible (Keskin et al. 2012, McLay et al. 2009) or conversely to make the trafficking activity as difficult as possible (Israeli and Wood 2002, Nguyen and Smith 2022).

In contrast, spatial optimization models focus on locating interdiction assets optimally rather than modifying the network structure or flows. Many spatial optimization models for interdiction are often derivations of classic formulations cast in the context of interdiction. Formulations are most often tested on generic networks that cannot realistically represent the operational environment unique to transnational counterdrug interdiction. However, interdiction operations take place across multiple spatial and temporal scales, with disparate types of interdiction forces or tactics, and with a wide variety of political, temporal, and resource constraints. Moreover, most existing interdiction models consider the structure of the illicit supply network to be static, rather than a dynamic part of the model, meaning the volume and location of drug shipments are treated as a known input. While some work has been done to model uncertainty in demand, or to stochastically model the amount of flow that is removed during a successful interdiction (Cormican et al. 1998, Losada et al. 2012), the network structure, and thus potential trafficking locations, are assumed to be static through time. However, the assumption that the network structure and volumes of all drug shipments are known to both the traffickers and interdictors (Smith & Song, 2020) is especially impractical. Extant interdiction models with objectives aimed at maximizing disruption or minimizing flow over an entire, static network therefore have limited practical utility.

Location covering models can be applied to spatial allocation problems for interdiction, which often require locating multiple types of facilities and cover multiple types of demands. A relatively small set of location allocation models are concerned specifically with drug interdiction, but a broader range of models have considered multiple types of facilities and demands. Of those that have considered multiple facility types (Baycik et al., 2018; Wilt and Sharkey, 2019), the models have not addressed co-locating multiple types of facilities at the same location. Multiple-type location models exist in numerous derivations and extensions applied to healthcare facilities, but typical constraints avoid multiple coverage of the same demand location (Farahani et al. 2019) or do not permit multiple facilities of the same type at the same location. Similarly, of those models that can accommodate multiple types of demands, many are concerned with locating a single facility type (Mirzaei et al. 2021), with a system of hierarchal facilities, or with maintaining existing service locations (Paul et al. 2017, Stanimirović et al. 2017). There are multi-objective formulations to model interdicting multiple types of flows (Jabarzare et al. 2020), but the typical objectives aim to maximize disruption over the entire network and do not account for isolating multiple types of demands at a single location. Others have examined locating multiple types of facilities across multiple time periods, albeit with the objective of maximizing coverage over the entire planning horizon (Porras et al. 2019, Zarandi et al. 2013).

Furthermore, interdiction is assumed to disrupt illicit activity at or near certain locations, yet little attention has paid to how the spatial allocation of counterdrug resources influences new spatial and temporal patterns of illicit trafficking. In reality, interdiction often results in changes to the illicit network's structure or capacity, and future interdiction scenarios should reflect that response (Price et al. 2022). Although there is significant work that integrates stochastic elements into optimization models, many actual operations are still described as static, and the approaches to them are deterministic. Thus, the primary limitation to existing methods is the inability to anticipate how the spatial allocation of counterdrug forces influences the volume, timing, and location of future illicit activity. Given the resilience and adaptability of narco-trafficking networks that have been observed, there is a need to realistically represent and account for traffickers' adaptive responses to interdiction operations. A truly optimal interdiction asset spatial allocation must co-evolve with traffickers' changing behaviors.

2.2 *Approaches to modeling network structure and behavior*

Research examining organized criminal groups, particularly drug trafficking organizations, have focused on deepening understanding of the structure of illicit networks to improve targeting of operational vulnerabilities (Bichler, 2017). This perspective applies the tools from network science to describe and analyze the properties of these networks. Anzoom et al. (2021) discusses pertinent studies that use network structure to classify illicit supply-chain networks, such as scale free, core and periphery sets, social network analysis, and multiplex networks, all of which fall within the realm of multi-layered networks as described by Kivela et al. (2014). Recently, an abundance of literature has been dedicated to the development of frameworks to classify multi-layer networks, inadvertently causing a lack of consensus in terminology (Kivela *et al.*, 2014). Relatedly, Bichler et al. (2017) applies social network analysis of drug supply networks to develop comparable metrics for concepts like network density or centrality with organizational behavior. While we recognize the importance and utility of a common network taxonomy, this approach and terminology is still limited to static networks and not well suited to analysis of the behavioral evolution of networks.

In the context of dynamic networks research, and particularly illicit networks, resilience is a key characteristic (Morselli 2009). Network resilience refers to the ability of drug trade organizations (DTOs) to resist and survive disruption from interdiction, as well as the capacity of the network to adapt following interruption (Bouchard 2007, Cavallaro et al. 2020). These network dynamics can be observed in structural changes to nodes, links, or groups within the network (Bright and Delaney, 2013). To study these adaptive network dynamics, researchers have used simulation to model network effects (Magliocca et al, 2019). Integrating agent-based simulation methods with network analysis enables the investigation of adaptive behaviors influenced by network structures that ABMs or network analysis alone do not provide. As illustrated in the recent review by Will et al. (2020), efforts to integrate ABMs and social network analysis have been motivated by questions relating to the processes producing diffusion of information (e.g., marketing), disease (e.g., epidemiology), or materials (e.g., supply chains) through a network of actors with particular interest in how network behavior or structures change in response to external perturbations. Importantly, there are few examples in which co-evolutionary dynamics of agent behaviors *and* network structure are both modeled (see Will et al., 2020 for more details). One example of a co-evolutionary approach is the proposed framework of Geographic Network Automata (Anderson and

Dragićević 2020a, b). The Geographic Network Automata (GNA) modeling framework captures endogenous network dynamics that influence and are influenced by agent behaviors within the network, and takes the additional step of embedding simulated networks in geographic space to represent spatial relationships. Application of the GNA framework has thus far focused on ecological networks (Anderson and Dragićević 2020b). Another example is AgentC (Vaněk et al. 2013) – a data-driven ABM of maritime traffic that explicitly models pirate activity and piracy countermeasures. AgentC was developed in collaboration with stakeholders to assess the effectiveness of alternative counterpiracy measures and support the design process of new maritime transit corridors.

2.3 *Integrated modeling approaches*

Integration of ABM simulation and network optimization methods has emerged among disparate fields. Logistics system modeling efforts adopting the theoretical perspective of complex adaptive systems use ABMs due to their ability to represent learning and adaptation of agents acting as nodes within a supply chain (Akanle and Zhang 2008, Thomas Y. Choi et al. 2001). This approach has allowed logistics researchers to investigate the effects of node- or link-level characteristics and behaviors on the network-level efficiency, resiliency, and/or optimal structure of logistics systems (Nair et al. 2009). In the context of network interdiction, the classic defender-attacker game was modeled by Kroshl, Sarkani and Mazzuchi (2015) using a combination of location optimization and agent-based models to allocate defensive resources to protect a spatially distributed physical network, and they found that the inclusion of an ABM provided greater insights into how to increase defender victories beyond those produced with a probabilistic risk analysis approach. The advantages of integrating agent-based simulation and location optimization approaches are clear, but such integration has yet to be implemented in the context of drug trafficking networks and counterdrug interdiction forces.

A number of researchers have approached supply chain operations more generally (Yue and You 2014, 2017), and interdiction operations more specifically (Sadeghi and Seifi 2019, Shen et al. 2021) as

Stackelberg games. This approach models both the interdicting agency and the traffickers as optimizing their operations. The work presented here takes a different modeling perspective based on our understanding of how the two competing organizations operate. Counterdrug interdiction operations are modeled as an optimizing agency, given that federal drug enforcement operations have stated goals which often can be described quantitatively, the number and kind of interdiction assets can be known, and the constraints under which they operate can be described and formulated mathematically. Although much of interdiction operations is classified and therefore unavailable to researchers, we know that the organizations formulate goals, attempt to use their resources most efficiently, and operate under well-known constraints. Therefore, an optimizing approach most closely mirrors their operations. Conversely, DTO's are much more flexible in their operations given that they do not need to follow policy proscribed goals, they actively work to undermine or avoid constraints imposed on them, and their operational assets are intentionally hidden. Therefore, the DTOs are modeled as agents whose behavior is not proscribed by a formal mathematical model, but rather emerges from their interactions within their complex operating environment.

