Modeling cocaine traffickers and counterdrug interdiction forces as a complex adaptive system

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Counterdrug interdiction efforts designed to seize or disrupt cocaine shipments between South American source zones and US markets remain a core US "supply side" drug policy and national security strategy. However, despite a long history of US-led interdiction efforts in the Western Hemisphere, cocaine movements to the United States through Central America, or "narco-trafficking," continue to rise. Here, we developed a spatially explicit agent-based model (ABM), called "NarcoLogic," of narco-trafficker operational decision making in response to interdiction forces to investigate the root causes of interdiction ineffectiveness across space and time. The central premise tested was that spatial proliferation and resiliency of narco-trafficking are not a consequence of ineffective interdiction, but rather part and natural consequence of interdiction itself. Model development relied on multiple theoretical perspectives, empirical studies, media reports, and the authors' own years of field research in the region. Parameterization and validation used the best available, authoritative data source for illicit cocaine flows. Despite inherently biased, unreliable, and/or incomplete data of a clandestine phenomenon, the model compellingly reproduced the "cat-and-mouse" dynamic between narco-traffickers and interdiction forces others have qualitatively described. The model produced qualitatively accurate and quantitatively realistic spatial and temporal patterns of cocaine trafficking in response to interdiction events. The NarcoLogic model offers a much-needed, evidence-based tool for the robust assessment of different drug policy scenarios, and their likely impact on trafficker behavior and the many collateral damages associated with the militarized war on drugs.

illicit supply networks | illicit economy | drug policy reform | transaction costs | agent-based model

Counterdrug interdiction efforts, designed primarily to seize or disrupt cocaine shipments in the "transit zone" between South American sources and US markets, continue to be at the core of US supply side drug policy and national security strategy (1–3) with $4.7 billion allocated to interdiction in fiscal year 2016, or about 18% of total federal drug control spending. In addition to "production zone" strategies like drug crop eradication, transit zone interdiction strives to create scarcity, increase the operating costs of drug trade organizations (DTOs), and ultimately raise retail prices to deter drug abuse in the United States (4, 5). However, the US government's own assessments have long showed that interdiction has at best only an ephemeral impact on retail prices and supply (5–11). In fact, wholesale cocaine prices in the United States have dropped significantly since 1980, deaths from cocaine overdose are rising (12), and the dismal rate at which counterdrug forces intercept cocaine shipments is well documented (13). Despite these failures, interdiction budgets increased in 2018 and 2019 (14, 15), signaling that interdiction continues to be a key part of US counterdrug strategy. A better understanding of the root causes of narco-trafficking dynamics

and interdiction ineffectiveness within the transit zone is needed to inform US drug policy (16).

Critics of interdiction point to failures to increase retail prices and reduce supply as evidence that interdiction itself is the problem (7–10). Moreover, interdiction has been qualitatively linked to the unintended spread and fragmentation of existing trafficking routes—known as the "balloon and cockroach effects," respectively—into new and more numerous locations (2, 4). As a result, the Western Hemisphere transit zone grew from 2 to 7 million square miles between 1996 and 2017 (17, 18), making it more difficult and costly for law enforcement to track and disrupt trafficking networks (2, 5, 19). This expansion has also brought a litany of collateral damages. Locations through which drugs are smuggled experience narco-fueled violence and corruption (20), infusion of unparalleled amounts of cash and weapons (21), dispossession and seizure of land from rural communities (22), and extensive and rapid environmental destruction (21–23). Critics add that interdiction is not a sustainable counterdrug strategy, because

Significance

The US government's cocaine interdiction mission in the transit zone of Central America is now in its fifth decade despite its long-demonstrated ineffectiveness, both in cost and results. We developed a model that builds an interdisciplinary understanding of the structure and function of narco-trafficking networks and their coevolution with interdiction efforts as a complex adaptive system. The model produced realistic predictions of where and when narco-traffickers move in and around Central America in response to interdiction. The model demonstrated that narco-trafficking is as widespread and difficult to eradicate as it is because of interdiction, and increased interdiction will continue to spread traffickers into new areas, allowing them to continue to move drugs north.

counterdrug forces will never be as well-capitalized, organized, or nimble as DTOs (24).

Proponents of interdiction, in contrast, locate the problem with drug traffickers. They argue that interdiction efforts are important for decreasing the total volume entering the United States, and are vital for deterring narco-trafficking activities in specific places (25). Indeed, seizure volumes are reaching all-time highs (26), and supply-side interdiction in source and transit zone countries has been linked to higher overall prices in consumption countries than would otherwise be attained in legal markets (19, 27–29). Furthermore, supporters have pointed to the symbolic and moral value of interdiction efforts, because narco-traffickers are criminals and actions must be taken to stop them (30, 31). Proponents also maintain that interdiction would be more effective by correcting a number of operational aspects: insufficient and inconsistent interdiction equipment, funding, and staffing (25); low capacity and corruption among transit zone country partners (32, 33); and ineffective intelligence sharing among US military and law enforcement agencies (34). In particular, collateral damages from interdiction could be minimized with better intelligence to support spatially targeted interdiction (26) and greater funding to support a "whole-region" approach to increase citizen security (35).