Specifically, an ABM of cocaine trafficking networks (Magliocca et al. 2019) is dynamically coupled with a spatial network interdiction optimization model (Price *et al.*, 2022) to address the conceptual and methodological gaps identified above. Leveraging the strengths of both approaches, the ABM simulates emergent and adaptive trafficking network dynamics in response to a more rigorous and realistic modeling of counterdrug interdiction operations. The spatially explicit nature of the location optimization model can accommodate spatial limitations on resource deployment and jurisdictional constraints (e.g., Coast Guard only has jurisdiction on high seas), and calculate new optimal spatial locations of interdiction assets as the trafficking network structure and routes evolve. Moreover, the model coupling maintains the information asymmetry that exists in reality between traffickers and interdiction forces, which only partially know one another's actions at limited times and locations. The coupled model framework also provides new analytical angles. Previous models, even those that couple ABMs and location optimization, have not used the tools of complex system science, which can link node-level behaviors to network-level outcomes to understand the causes of emergent network dynamics. Here we investigate the spatial and operational changes in trafficker behavior vis-à-vis varying amounts of interdiction assets. Ultimately, the goal is to support interdiction strategies that more efficiently allocate resources while also being attentive to the unintended consequences of traffickers' spatial adaptation to interdiction.

3. Methods

3.1 *Agent-Based Model of Narco-Trafficking Networks*

Drug traffickers and trafficking networks are highly dynamic, flexible, and constantly shifting due to law enforcement pressure and internal and external conflicts/realignments (Bright and Delaney, 2013; Caulkins *et al.*, 2013; Dudley, 2010; Magliocca *et al.*, 2021). Such traits are hallmarks of complex adaptive systems (Choi *et al.*, 2001; Manson, 2001), which are best represented through a simulation approach based on bounded rationality decision heuristics to navigate local and network-wide transaction costs (Basu, 2014). Thus, the dynamic, spatial (re)organization of narco-trafficking networks in the 'transit zone' of Central America and surrounding maritime spaces were simulated using the agent-based model NarcoLogic (Magliocca et al., 2019). NarcoLogic is a theoretical simulation model developed based on extensive ethnographic knowledge of narco-trafficking operations that 1) reproduced spatial adaptive dynamics that had only previously been described qualitatively, and 2) produced spatio-temporal, quantitative patterns of cocaine flows that compared favorably to the best available estimates from law enforcement and intelligence communities. The original version of the NarcoLogic model was validated by comparing simulated volumes of cocaine flows, overall trajectories, and timing of peak cocaine flows reported at the department-level (i.e., administrative unit equivalent to U.S. counties) in the Consolidated Counterdrug Database (McSweeney 2020b). At the Central America scale, NarcoLogic also successfully recreated the historical southward shift of narco-trafficking extent and intensity (Magliocca *et al.*, 2019). A full Overview, Design Concepts, and Details (ODD) protocol for NarcoLogic is provided in Appendix A.

Changes in the trafficking network's spatial footprint and location-specific cocaine flows were produced by interactions between two types of agents in response to interdiction events generated by the optimization model. Network Agents represented the top-down coordination of DTOs. Network Agents observed interdiction events within their network and updated their assessment of transaction costs based on perceived profit and risk among active nodes. Network Agents decided to expand or consolidate existing trafficking routes and 'activate' (i.e., receive shipments) or 'deactivate' specific trafficking nodes over time. Nodes Agents had a fixed spatial position operating each trafficking node. Node Agents that were 'activated' by their Network Agent purchased a shipment of cocaine from a supplying Node Agent, and decided how to allocate the volume of the shipment among potential buyer nodes along possible trafficking routes. Node agents observed (a) prices offered at each buying node and (b) whether an interdiction event occurred and effected it or its neighbors in previous time steps. Over time, Node Agents learned transaction costs among neighboring nodes and allocated shipments to maximize profit and minimize risk of interdiction.

The cocaine trafficking network structure was based on integrated ethnographic, remote sensing, and statistical analyses of narco-trafficking activities in Central America (Magliocca *et al.,* 2019; McSweeney, 2020a). The bi-level structure of the simulated trafficking network (i.e., Network and Nodes Agents) reflected the evolving nature of narco-trafficking. A semi-decentralized or horizontally integrated cocaine trafficking organizational structure is a relatively new development in cocaine trafficking compared to the better-known Colombian groups of the Medellín and Calí cartels that dominated in the late twentieth century. After substantial disruption of those vertically integrated cartels in the early 2000s, cocaine trafficking routes shifted to Central America, and combined with the rise of Mexican cartels, a more decentralized and regional drug trafficking organizational model dominated (Bagley, 2013; Dell, 2015; Dudley 2010, 2012; McSweeney et al., 2014, 2018; Tidd, 2018). Although hierarchy still exists in drug supply chains, organizational structure is much flatter overall than it used to be.

Trafficking node locations were selected based on statistical estimates of landscape suitability (Magliocca *et al.*, 2022), and links between trafficking nodes were unidirectional (roughly southeast to northwest), exogenously specified, and remained constant throughout the simulation. The values of cocaine shipments at each trafficking node increased with every transaction advancing closer to consumption markets, and were estimated from law enforcement reports and case studies (Pearson *et al.*, 2022; UNODC, 2010, 2018). Movement of cocaine from one node to another incurred a transaction cost, which were partly exogenously and endogenously specified. The exogenous portion of transaction costs was based on distance between any two nodes, volume being transported, and mode of transportation. The endogenous component of transaction costs was related to perceived risk of interdiction between two nodes in the form of a dynamically updated 'risk premium' (Caulkins et al., 1993). Dynamic differences between perceived profitability and transaction costs for each node influenced where, when, and how much cocaine was moved through the trafficking network.

A key uncertain parameter that was explored in this version of NarcoLogic was the probability of successful *interception* of cocaine shipment. Trafficking routes vary in their vulnerability to counterdrug interdiction given their geographic context and the logistics involved in locating interdiction assets that can intercept shipments (JIATF-S, personal communication, 2019). The probability of successful interdiction when interdiction resources were located at nodes with active cocaine flows was based on the number of network links directed to the node (i.e., node degree) and characteristics of the sending links. The baseline probability of successful interception represented the minimum across the entire network and was experimentally modified to investigate the effects on overall interdiction outcomes and trafficker behaviors. A detailed description and local sensitivity analysis of this parameter are provided in section 1.3.1 of Appendix C in the Supplemental Online Materials.

3.2 *Optimal interdiction location modeling*

A review of the extant objectives and constraints in the spatial optimization literature with the agency charged with detection and monitoring of air and maritime drug trafficking in the Central American transit zone confirmed that the objectives and constraints in the literature are a mismatch with the operational constraints that they face when making interdiction location decisions. For example, constraints on interdiction operations go beyond (mostly) observable resource constraints to include jurisdictional constraints, legal restrictions, and political considerations (Price et al., 2022). In contrast to much of the interdiction optimization literature, the goal here is not to model or demonstrate how interdiction forces *could* or *should* operate but rather how they *do* operate. In order to address that mismatch, this effort began with interviews of interdiction forces – to the extent possible in an unclassified environment – to identify the objectives and constraints most pertinent to their short- and medium-term operations. A family of spatial optimization models designed to reflect the realistic constraints, objectives, and procedures on interdiction operations can be seen in (Price et al. 2022), and among those is the Multiple-Type Maximal Covering Location Problem (MT-MCLP) applied in this work. The full model formulation is available in Appendix B.

The MT-MCLP considers interagency cooperation, jurisdictional limits, resource availability, and interdiction target type as interdiction facilities (known as force packages) may have different skillsets, equipment, or jurisdictional permissions to act (e.g., U.S. Coast Guard cannot operate in another country' Exclusive Economic Zone without permission). Force package is a term used by federal counterdrug agencies to describe the mix of personnel and equipment that can be employed for an interdiction operation. In the air and maritime domain this is typically a mix of ships (e.g., Coast Guard cutters, high speed pursuit boats) and aircraft (e.g., armed helicopters, maritime patrol aircraft) sourced from across federal agencies with law enforcement powers, along with vehicles from the appropriate foreign governments (Munsing and Lamb 2011). The personnel that operate these vehicles can include Coast Guard Law Enforcement Detachments, Maritime Safety and Security Teams, and other deployable specialized forces personnel (GAO 2019, USCG 2020). For land-based operations we expand the use of the term force package to include any U.S. or foreign law enforcement or military detachment that has the equipment and personnel capable of conducting an interdiction operation. Such detachments can range from drug interdiction road blocks (Guerra 1992) to specialized and targeted SWAT or military-style operations (Goodman and Coyne 2021).

In the MT-MCLP, the objective is to maximize the coverage of estimated drug trafficking activity by locating force packages of varying types at trafficking nodes. Each trafficking node j is assigned the set U_j, defined as the set of types t of force packages that are excluded from locating at j. For those types that can locate at a given node, one or more may locate at that node if this leads to maximal coverage. Only the estimated volume that can be captured by a given type (a_{it}) will be captured by the force package of that type. Constraints ensure that no force packages of a prohibited type are assigned to any potential interdiction locations. The decision variables x_{jt} and y_{it} indicate which types t of force packages are located at node j and which demand i is interdicted by a force package of type t. The set of potential force package locations j remain the same throughout the simulation, while the demand for each interdiction type a_{it} can change at the interdiction locations j from the previous time step.

The MT-MCLP can accommodate multiple variants of constraints on the interdiction operations by assigning the set U_j to each node. For example, jurisdictional limits are represented by assigning each Central American nation to a unique interdiction type. In the results reported here, each node in a dataset may be targeted by one or more of the nine force package types (P_t) associated with the Caribbean Coast, Pacific Coast, and one type for each of the seven Central American partner nations. For instance, nodes within 20 km of the coast can be interdicted by either a coastal force package or by counterdrug efforts within a partner nation and thus have U_j values with the seven partner country types. Coastal interdiction operations are free to locate in any of the partner nations, and similarly interior force packages are free to locate at coastal nodes, in which case expected seizure volume at a coastal node would be divided among the country and coastal force package types.

3.3 *Coupled model structure description*

As discussed in the previous sections, we model the influence of varying levels of interdiction assets on the degree, timing, and locations of cocaine trafficking. The operational environment used here represents the Central American transit zone and consists of 1) Nodes where trafficking can occur and where interdiction can take place and 2) links through which simulated volumes of cocaine are trafficked between those nodes (Magliocca et al. 2019, 2022). The nodes vary in their connectivity, although links were preferentially established between spatially proximate nodes, and all nodes have a connection to the consumer and producer nodes. This reflects the realistic situation in which any transshipment node can be the only stop before reaching Mexico, or one stop among many en route to Mexico. Although the volumes of cocaine are assigned to links, interdiction takes place at the nodes and the demand available to interdict at a node is the sum of the flows on the links entering that node. At initialization, the baseline potential volume of cocaine (demand) at each trafficking node was estimated using country-level CCDB estimates of primary shipments. Solving the MT-MCLP using the baseline values returns the optimal spatial allocation of interdiction assets, which represents the presence of counterdrug forces within the simulated environment provided by NarcoLogic. At each time step, the Network Agents update their perceived risk of interdiction at each node, and the volume of cocaine present at force package locations is returned to the optimization model, which in turn are used to update estimated cocaine flow values for the next time step. **Error! Reference source not found.**1 illustrates the conceptual model guiding model coupling, and Figure 2 provides a snapshot example of the coupled NarcoLogic and optimization model execution. Figure A1 provides a data and process diagram of the coupled modeling system accompanied by a technical description of the coupled model workflow in section 1.4 of Appendix A.

Several metrics were used to evaluate changes in trafficking network dynamics resulting from interdiction events. Cocaine shipment seizure volumes were recorded for all successful interdiction events at each model time step. Values of seized shipments were estimated based on empirically estimated wholesale cocaine prices that varied geographically and increased in value with northward distance traveled

(Magliocca et al., 2019). The numbers of active nodes and edges throughout the trafficking network were recorded based on the presence of a cocaine shipment at a given node and its linked edges during each time step. The number of successful interdiction events measured the number of instances per time step when force packages were located at active nodes and a randomly generated number exceeded one minus the probability of successful interception. Finally, two metrics of network structure were used to assess topological effects of successful interdiction events on the trafficking network. Node degree measured the number of active edges per node at each time step. Flow diversity, based on Shannon's Diversity Index (Shannon, 1948), measured the evenness of cocaine flows among active nodes at each time step. The formula and description of flow diversity is provided in Appendix C.

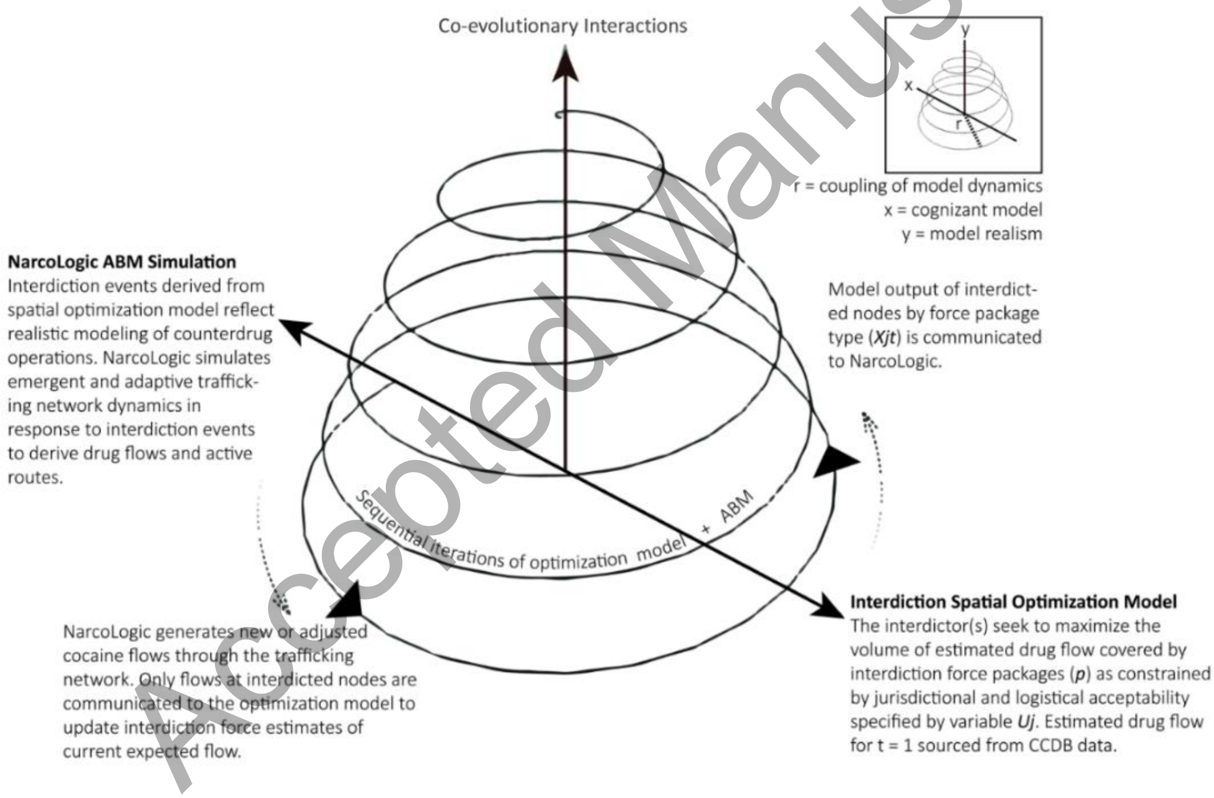

Figure 1: Conceptual model for coupling the agent-based cocaine trafficking network model, NarcoLogic, with the interdiction spatial optimization model to simulate co-evolutionary interactions between traffickers and counterdrug interdiction forces.