Clearly, the latter logic animates current policy, even as there is widespread recognition that ongoing approaches are ineffective and have unintended collateral damages. Indeed, the need for change is recognized by both sides (17). Agreement on how national and international interdiction polices should change, however, remains elusive, in part because the processes that link observed narco-trafficking proliferation (i.e., the balloon and cockroach effects) and interdiction operations are poorly understood. Simulation models have been a primary tool for studying trafficking–interdiction interactions among academic (5, 10, 19) and military (36–38) operations researchers for at least 30 y. However, existing models are constrained by poor data, focus only on partial trafficking strategies (e.g., maritime only) (37), and/or treat the transit and interdiction space as a "black box" (e.g., refs. 5, 35, and 38). Understanding the full effects of interdiction requires a model that integrates price, volume, and spatial responses of narco-traffickers to shifting levels of interdiction in a geographically realistic model space.

The central contribution of this paper is the development of a spatially explicit agent-based model (ABM), called NarcoLogic, to model the decision-making processes of narco-traffickers in response to interdiction efforts. NarcoLogic differs from previous modeling approaches because it simultaneously models local- and network-level narco-trafficking dynamics in response to interdiction. Additionally, NarcoLogic is calibrated and validated with, what is to our knowledge, the only non-US government-affiliated or -commissioned (e.g., ref. 39) application of data from the Consolidated Counterdrug Database (CCDB), which includes event-based estimates that "are the best available authoritative source for estimating known illicit drug flow through the Transit Zone" (13). The model enables us to test our main hypothesis: the spatial proliferation and resiliency of narco-trafficking is not a consequence of ineffective interdiction, but rather a part and natural consequence of interdiction itself—that is, we theorize their interplay as a complex adaptive system (40). In other words, interdiction ineffectiveness in not the result of either interdiction or traffickers, but rather their interaction over many years. We test this hypothesis by comparing NarcoLogic's predictions of where, when, and how cocaine shipments where trafficked during 2000–2014 against actual spatial and temporal patterns of cocaine flows recorded in CCDB. We also compare predictions from a counterfactual model version that omits top–down coordination from DTOs to test our hypothesized multilevel mechanism for spatial and dynamic reorganization of trafficking networks in response to interdiction.

Approach

Our theoretical framing of the organization, decision making, and spatial dynamics of narco-trafficking networks draws from literatures on geographies of crime and transaction cost theory. Crime geography provides two key insights: (*i*) locations of criminal activities can be predicted by an intersection of social, political, and environmental features that lower the risk of detection, and (*ii*) the scale of analysis must be consistent with that at which criminal activities are perpetrated (41). Narco-trafficking has been associated with sociopolitical settings of weak governance, conflicting property rights, and high levels of poverty and inequality (22, 42, 43). Remote areas, often within forested and/or protected areas, are also targeted by narco-traffickers due to weak law enforcement (21, 23). Understanding of why narco-traffickers exploit certain locations within the transit zone has not been explicitly modeled, since geographic considerations of the illicit drug trade have focused on producing and consuming locations (44, 45).

Transaction costs are essential to consider, because similar to legitimate supply chain actors, DTOs derive earnings based on their logistical abilities to maximize profit and efficiency while managing risks to supply disruptions (5, 46, 47). Narco-trafficking networks tend toward vertical integration in an effort to minimize transaction costs associated with incomplete price information and labor supply, identifying reliable transaction partners, and enforcing transaction agreements (1, 48, 49). However, interdiction disrupts that vertical integration, forcing decentralization of trafficking decisions to minimize risk (1–3). We posit that such adjustments are primarily spatial in nature: active trafficking nodes will emerge in locations with lower perceived transaction costs. While these effects have been anecdotally observed (i.e., "balloon effect" and "cockroach effect"), and transaction cost theory provides a plausible rationale, the dynamic, spatial implications of this mechanism have never been modeled in the context of an illicit supply network.

The NarcoLogic Model

NarcoLogic (50) formalizes these theoretical principles into quantitative predictions of the spatial structure, dynamics, and adaptation of narco-trafficking networks in response to interdiction within the transit zone of Central America. Specifically, the model implements a logic for DTO and individual trafficker node (i.e., locations of transshipment) behavior through partially coordinated but disaggregated decision making based on "first principles" of profit maximization and risk management. This logic is informed by empirical studies on cocaine trafficking and traffickers, media reports, and the authors' own years' of research in the region. Higher profits are captured by minimizing the number of nodes through which shipments flow (i.e., profits split between smaller number of supply chain actors), but interdiction risk for any single movement increases with transit distance. Thus, the fewer the intermediaries, the higher the overall profits captured by a DTO or trafficking node, but at an increased risk of interdiction. Operationally, a DTO may choose to consolidate existing trafficking routes to maximize profit, or expand their network to new nodes to diffuse overall risk and minimize losses. Individual trafficking nodes make similar decisions to concentrate or evenly distribute shipments among potential downstream buyer nodes. Management of the profit-to-risk trade-off in response to interdiction events is the main adaptive decision-making process producing emergent trafficking network behaviors and location-specific cocaine flows that can be compared against existing data.