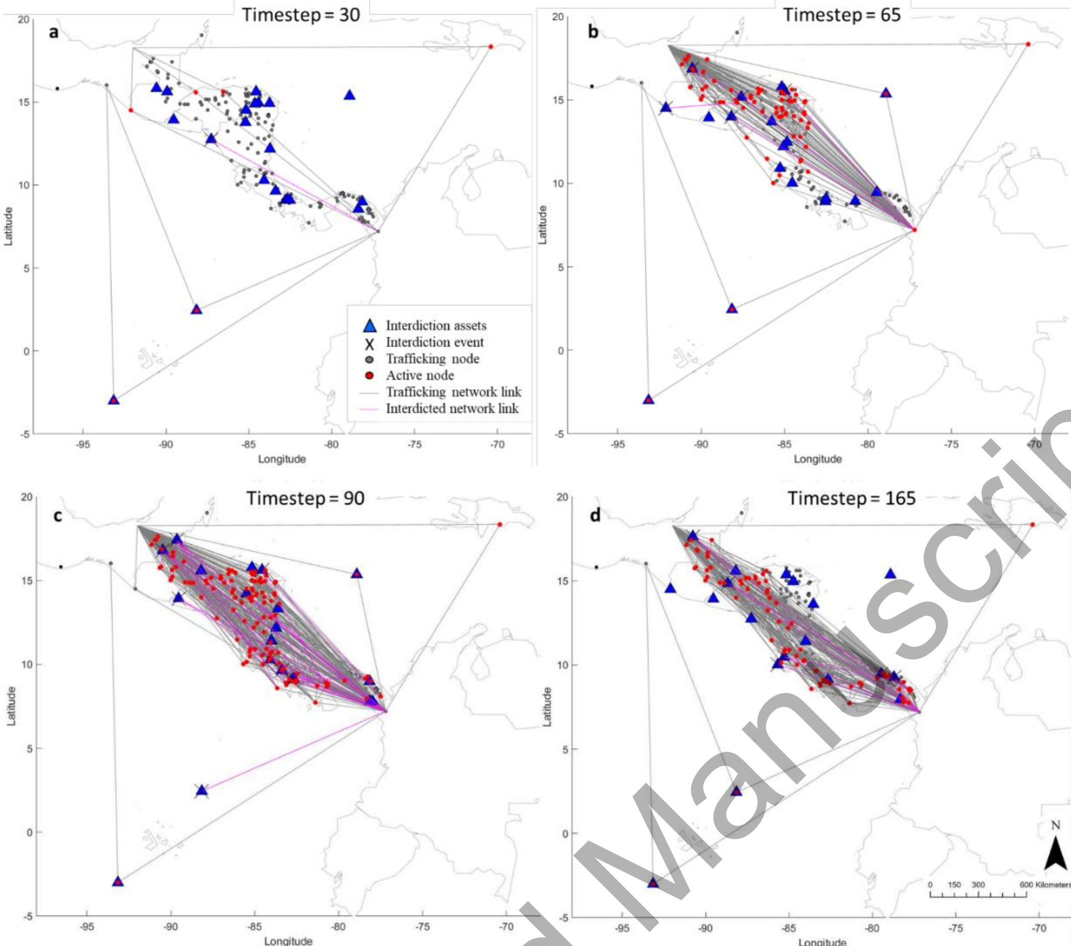

Figure 2: A snapshot of the coupled trafficking network and spatial interdiction optimization model execution: a) consolidated trafficking network; b) expanded trafficking network in response to early interdiction; c) fully expanded network (e.g., cocaine shipments as far south as Panama) in response to increased interdiction success; and d) some consolidation (e.g., away from Eastern Honduras) and reduction of active nodes. Points and lines represent drug trafficking nodes and network links, respectively. Highlighted nodes represent the location of active cocaine shipments with the size of the nodes scaled to volume. Triangles represent the location of counterdrug interdiction forces. Black 'X's over nodes and highlighted network links represent the location of successful interdictions.

Local sensitivity analyses were also conducted using a one-factor-at-a-time approach (ten Broeke et al. 2016, Ligmann-Zielinska et al. 2020). Thirty replications of the coupled model simulation were conducted for each force package scenario to assess the sensitivity of interdiction outcomes and trafficking network behavior to varying baseline probabilities of successful interception. A detailed description of sensitivity analysis methods and results are provided in Appendix C.

4. Results

4.1 *Effects on increased interdiction on the trafficking network*

We first examined network-level outcomes in response to varying levels of interdiction assets (i.e., force package scenarios). Sixteen total force packages were allocated and evenly distributed per country within the transition zone (Guatemala, El Salvador, Honduras, Nicaragua, Costa Rica, and Panama) and held constant across all modeling scenarios. Additional force packages varied with each modeling scenario and were allocated in different combinations between the Eastern Pacific (maximum of 6) and Caribbean (maximum of 4) maritime theaters. The coupled model was executed 30 times at the baseline probability of successful interception (0.1) for each scenario to assess variability in outcomes based on stochastic processes (e.g., probability of successful interception; probabilistic choices by trafficking Node Agents between equally valued trafficking routes).

Both the number of successful interdiction events (Fig. 3a) and total volume of seizures (Fig. 3b) increased consistently as the number of force packages increased. There were significant statistical differences between the lowest and highest third of force package scenarios for both outcomes (Fig. 3). This was an expected outcome and suggested that increased force packages translated into more successful interdictions and higher total volumes of cocaine removed from the supply network. In contrast, increased force packages had little effect on the number of active edges in the trafficking network (Fig. 4a) and total value of cocaine seizures (Fig. 4b). No statistically significant differences were observed in these two outcomes across the force package scenarios. Despite increasing seizure volumes, the simulated trafficking network adapted to increased interdiction pressure so that the value per seizure decreased. Agents within the trafficking network learned to minimize profit losses by distributing to more trafficking nodes, sending smaller shipments, and choosing closer receiving nodes that required shorter and less risky transport. This behavioral adaptation by the Network and Nodes Agents underlies the larger scale, network-wide shifts in trafficking routes that drive the expansion of active nodes in response to interdiction pressure. Importantly, the findings presented in Figure 5 would not have been possible without the simulation of the dynamic, spatial adaptation of the trafficking network.

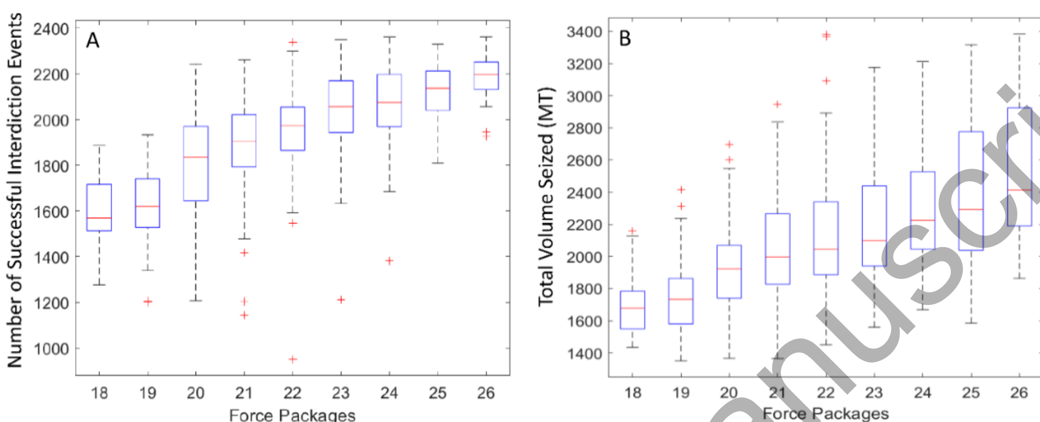

Figure 3. Distributions of A) the total number of successful interdiction events and B) total volume of cocaine seized for all 30 model replications for each force package scenario. Median scenario values are indicated by the red, horizontal lines, first-third interquartile ranges are represented by the blue boxes, dashed whiskers extend to the most extreme data points not considered outliers, and the outliers are plotted individually using the '+' symbol.