The model environment is a spatially explicit representation of Central America in which narco-trafficking nodes are georeferenced within the administrative boundaries of Guatemala, Honduras, El Salvador, Nicaragua, Costa Rica, and Panama (Fig. 1). Geographic suitability for trafficking nodes is assumed to be a function of proximity to country borders, remoteness, tree

cover, market access, slope, protected area status, and existing land uses (*SI Appendix*, Table S1). Node locations remain fixed through the simulation linked through a predefined, randomly generated network. The total volume of cocaine entering the trafficking network increases throughout the simulation period based on estimates from the CCDB.[†] Based on empirical estimates (51, 52), the model assumes the price of a kilo of cocaine increases as it moves northward along the trafficking network (*SI Appendix*, S2.1.2). Movement of cocaine from one node to another incurs an exogenous transaction cost based on distance between any two nodes, volume being transported, and mode of transportation; and an endogenous transaction cost of a "risk premium" related to dynamic perceptions of node-to-node interdiction risk (5) (*Methods*).

Three types of agents are modeled. "Network Agents" are a simplified representation of the known role of Mexican/Colombian-based DTOs in orchestrating trafficking throughout the region (1, 2). Two competing DTOs are modeled to explore differential effects of interdiction strategies on each DTO's trafficking network. "Node Agents," representing *transportista* (local drug transport coordination groups) actors observed on the ground (2, 22), have a fixed spatial position operating each trafficking node. Node Agents that are "activated" by their Network Agent purchase shipments of cocaine from supplier nodes, and decide how to allocate the shipment among potential buyer nodes along trafficking network ties. Node Agents only interact with other Node Agents to which they are directly linked in the trafficking network (i.e., immediate neighbors). A single "Interdiction Agent" represents the collective interdiction activities of various law enforcement and military entities coordinated by the US Joint Interagency Task Force–South and in-country partners across Central America and associated maritime areas. Reflecting current practice (53), the Interdiction Agent decides when and where to deploy limited interdiction resources among suspected trafficking route segments (i.e., network linkages) to meet an annual interdiction volume target.

The model is run at a monthly time step for the period of 2001–2014, or 180 mo, which corresponds with the period during which Central America became the preferred trafficking corridor following interdiction campaigns in Mexico and the eastern Caribbean (54). Attempting to recreate the evolution of trafficker–interdiction dynamics during the transition to Central America, agents are assumed not to have preexisting knowledge of optimal routes or interdiction allocation. At each time step, each Network Agent selects Node Agents to "activate" based on profit expectations and past experiences with interdiction. Independently, the Interdiction Agent allocates interdiction capacity to trafficking route segments with the highest perceived probability of interdiction success. Interdiction events occur if shipments move along policed routes. The entire volume is seized and affected trafficking nodes (both sending and receiving) update perceived interdiction risk. At the end of each time step, Network Agents may choose to expand or consolidate existing trafficking nodes for future shipments based on the value of losses to interdiction. Independently, the Interdiction Agent adjusts future interdiction capacity based on the volume of cocaine seized relative to a target volume (*Methods*). Based on the "arms race" mentality of US interdiction policy, interdiction capacity is assumed to increase with seizure volumes (26, 55).

Results

We tested our assumptions about the structure, function, and adaptation of narco-trafficking to interdiction by implementing two alternative model versions—with and without a Network Agent. Only local transaction costs were considered by individual Node Agents in the model version without a Network Agent, whereas both local and global (i.e., network-wide) transaction costs were used to coordinate trafficking routes in the version with a Network Agent. Outcomes of alternative model versions were compared with multiple "target patterns" in empirical data (*Methods*): (*i*) notable increases in narco-trafficking activity were first observed in Guatemala and Honduras in the early 2000s, and shifted southward in geographic extent and intensity during the study period (2, 21, 54); and (*ii*) the timing and magnitude of cocaine flows reported in select administrative departments (based on data completeness) in the CCDB database.[‡]

As Fig. 1 shows, the model version with Network Agents outperformed the alternative version at both the subnational and Central American scales, and produced statistically significant cross-correlations with the CCDB time series data in Colón (Honduras), Gracias a Dios, Atlántico Norte and Sur, and Costa Rica (*SI Appendix*, Table S2.1 and SI2.1.1). Predicted volumes of cocaine flows were qualitatively consistent with—and at many points in time within a quartile of—observed flows reported in CCDB for all of the subnational units (i.e., departments, $n = 8$) analyzed except the Petén (*SI Appendix*, SI2.1.5). In many cases, the overall trajectory and timing of peak cocaine flows were also consistent with observed data. These quantitative and qualitative findings supported our assumption that a combination of top-down and bottom-up coordination between Network and Node Agents was realistic. At the Central America scale, the model successfully recreated the historical southward shift of narco-trafficking activity (Fig. 2*A*). Early in the simulation, direct transport routes to northern countries were the most profitable (i.e., fewest intermediate nodes with greatest profit margins) and were exploited first, but these were also at the greatest risk of interdiction because of long transit distances. As a result of interdiction, shorter and relatively less profitable routes were gradually adopted, shifting trafficking activity south.

The model also provided insight into how DTO and individual node decisions created balloon and cockroach effects at the regional scale. For example, Fig. 2*A* indicates that the first cocaine shipments moved through Panama during 2006–2008, which corresponded with the timing of peak per node shipment volumes in Fig. 2*B*. As narco-trafficking moved into new areas (balloon effect), shipments concentrated in one or a few nodes. However, as narco-trafficking became entrenched and interdictions occurred in these areas, routes and shipments fragmented (cockroach effect), leading to lower flows through any given node despite relatively unchanged or increasing overall flows through the area. This resulted in, for example, Panama's numerous shifting nodes while also increasing volumes by 2012.