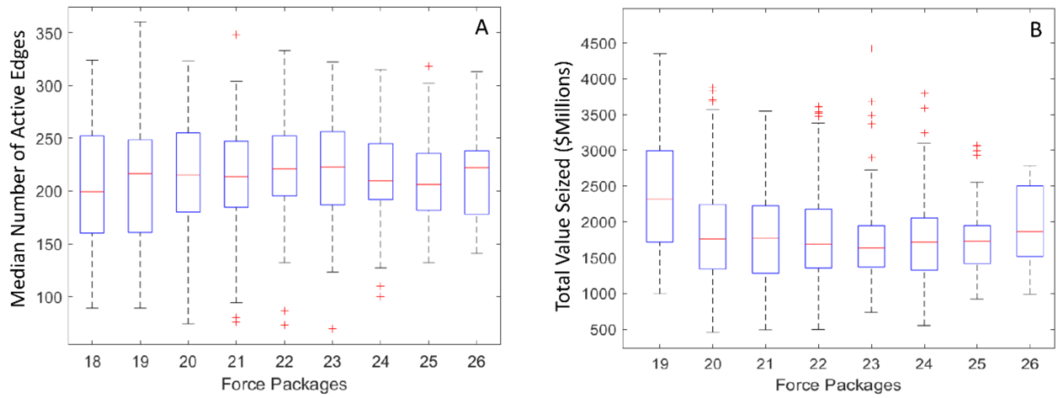

Figure 4. Distributions of A) the median number of active edges per model replication and B) total value of cocaine seized for all 30 model replications for each force package scenario. Figure details the same as Figure 3.

As has been demonstrated theoretically (Caulkins et al. 1993, Magliocca et al. 2019) and empirically (Bright and Delaney 2013, McSweeney 2020b), trafficking networks adapt to interdiction pressure mainly by reorganizing their spatial structure and shifting routes to avoid detection. This general trend was replicated in our model outcomes measuring changes in the number of active nodes (Fig. C1) and flow diversity (Fig. 5) in response to the number of successful interdiction events over time. Relatively low levels of interdiction success were associated with fewer active nodes and low levels of flow diversity (i.e., few active routes with large, concentrated shipments) in the trafficking network as trafficking routes were consolidated to increase profits and minimize exposure to detection. As interdiction pressure increased, either through increased force packages or improved location of existing force packages, the number of active nodes and flow diversity increased. Time series for a single coupled model execution illustrated the expansion and contraction dynamics of the trafficking network in response to successful interdiction events (Fig. C2). Regardless of the level of force packages allocated, the trafficking network was generally attracted to a state of moderately high flow diversity (between index values of 6 and 10) and moderately low numbers of successful interdiction events (between 5 and 10 per time step). This state attractor also appeared stronger (as indicated in Figure 5b with tighter clustering of points in the latter half of the simulation) with increased interdiction force packages and more successful events.

These results mirrored observed spatial adaptations made by narco-traffickers in response to counterdrug interdiction (i.e., the "balloon" and "cockroach" effects; Bagley, 2013; Magliocca et al., 2019). This is the main unintended consequence of current counterdrug interdiction strategies – increased interdiction pressure pushes narco-traffickers into new areas of operation and expands the active 'transit zone'. For all force package scenarios, increased interdiction volume led to positive flow diversity changes (i.e., more evenly distributed flows), whereas negative changes to flow diversity (i.e., network contraction and/or shipment consolidation) were observed when interdiction volumes were low (Fig. C3). Figure C3 demonstrates that while larger interdiction volumes prompted spatial displacement and expansion of trafficking routes, more even dispersal of cocaine shipments was the primary adaptive response to interdiction to maintain profits. A more detailed explanation of these trafficking network dynamics is provided in Appendix C of the Supplemental Online Materials.

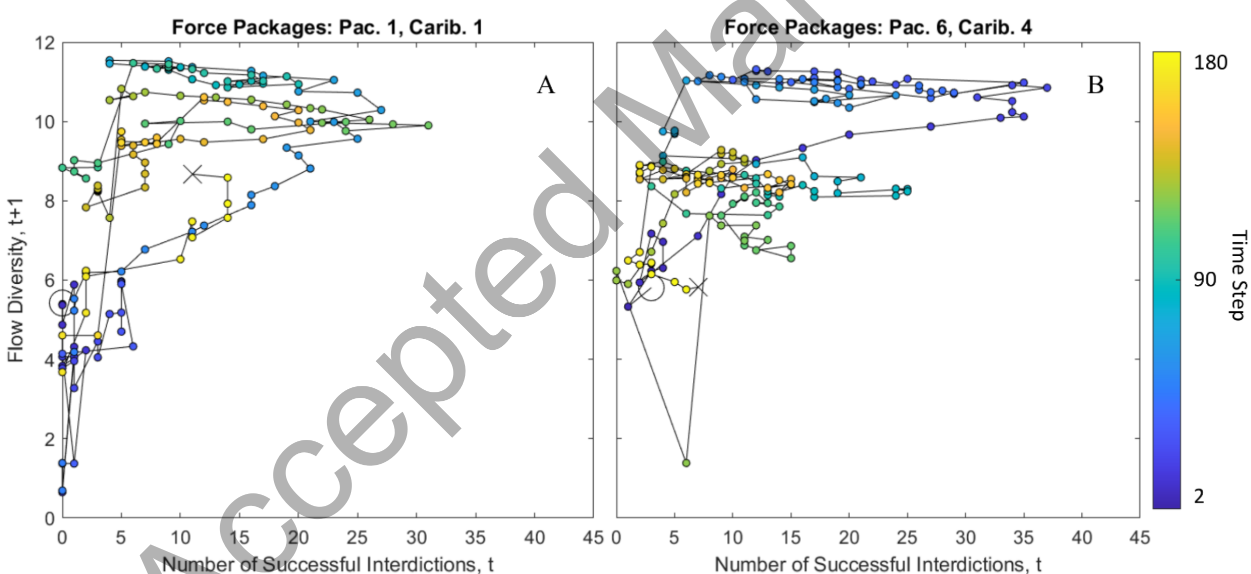

Figure 5. State space plots of the evolution of flow diversity following successful interdiction events in the previous time step. The clear, open circle marks the start of the simulation, and the 'X' indicates the state at the final time step. Filled circles are plotted for every time step with the color indicating which time step. The a) minimum and b) maximum interdiction force package scenarios are shown for a single model execution.

Local sensitivity analyses explored variations in model outcomes based on the OFAT approach, and particular attention was given to time-varying model sensitivities to detect the presence of path-dependent dynamics. The overall interdiction rate was insensitive to changes in the probability of successful interception at values 75% of the baseline value and above (Fig. C5). Trafficking network behavior, measured as the number of active edges and primary shipments, was found to be path-dependent with outcomes diverging into distinct high and low states (Fig. C6), but interdiction dynamics did not display path-dependency (Fig. C7). A detailed description of sensitivity analysis methods and results is provided in Appendix C.