The model version without a Network Agent failed to produce or produced substantially underestimated and/or delayed cocaine shipments in all departments except the Petén, for which it substantially overestimated known shipment volumes (*SI Appendix*, SI2.1.5). Failure of this model version indicated the importance of top-down route selection to balance risk and profit across the entire trafficking network. The Network Agent was able to perceive and act on network-wide interdiction risk information enabling trafficking to shift to lower risk yet still profitable locations elsewhere in the network; without a Network Agent trafficking only exploited locally viable locations. Consequently, perceived risks were not great enough to reroute into remote areas (e.g., Gracias a Dios, Darién, for which zero flow values were predicted; Fig. 1) that were less risky, but less direct and more expensive to reach. Differences in outcomes between the alternative model versions demonstrated that the two-level structure of narco-trafficking decision making was more realistic (56).
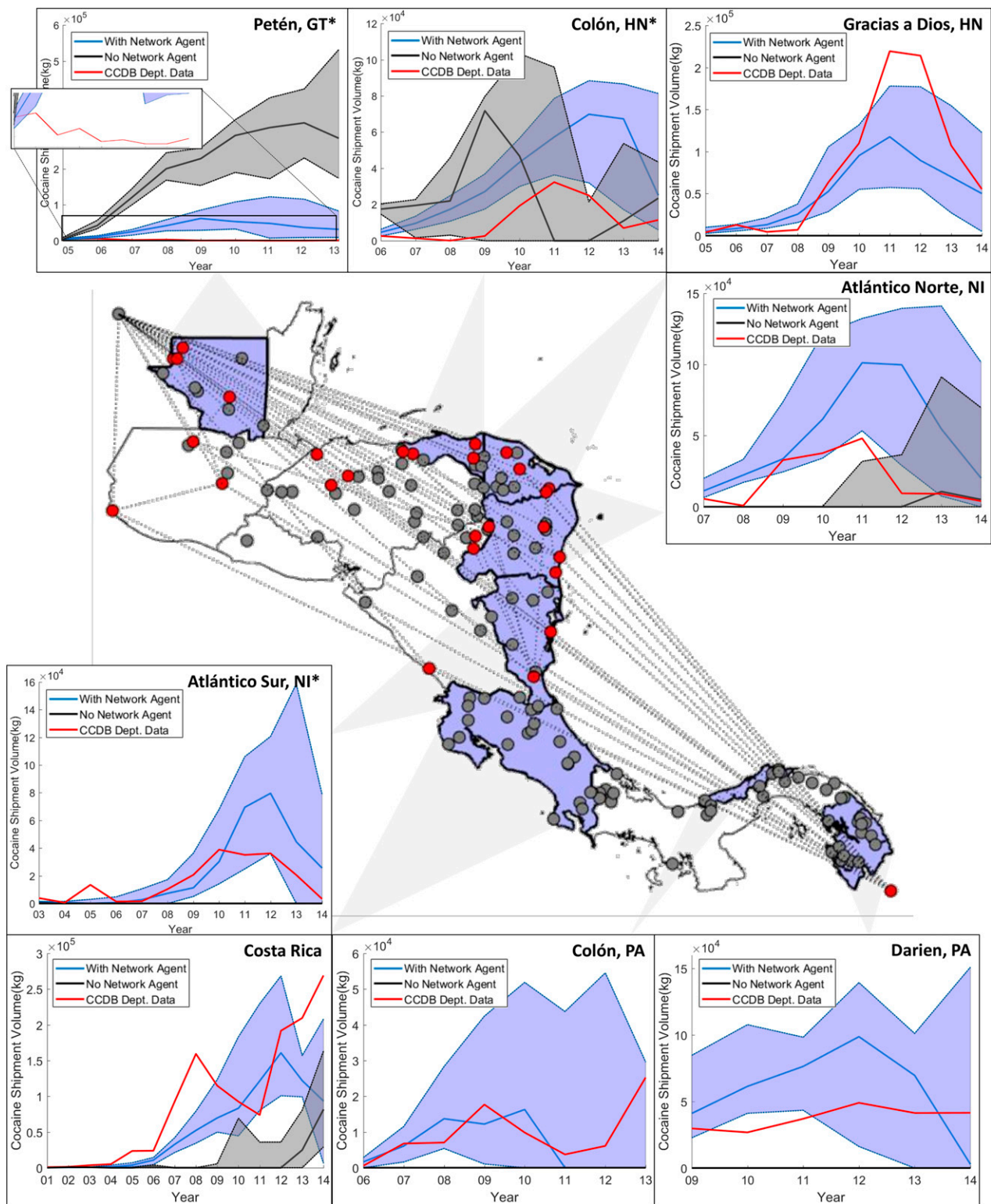
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Fig. 1. Central America modeling domain (center) with an example simulated narco-trafficking network consisting of inactive nodes (gray circles), active nodes (red circles), and trafficking routes between each active node (dashed lines). The most southern and northern nodes outside of the model domain represent supply (e.g., Colombia) and demanding nodes (e.g., Mexico), respectively. Around the periphery, comparisons of subnational cocaine shipment volumes (blue regions in map) reported at the administrative level of departments in the Consolidated Counterdrug Database (CCDB) (red line) and median volumes simulated by model versions with (blue line) and without (black line) a Network Agent. Shaded regions represent the bounds of the second and third quartiles of simulated cocaine volumes. Departments were selected to include at least one location per country and on the basis of having at least 5 y of continuous observations reported in CCDB. Cocaine flows in departments with an asterisk (*) were predicted independent of model calibration (*Methods*).
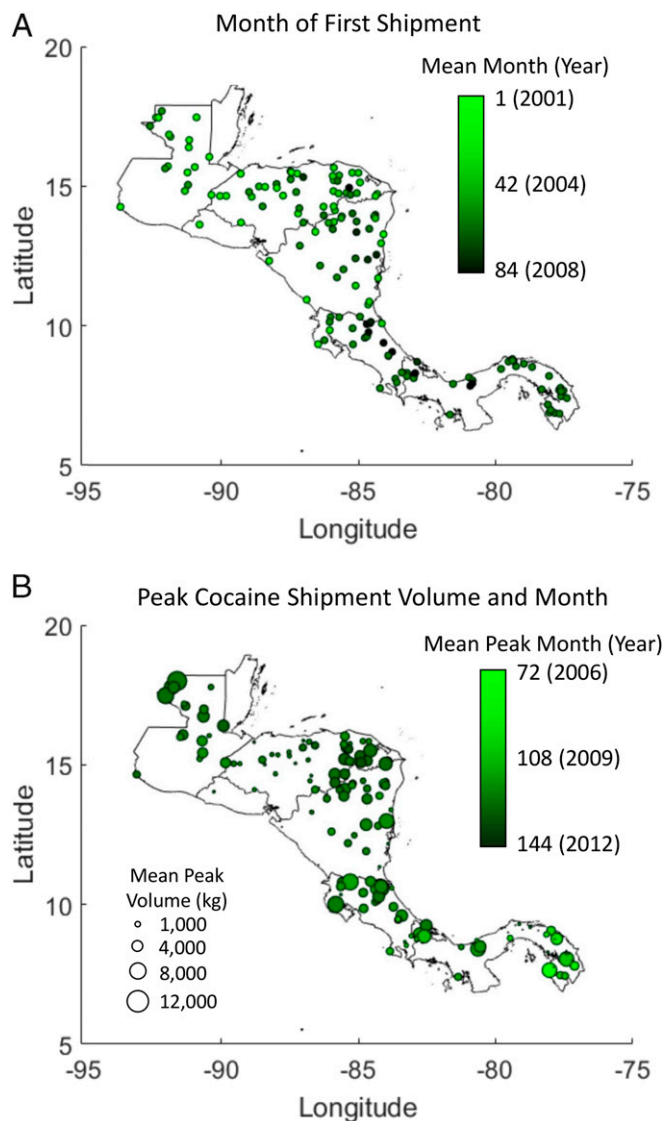
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Fig. 2. Southward progression of narco-trafficking over time measured by the average month (year) of the first cocaine shipment at each trafficking node (*A*). Trafficking intensity, measured as the average month (year) and median volume of the largest annual total shipments for each node, shows a nearly inverse pattern (*B*).

Local sensitivity analysis was performed (*Methods*) on all calibrated parameters using a genetic algorithm (*SI Appendix*, Table S1 and SI2.3). Interdiction's role in the evolution of narco-trafficking behavior was particularly clear with variations in interdiction capacity. Increased interdiction capacity resulted in increased total seizure volumes (Fig. 3*A*) and decreased median delivery sizes (Fig. 3*B*). This was consistent with interdiction's goal of removing as much volume from the supply chain as possible. However, narco-traffickers concurrently succeeded in maximizing profits and minimizing the value of shipments lost. No statistically significant difference in the median value of seizures resulted from increased interdiction capacity beyond its lowest level (Fig. 3*C*). Similarly, no significant difference resulted in the total value seized among baseline and higher interdiction capacities (Fig. 3*D*). Furthermore, increased interdiction capacity did not reduce the number of active nodes (Fig. 3*E*). In fact, trafficking at each node intensified by forcing the same value of cocaine through fewer routes at any one time (Fig. 3*F*), resembling the boom–bust eco-

nomic fluctuations observed anecdotally at individual nodes within transit zones (57). Even when it appeared that interdiction was effective (i.e., increased seizure volumes), there was little effect on the value of cocaine trafficked and geographic extent of narco-trafficking's influence.

Discussion

The US government's cocaine interdiction mission in the transit zone is now in its fifth decade. This is despite its long-demonstrated ineffectiveness, both in cost and results (9, 21). More cocaine entered the United States in 2015 than in any other year, inspiring a Department of Homeland Security-commissioned study that concluded "additional work is required to gain a better understanding of exactly how these drugs are successfully evading US law enforcement interdiction efforts" (ref. 58, p. 53).

The NarcoLogic model points to a clear, reproducible, and testable answer. The model produced realistic predictions of where and when narco-traffickers move in and around Central America in response to interdiction. In the process, it shows that the spatial dynamics of trafficker activity result from adaptive interactions with interdiction agents. In other words, narco-trafficking is as widespread and difficult to eradicate as it is because of interdiction, and increased interdiction will continue to spread traffickers into new areas, allowing them to continue to move drugs north.