5. Discussion

This research makes methodological and conceptual cross-disciplinary contributions. This work contributes to the literature regarding interdiction operations by providing a more realistic representation of the counterdrug interdiction operational environment than previously done. The objective of maximal covering most closely matches the interdiction reality of far fewer interdiction resources than traffickers to interdict. The ability to model constraints regarding jurisdiction or force package type, in addition to the number of interdiction resources, captures real-world interdiction necessities. The spatially explicit nature of the location optimization model can accommodate spatial limitations on resource deployment and jurisdictional constraints (e.g., Coast Guard only has jurisdiction on high seas). Most importantly, however, interdiction operations and traffickers' behavior are treated here as coupled systems, which allows us to integrate qualitative, operational knowledge gleaned from our collaborators into a spatially explicit modeling environment to investigate the likely consequences of such constraints for trafficker behavior and interdiction effectiveness. Conceptually, the lens and analytical tools of complex system provide insights into the actions and reactions driving emergent, adaptive behaviors and their effects on goal-oriented effectiveness. The exact problems with current approaches to disrupting transnational cocaine trafficking are difficult to identify, potential solutions are socially contested, and unintended consequences are more the norm than exception. Conceptualizing this activity space as a complex adaptive system with co-evolving prescribed planning elements and emergent agent behavior increases our depth of understanding of the system as it matures. Interdiction location allocations necessarily co-evolve with spatial patterns of narco-trafficking activity as more information is learned. Reflecting this information asymmetry replicates the reactive, tactical nature of current counterdrug interdiction operations.

The research presented here has some non-trivial limitations; unsurprising given that neither traffickers nor interdiction forces typically share information about their operations, or what they know about the operations of the opposing side. With regard to modeling narco-trafficking, we know that what are treated here as narco-trafficking network aggregates, are in reality many separate and distributed DTOs' networks with their own complex cooperative and competitive dynamics (Dudley 2010). The current version of NarcoLogic assumes that connections between all trafficking node agents are possible, which enables a more fluid response to interdiction than is likely possible in reality. Additionally, NarcoLogic assumes that all cocaine that enters the trafficking network is destined for Mexico, which fails to recognize international ports within the transit zone, such as Límon in Costa Rica (Robins 2019), as possible destinations to connect to the transatlantic drug trade (European Monitoring Centre for Drugs and Addiction 2019). Both assumptions influence the fluidity and geography of simulated trafficking network responses to interdiction.

Perhaps more importantly, given the secretive nature of the trafficking and interdiction operations, and the impossibility of testing alternative interdiction strategies on a nearly hemispheric scale, differences among the model scenarios should only be interpreted qualitatively. While the NarcoLogic model was previously validated against empirically estimated northbound cocaine flows in the transit zone, rigorous empirical validation of the coupled modeling framework is not currently possible, because it would require spatially and temporally explicit information about both narco-trafficking and counterdrug interdiction operations; information which is simply not available.

With regard to interdiction operations more specifically, current force package allocations vary regularly and are considered sensitive (or even classified) information due to security concerns. We can currently approximate a calendar year's average force package level and allocation between Caribbean and Pacific theaters, but specific spatial locations, timing, and deployment levels of operations are not publicly available. To address this limitation, we bounded observed historical average force package levels by theoretical minimum and maximum scenarios. Similarly, precise operational objectives of the interdiction operations are not well defined and are even a matter of debate among actors across the interdiction planning process. While overall U.S. government drug policy is known, operational objectives and constraints on relatively short timelines are much less transparent. Based on discussions with interdiction forces, our implementation of covering models that support multiple types of interdiction forces is the best representation, but there are certainly additional measures of success and operating constraints that could more fully approximate their operations. More broadly, this highlights a salient tradeoff between model realism and empirical validity. Increasing the realistic constraints and adaptive behaviors included in the models demands comparable yet independent empirical data against which the model outcomes can be validated. Although a more stylized model may lack geographic and operational realism, empirical validation is more feasible in principle. Given the limited knowledge and data describing either narco-trafficking or counterdrug interdiction operations, validation is difficult for each model individually and is compounded through their coupling.

6. Conclusions

While recognizing these limitations, this work has modeled the influence of counterdrug efforts on the spatially and temporally adaptive behaviors of narco-traffickers using a coupled agent-based and spatial optimization framework, which provides a more realistic and insightful strategy than current approaches that treat interdiction and trafficking operations as static. For instance, a particularly robust finding from experiments with 24 different scenarios of interdiction asset levels and geographic deployment was that increasing interdiction levels increased the volume seized (which was expected and has been established by other optimization modeling approaches) but had little effect on the value of seized shipments nor the number of active nodes throughout the network (which was unexpected). The latter findings provided insights into the mechanisms driving the expansion of trafficking areas and the increased challenge of meeting counterdrug interdiction goals with limited resources. Moreover, these findings would not have been possible without the simulation of a dynamic and adaptive trafficking network.

The coupled optimization and simulation approach has also opened a number of new research avenues. The coupled model environment developed for this research can accommodate multiple interdiction strategies and trafficker responses, which in turn will facilitate the development of new optimization models to support counterdrug operations. For example, intercepting shipments along preferred trafficking routes (flow covering), minimizing the opportunity for adjacent spatial displacement of known trafficking activity (gradual covering), and preventing the emergence of new trafficking locations in more distal parts of the network (dispersion). These interdiction models could also be extended to accommodate dynamic asset availability, due to budget constraints or equipment downtime for instance, by allowing the number of force packages to vary across time steps. Potential formulations could also incorporate maintaining interdiction presence across subsequent time steps, or anticipating demand values via trafficker behavior such as displacement or stockpiling. Having made the novel modeling choice to treat interdiction forces as optimizers and DTOs as agents, the advance here is coupling those models in a way that permits the examination of how DTOs change their operations as the amount and type of interdiction force being applied changes. This coupled model framework will also promote future research focusing on deriving new metrics for interdiction outcomes that move beyond conventional variables of illicit supply network operations, e.g., cocaine value seized, money seized, and number of shipments disrupted, to mine relationships that more directly measure the effects of interdiction of narco-trafficking network function. For example, return time for each interdiction location node; changes in trafficking pressure on partner countries due to geographic displacement of smuggling routes; trafficker displacement intensity measured as the combination of space and time displacement from the original smuggling route; and changes in interception likelihood. Further, the applicability of multi-layer complex network measures to characterize different aspects of network structural evolution over time should be investigated. More broadly speaking, the tight integration of agent-based and spatial optimization models has potential research application in a large number of social science research areas where complex (wicked) problems are best modeled as planning exercises, where goals are set amid well-known constraints, but the behavior of actors emerges as the system matures.

Data Availability Statement

The data that support the findings of this study are openly available through the Laboratory for Human-Environment Interactions Modeling and Analysis (HEIMA) data repository at https://heima.ua.edu/data.html.

Acknowledgements

This research was supported by the U.S. National Science Foundation (NSF) EAGER ISN #1837698 and NSF D-ISN: #2039975.

References

Akanle OM, Zhang DZ (2008) Agent-based model for optimising supply-chain configurations. *International Journal of Production Economics* 115(2):444–460.

Altner DSD, Ergun Ö, Uhan NA (2010) The Maximum Flow Network Interdiction Problem: Valid inequalities, integrality gaps, and approximability. *Operations Research Letters* 38(1):33–38.

An L, Grimm V, Sullivan A, TurnerII BL, Malleson N, Heppenstall A, Vincenot C, et al. (2021) Challenges, tasks, and opportunities in modeling agent-based complex systems. *Ecological Modelling* 457:109685.

Anderson T, Dragićević S (2020a) Representing Complex Evolving Spatial Networks: Geographic Network Automata. *ISPRS International Journal of Geo-Information 2020, Vol. 9, Page 270* 9(4):270.

Anderson T, Dragićević S (2020b) Complex spatial networks: Theory and geospatial applications. *Geography Compass* 14(9):e12502.