Conceptually, the NarcoLogic model offers three lessons. (*i*) It operationalizes, in a model space, the balloon and cockroach effects, by testing and identifying simple decision rules—based on first principles of profit maximization and transaction cost management—that produce qualitatively accurate and quantitatively realistic spatial and temporal patterns of cocaine trafficking in response to interdiction events. (*ii*) Dynamic interactions between narco-trafficking networks and interdiction forces are best understood as a complex adaptive systems. Narco-trafficking networks are emergent, self-organized, and highly adaptive systems, and their evolution and spatial manifestations are highly path dependent—that is, they result from the location and timing of past interdiction events. Modeling these interactions as a complex adaptive system compellingly reproduces the cat-and-mouse dynamic others have qualitatively described (e.g., ref. 2). (*iii*) The model is also innovative in spatializing transaction cost theory, within an ABM or otherwise, which is essential to the application of transaction cost theories to illicit activities. Compared with licit economies, clandestine activities have distinct spatial dynamics (1, 44) that are fundamental to their operation and persistence, and are thus central to their analysis.

Methodologically, the performance of the NarcoLogic model is remarkable considering the substantial knowledge and data gaps associated with studying clandestine phenomena, particularly in transit spaces, which are often the largest and least visible phase of the supply chain (44). Testing the balloon and cockroach effect hypotheses was thought to be impossible given these gaps (59), but the spatially explicit and process-based nature of NarcoLogic enables "connecting the dots" among sparse cocaine flow data in the CCDB. The model also reconciles a methodological gap in the study of illicit dynamics: the spatial scale and/or organizational level at which illicit activities are analyzed is often different from that at which they are enacted. NarcoLogic formalized and tested our assumptions about the multilevel nature of narco-trafficking decisions, and provided a mechanism of network function and location adaptation that explains the apparent contradiction between increased seizure volumes and stable cocaine prices. Similarly, the model links interdiction and its unintended consequences (i.e., intensified trafficking, spreading to new nodes) in space, which are both cause and consequence of the same narco-logic of adaptation.
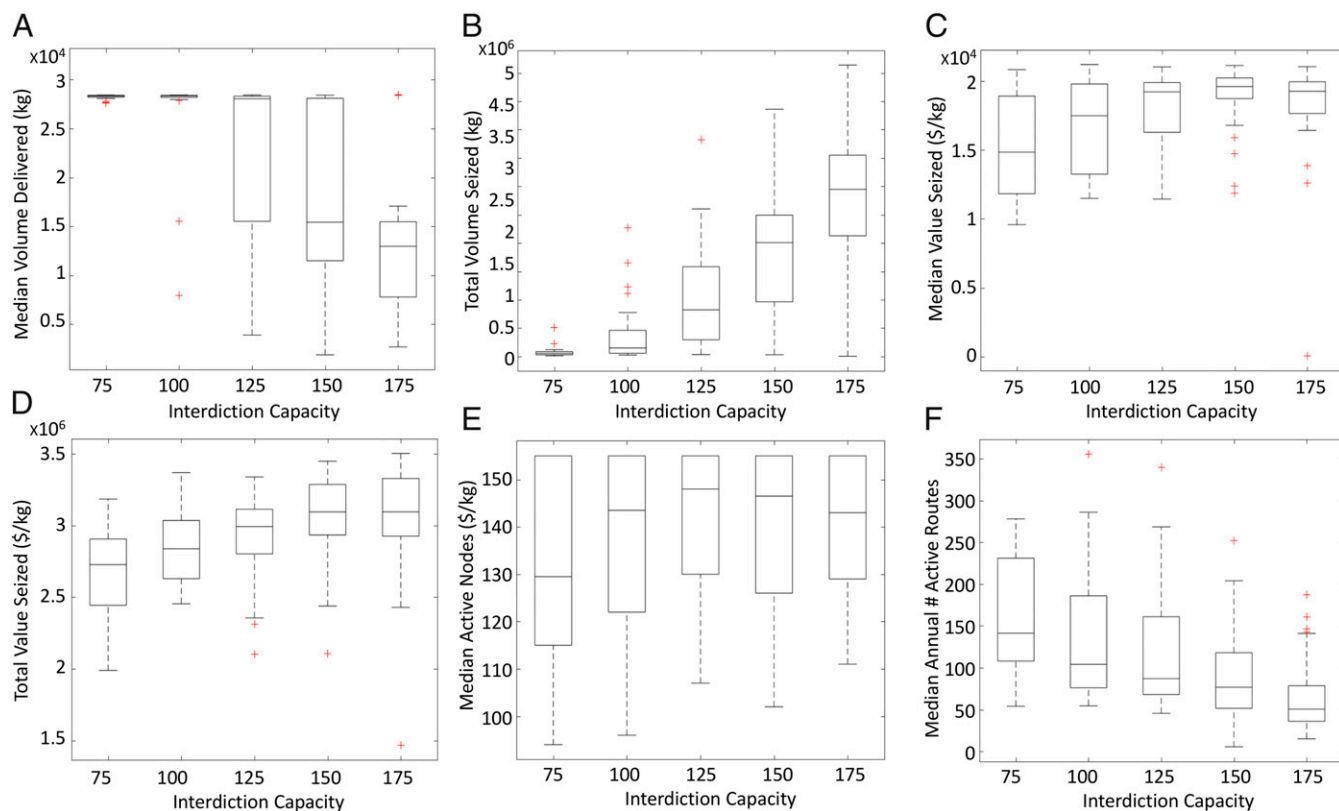
Fig. 3. Median (*A*) and total (*B*) volume of seized shipments, median (*C*) and total (*D*) value of seized shipments, and median number of active nodes (*E*) and routes (*F*) with variations in interdiction capacity. Calibrated and baseline value of interdiction capacity was 125 route segments that can be policed per month. Red plus signs (+) represent outliers in the distribution of outcomes from 30 model executions.

Finally, the NarcoLogic model offers a preliminary tool for the robust assessment of different drug policy scenarios, and their likely impact on trafficker behavior and the many collateral damages associated with the militarized war on drugs (60). For example, the model could be used to test elements of the four scenarios laid out by the Organization of American States in their pathbreaking 2013 report (61). How—for example—would traffickers be likely to respond to the relaxation of hemisphere-wide interdiction activities—spatially, economically, and organizationally? Or if transit zone countries were to pursue different approaches, how would that response compare with a drawdown of interaction assets? The NarcoLogic model offers a much-needed, evidence-based tool to move this deadlocked issue forward.

Methods

General Model Logic. The purpose of NarcoLogic was to formalize alternative, theoretically informed principles of DTO operational decision making, and test which model version could accurately predict DTOs' spatial responses to interdiction in real geographic space. Hypothesized narco-trafficker decision making was operationalized with estimates of space- and time-varying cocaine prices and endogenously updated risk premiums and interdiction effort. Adaptive spatial responses to interdiction emerged from first principles of goal-seeking behavior and risk management decisions. A full model description in ODD format is provided (*SI Appendix*, SI1).

Model Environment. Trafficking nodes were georeferenced with latitude and longitude within the administrative boundaries of the modeled Central American countries (Fig. 1). Geographic location informed trafficking node suitability, position in the supply chain, and exogenous transportation costs.

Suitability for trafficking nodes was represented with 30-m raster data layers and assumed to be a function of proximity to country borders, remoteness, tree cover, market access, slope, protected area status, and suitability of existing land use (*SI Appendix*, Table S1). Risk of interdiction and increase in cocaine value were highest at border crossings, making

these strategic locations for trafficking nodes (i.e., high suitability). In general, remote locations (using population density and market access as proxies) and locations with more tree cover were more suitable because of reduced risk of detection. Slope negatively influenced the suitability of the location for a given land use (licit or illicit) and/or airstrips. Protected areas were considered suitable because detection risk is low and/or governance is often weak. Finally, land cover types classified as shrubs, trees, and pasture were rated highly suitable, whereas all other land uses (e.g., built-up areas, row crops, established plantations) were deemed unsuitable. Node locations were randomly selected among the top 30% overall most suitable cells within each department, and their locations remained fixed through the simulation. Depending on node characteristics and dynamic interactions within the trafficking network, any given node may or may not become active (i.e., receive shipments). The model was executed 30 times for each unique parameterization to account for the effects of stochasticity in node location.

Links between trafficking nodes were unidirectional (roughly southeast to northwest), randomly generated, and remained constant throughout all simulations. The producer node represented a South American-producing region and was not explicitly simulated as a node agent. The producer node was the starting point for all shipments and was connected to all other nodes. The end node represented Mexico and was not explicitly represented as a Node Agent. All nodes within the trafficking network had a link to the end node, which was the ultimate destination for shipments that were not seized or lost in transit. Nodes within the trafficking network were linked with a number of other nodes randomly chosen between 1 and 10% of remaining nodes in the network. Nodes located closer to the end node had fewer possible routes remaining to the end node.

Movement of cocaine from one node to another incurred both exogenous and endogenous transaction costs. Exogenous transaction costs were based on distance between any two nodes, volume being transported, and mode of transportation. Volume-based transport costs per kilogram were parameterized as follows: $160/kg by sea, $371/kg by land, and $3,486/kg by air (5). Total transport costs for any given segment in the trafficking network were then the product of volume-based costs and the distance between nodes of that route segment. Variations in these costs related to the number of

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people involved in the trafficking and the relative risk of each mode. The mode of transportation depended on the distance between nodes and/or proximity to the coastline. If both sending and receiving nodes were within 20 km of the coast, maritime transport was possible. Movements that exceeded 500 km between nodes were eligible for air transport. Movement over land was possible between all nodes.

Endogenous transaction costs were related to perceived risk of interdiction between two nodes. Increased interdiction risk resulted in a higher risk premium (5) added to the cost to transport between nodes. Risk premiums were based on dynamic, subjective perceptions of risk of interdiction between each node, which were independently learned over time by each node through interactions with the interdiction agent.