Anzoom R, Nagi R, Vogiatzis C (2021) A Review of Research in Illicit Supply-Chain Networks and New Directions to Thwart them. *IISE Transactions*:1–59.

Basu G (2014) Concealment, corruption, and evasion: A transaction cost and case analysis of illicit supply chain activity. *Journal of Transportation Security* 7(3):209–226.

Berglund EZ (2015) Using Agent-Based Modeling for Water Resources Planning and Management. *Journal of Water Resources Planning and Management* 141(11):04015025.

Boivin R (2014) Risks, prices, and positions: A social network analysis of illegal drug trafficking in the world-economy. *International Journal of Drug Policy* 25(2):235–243.

Bouchard M (2007) On the Resilience of Illegal Drug Markets. *Global Crime* 8(4):325–344.

Bright DA, Delaney JJ (2013) Evolution of a drug trafficking network: Mapping changes in network structure and function across time. *Global Crime* 14(2–3):238–260.

ten Broeke G, van Voorn G, Ligtenberg A (2016) Which sensitivity analysis method should i use for my agent-based model? *JASSS* 19(1).

Caulkins J, Crawford G, Reuter P (1993) Simulation of adaptive response: A model of drug interdiction. *Mathematical and Computer Modelling* 17(2):37–52.

Cavallaro L, Ficara A, Meo P De, Fiumara G, Catanese S, Bagdasar O, Song W, Liotta A (2020) Disrupting resilient criminal networks through data analysis: The case of sicilian mafia. *PLoS ONE* 15(8 August).

Centers for Disease Control and Prevention (2020) Products - Vital Statistics Rapid Release - Provisional Drug Overdose Data. *Vital Statistics Rapid Release - Provisional Drug Overdose Data*. Retrieved (November 8, 2021), https://www.cdc.gov/nchs/nvss/vsrr/drug-overdose-data.htm.

Choi Thomas Y, Dooley KJ, Rungtusanatham M (2001) Supply networks and complex adaptive systems: control versus emergence. *Journal of Operations Management* 19(3):351–366.

Cormican K, Morton DP, Wood RK (1998) Stochastic network interdiction. *Operations Research* 46:184–197.

Dell M (2015) Trafficking networks and the Mexican drug war. *American Economic Review* 105(6):1738–1779.

Devine JA, Wrathall D, Currit N, Tellman B, Langarica YR (2020) Narco-Cattle Ranching in Political Forests. *Antipode* 52(4):1018–1038.

Dudley SS (2010) *Drug Trafficking Organizations in Central America: Transportistas, Mexican Cartels and Maras.* (San Diego, CA).

Dudley SS (2011) Drug Trafficking Organizations in Central America: Transportistas, Mexican Cartels and Maras. Woodrow Wilson Center Reports on the Americas #29. *Organized Crime in Central America: The Northern Triangle*:63–94.

Elsawah S, Filatova T, Jakeman AJ, Kettner AJ, Zellner ML, Athanasiadis IN, Hamilton SH, et al. (2020) Eight grand challenges in socio-environmental systems modeling. *Socio-Environmental Systems Modelling* 2:16226.

European Monitoring Centre for Drugs and Addiction (2019) *EU Drug Markets Report 2019* (Lisbon, Portugal).

Farahani RZ, Fallah S, Ruiz R, Hosseini S, Asgari N (2019) OR models in urban service facility location: A critical review of applications and future developments. *European Journal of Operational Research* 276(1):1–27.

GAO (2019) *Assessing Deployable Specialized Forces ' Workforce Needs Could Improve Efficiency and Reduce Potential Overlap or Gaps in Capabilities* (Washington, DC).

Goodman N, Coyne CJ (2021) *U.S. Border Militarization and Foreign Policy: A Symbiotic Relationship* (Fairfax, VA).

Guerra S (1992) Domestic Drug Interdiction Operations : Finding the Balance. *The Journal of Criminal Law and Criminology* 82(4):1109–1161.

Holland JH (1995) *Hidden Order* (Addison-Wesley, Reading, WA).

Hudson R (2014) Thinking through the relationships between legal and illegal activities and economies: Spaces, flows and pathways. *Journal of Economic Geography* 14(4):775–795.

Israeli E, Wood RK (2002) Shortest-Path Network Interdiction. *Networks* 40(2):97–111.

Jabarzare Z, Zolfagharinia H, Najafi M (2020) Dynamic interdiction networks with applications in illicit supply chains. *Omega* 96:102069.

JIATF-S (2019) LTC A. Ajamian. (July 15).

Keskin BB, Li SR, Steil D, Spiller S (2012) Analysis of an integrated maximum covering and patrol routing problem. *Transportation Research Part E: Logistics and Transportation Review* 48(1):215–232.

Kroshl WM, Sarkani S, Mazzuchi TA (2015) Efficient Allocation of Resources for Defense of Spatially Distributed Networks Using Agent-Based Simulation. *Risk Analysis* 35(9):1690–1705.

Liebman JC (1976) Some Simple-Minded Observations on the Role of Optimization in Public Systems Decision-Making. *https://doi.org/10.1287/inte.6.4.102* 6(4):102–108.

Ligmann-Zielinska A, Siebers PO, Magliocca N, Parker D, Grimm V, Du EJ, Cenek M, et al. (2020) 'One size does not fit all': A roadmap of purpose-driven mixed-method pathways for sensitivity analysis of agent-based models. *JASSS* 23(1).

Losada C, Scaparra MP, Church RL, Daskin MS (2012) The stochastic interdiction median problem with disruption intensity levels. *Annals of Operations Research* 201(1):345–365.

Magliocca NR, McSweeney K, Sesnie SE, Tellman E, Devine JA, Nielsen EA, Pearson Z, Wrathall DJ (2019) Modeling cocaine traffickers and counterdrug interdiction forces as a complex adaptive system. *Proceedings of the National Academy of Sciences* 116(16):7784–7792.

Magliocca NR, Summers DS, Curtin KM, McSweeney K, Price AN (2022) Shifting landscape suitability for cocaine trafficking through Central America in response to counterdrug interdiction. *Landscape and Urban Planning* 221:104359.

Magliocca NR, Torres A, Margulies J, McSweeney K, Arroyo-Quiroz I, Carter N, Curtin K, et al. (2021) Comparative Analysis of Illicit Supply Network Structure and Operations: Cocaine, Wildlife, and Sand. *Journal of Illicit Economies and Development* 3(1):50–73.

Malaviya A, Rainwater C, Sharkey T (2012) Multi-period network interdiction problems with applications to city-level drug enforcement. *IIE Transactions (Institute of Industrial Engineers)* 44(5):368–380.

Manson SM (2001) Simplifying complexity: A review of complexity theory. *Geoforum* 32(3):405–414.

Mcdermott J, Bargent J, den Held D, Fernanda Ramírez M (2021) *The Cocaine Pipeline to Europe*

McLay LA, Lloyd JD, Niman E (2009) Interdicting nuclear material on cargo containers using knapsack problem models. *Annals of Operations Research* 187(1):185–205.

McSweeney K (2020a) Cocaine Trafficking and the Transformation of Central American Frontiers. *Journal of Latin American Geography* 19(3):159–166.

McSweeney K (2020b) Reliable drug war data: The Consolidated Counterdrug Database and cocaine interdiction in the "Transit Zone." *International Journal of Drug Policy* 80:102719.

McSweeney K, Nielsen EA, Taylor MJ, Wrathall DJ, Pearson Z, Wang O, Plumb ST (2014) Drug policy as conservation policy: Narco-deforestation. *Science* 343(6170):489–490.

McSweeney K, Wrathall DJ, Nielsen EA, Pearson Z (2018) Grounding traffic: The cocaine commodity chain and land grabbing in eastern Honduras. *Geoforum* 95(July):122–132.

Mirzaei M, Mirzapour Al-e-hashem SMJ, Akbarpour Shirazi M (2021) A maximum-flow network interdiction problem in an uncertain environment under information asymmetry condition: Application to smuggling goods. *Computers and Industrial Engineering* 162(September):107708.

Morselli C (2009) Hells Angels in springtime. *Trends in Organized Crime* 12(2):145–158.

Morton DP, Pan F, Saeger KJ (2007) Models for nuclear smuggling interdiction. *IIE Transactions (Institute of Industrial Engineers)* 39(1):3–14.

Munsing E, Lamb CJ (2011) *Joint Interagency Task Force-South: The Best Known, Least Understood Interagency Success* (Washington, DC).

Nair A, Narasimhan R, Choi TY (2009) Supply networks as a complex adaptive system: toward simulation-based theory building on evolutionary decision making. *Decision Sciences* 40(4):783–815.

Nguyen DH, Smith JC (2022) Network interdiction with asymmetric cost uncertainty. *European Journal of Operational Research* 297(1):239–251.

Niamir L, Filatova T, Voinov A, Bressers H (2018) Transition to low-carbon economy: Assessing cumulative impacts of individual behavioral changes. *Energy Policy* 118:325–345.

O'Sullivan D (2004) Complexity science and human geography. *Transactions of the Institute of British Geographers* 29(3):282–295.

Paul NR, Lunday BJ, Nurre SG (2017) A multiobjective, maximal conditional covering location problem applied to the relocation of hierarchical emergency response facilities. *Omega (United Kingdom)* 66:147–158.

Porras C, Fajardo J, Rosete A (2019) Multi-coverage dynamic maximal covering location problem. *Investigacion Operacional* 40(1):140–149.

Price A, Curtin KM, Magliocca NR, Turner D, Mitchell P, McSweeney K, Summers DL (2022) A Family of Models in Support of Realistic Drug Interdiction Location Decision Making. *Transactions in GIS, 26(4): 1962-1980.*

Resig M, Woodaman R, Curtin K (2020) Operational-Level Autonomous Logistics: A Multi-Objective Model Formulation and Solution Procedure. *Military Operations Research* 25(3).

Rittel HWJ, Webber MM (1973) Dilemmas in a general theory of planning. *Policy Sciences 1973 4:2* 4(2):155–169.

Robbins S (2019) Costa Rica's Port of Limón Feeds European Cocaine Pipeline. *Insight Crime* (March 12).

Robles G, Calderón G, Magaloni B (2013) The economic consequences of drug trafficking violence in Mexico. *Poverty and Governance Series Working Paper, Stanford University*.

Sadeghi S, Seifi A (2019) Stochastic Maximum Flow Network Interdiction with Endogenous Uncertainty. *International Journal of Supply and Operations Management* 6(3):2383–2525.

Schwarz N, Dressler G, Frank K, Jager W, Janssen M, Müller B, Schlüter M, Wijermans N, Groeneveld J (2020) Formalising theories of human decision-making for agent-based modelling of social-ecological systems: practical lessons learned and ways forward. *Socio-Environmental Systems Modelling* 2:16340.

Sesnie SE, Tellman B, Wrathall D, McSweeney K, Nielsen E, Benessaiah K, Wang O, Rey L (2017) A spatio-temporal analysis of forest loss related to cocaine trafficking in Central America. *Environmental Research Letters* 12(5).

Shen Y, Sharkey TC, Szymanski BK, Wallace W (Al) (2021) Interdicting interdependent contraband smuggling, money and money laundering networks. *Socio-Economic Planning Sciences*:101068.

Stanimirović Z, Mišković S, Trifunović D, Veljović V (2017) A two-phase optimization method for solving the multi-type maximal covering location problem in emergency service networks. *Information Technology and Control* 46(1):100–117.

Tellman E, Sesnie SE, Magliocca NR, Nielsen EA, Devine JA, McSweeney K, Jain M, Wrathall DJ, Benessaiah K, Aguilar-Gonzalez B (2020) Illicit drivers of land-use change: Narcotrafficking and forest loss in Central America. *Global Environmental Change*.

UNODC (2020) *World Drug Report 2020* (Viennna, Austria).

USCG (2020) *United States Coast Guard Annual Performance Report Fiscal Year 2020* (Washington, DC).

Vaněk O, Jakob M, Hrstka O, Pěchouček M (2013) Agent-based model of maritime traffic in piracy-affected waters. *Transportation Research Part C: Emerging Technologies* 36:157–176.

Widener MJ, Horner MW, Ma K (2015) Positioning Disaster Relief Teams Given Dynamic Service Demand: A Hybrid Agent-Based and Spatial Optimization Approach. *Transactions in GIS* 19(2):279–295.

Will M, Groeneveld J, Frank K, Müller B (2020) Combining social network analysis and agent-based modelling to explore dynamics of human interaction: A review. *Socio-Environmental Systems Modelling* 2:16325.

Williams P, Godson R (2002) Anticipating organized and transnational crime. *Crime, Law and Social Change* 37(4):311–355.

Wilt J, Sharkey TC (2019) Measuring the Impact of Coordination in Disrupting Illicit Trafficking Networks. Romeijn HE, Schaefer A, Thomas R, eds. *Proceedings of the 2019 IISE Annual Conference*. (Orlando, FL), 767–772.

Wood RK (1993) Deterministic network interdiction. *Mathematical and Computer Modelling* 17(2):1–18.

Wrathall DJ, Devine J, Aguilar-González B, Benessaiah K, Tellman E, Sesnie S, Nielsen E, et al. (2020) The impacts of cocaine-trafficking on conservation governance in Central America. *Global Environmental Change* 63(August 2019):102098.

Yue D, You F (2014) Game-theoretic modeling and optimization of multi-echelon supply chain design and operation under Stackelberg game and market equilibrium. *Computers and Chemical Engineering* 71:347–361.

Yue D, You F (2017) Stackelberg-game-based modeling and optimization for supply chain design and operations: A mixed integer bilevel programming framework. *Computers and Chemical Engineering* 102:81–95.

Zarandi MHF, Davari S, Sisakht SAH (2013) The large-scale dynamic maximal covering location problem. *Mathematical and Computer Modelling* 57(3–4):710–719.

Zeng W, Hodgson MJ, Castillo I (2009) The Pickup Problem: Consumers' Locational Preferences in Flow Interception. *Geographical Analysis* 41(1):149–168.

Author Biographies

Nicholas R. Magliocca received his PhD in the Department of Geography at the University of Maryland, Baltimore County. He is currently an Associate Professor in the Department of Geography at the University of Alabama. His research interests include social-ecological systems, agent-based modeling, and geospatial analysis.

Ashleigh N. Price received her MS in Geography from the University of Southern Mississippi. She is currently a PhD candidate in the Department of Geography at the University of Alabama. Her research interests are in crime geography, hazard vulnerability & resilience, and spatial optimization.

Penelope Mitchell received her MS in Geography from the University of Alabama. She is currently a PhD candidate in the Department of Geography at the University of Alabama. Her research interests are geographic information systems, spatial analysis, and spatial optimization methods in the context of health and behavioral geography.

Kevin M. Curtin received his PhD in Geography from the University of California, Santa Barbara. He is currently a Professor in the Department of Geography at the University of Alabama. He performs primary research in the field of Geographic Information Science with specializations in location science, transportation and logistics, urban resource allocation, spatial statistics, and network GIS.

Matthew Hudnall received his PhD in Computer Science at the University of Alabama. He is currently an Assistant Professor in Management Information Systems in the Department of Information Systems, Statistics, and Management Science at the University of Alabama. Dr. Hudnall is also the Deputy Director of the Institute of Data & Analytics. His research interests include data security, big-data analytics, cybersecurity, and leveraging software systems to improve society.

Kendra McSweeney received her PhD in Geography from McGill University. She is currently a Professor of in the Department of Geography at the Ohio State University. Her research interests are in human-forest interactions and uses of political ecology approaches to study them.