The baseline cocaine price started with the wholesale price in Panama of \$4,500 kg^{-1} (52) and increased \$4.46 kg^{-1}·km^{-1} northward along the trafficking network. The price could increase endogenously with the risk premium, Y, to reflect dynamic risk of interdiction along a given trafficking route. The risk premium increased transaction costs at a given node based on the ratio of perceived interdiction risk, $E(p_{ij})$ (defined in the next section), to a risk threshold. For the route between nodes i and j at time t, the risk premium modified the price, P, at node j:

$$P(j, t) = P(j, t-1)\left[(1-\delta)Y_{i,j,t-1} + \delta\frac{E(p_{ij})}{I^*}\right],$$

where I^* is the risk premium threshold and δ is the learning rate (*SI Appendix*, Table S1 and SI2.1.2).

Agent Decision Models. The timing and location of active trafficking nodes emerged from profit-maximization and risk aversion/seeking behaviors of Nodes and Network Agents. Node Agents observed prices offered at each buying node in the trafficking network, and whether an interdiction event occurred and affected it or its neighbors in previous time steps. Over time, Node Agents learned how best to allocate shipments among neighboring nodes to maximize profit and minimize risk of interdiction.

Risk perception was grounded in theories of availability bias and salience (*SI Appendix*, SI1.3.4). Availability bias reflects the tendency to place more weight on recent risk information than past information (62) and was simulated with a time-weighting factor (63, 64). Following the formalization of Gallagher (64) for risk perception of discrete events, the expected probability of an interdiction event $E(p_{ij})$ between nodes i and j, or subjective risk perception, at time t was formalized as follows:

$$E\left(p_{ij}|I'_t, t'\right) = \frac{I'_t + \alpha}{t' + \alpha + \beta},$$

where $\alpha = 2$ and $\beta = 0.5$ are parameters of a beta distribution, $I'_t = \sum_{b=1}^{t} y_{ij}\varphi^{t-b}$ are weighted interdiction event observations between nodes i and j, and $t' = \sum_{b=1}^{t}\varphi^{t-b}$ is the number of time step "observation equivalents" with time-weighting parameter $\varphi = 1$ as the baseline value.

Salience theory (ST) (65) is similar to prospect theory (66) in that there is risk aversion relative to a reference point. However, it goes beyond prospect theory to also address risk-seeking behavior. ST frames decisions under risk as a choice problem between payoffs from two or more "lotteries" (L). Salience is expressed as a salience value for each lottery outcome where the perceived probability of a discrete event is distorted based on its relative salience. For example, the expected payoff from a risky but highly profitable trafficking route is increasingly distorted upward relative to lower profit but less risky routes as the difference in payoffs becomes larger (i.e., more salient). A full enumeration of the behavioral options and calculation of salience is provided in *SI Appendix*, SI1.3.4.2. Based on this information and knowledge of transportation costs, node agents decided how to allocate shipment volumes among neighboring nodes.

The Network Agent decided when and where to expand or consolidate trafficking routes depending on the total losses experienced to interdiction during a time step relative to a loss tolerance (*LossTol*). Network Agents were more tolerant of losing larger volume, low value shipments early in the supply chain (e.g., Panama) than smaller, higher value shipments further along in the supply chain (e.g., Guatemala). Thus, loss tolerance was set to a percentage (*LossLim*) of the maximum profit margin obtained during a given time step. This value was compared against the total losses (*TotLoss*) from nodes experiencing an interdiction event, N_I, given the price (P) difference between sending node i and receiving node j and associated transportation costs (C_{ij}^{trans}):

$$LossTol = LossLim * \max\left[Q_{ij}\left(P_j - P_i - C_{ij}^{trans}\right)\right],$$

$$TotLoss = \sum_{j=1:N_I} Q_{ij}\left(P_j - P_i - C_{ij}^{trans}\right).$$

If losses to interdiction exceeded the tolerance level (*TotLoss* > *LossTol*), the Network Agent activated new nodes and directed shipments away from a susceptible location. The number of new nodes to be activated was given by the ratio of *TotLoss* to *LossTol* up to the maximum value specified by *Exp-Rate* (*SI Appendix*, Table S1). If losses were below or equal to this value (*TotLoss* ≤ *Loss Tol*), the Network Agent consolidated current trafficking routes by discontinuing shipments to the highest risk nodes. The number of nodes to be eliminated was given by the ratio of *LossTol* to *TotLoss*, such that route consolidation increased as losses approached the tolerance level (*SI Appendix*, SI1.3.4.4).

The Interdiction Agent's main decisions were which trafficking routes to interdict and how to allocate limited resources to maximize volume seized. At initialization, all trafficking route segments lacked information about past trafficking activity, and the Interdiction Agent estimated expected probabilities of successful interdiction based on node suitability. Three factors were used to estimate the success of interdiction (and thus probability of interdicting a given route segment): remoteness (−), proximity to the coast (−), and transportation distance (+). The minus and plus signs indicate an inverse or direct relationship, respectively, with probability of interdiction success (*SI Appendix*, SI1.3.4.1). Overall, the probability of successful interdiction was given as the mean of these three factors, which accounted for the setting of each node and trafficking routes between them.

When information about past interdiction for a given trafficking route segment was available, a reinforcement learning algorithm modified the initial suitability-based probability of successful interdiction in proportion to the normalized volume of cocaine seized (i.e., trafficking route segment with the largest seizure receives a weight of 1). Trafficking route segments with large volume seizures were more likely to experience additional interdiction events in the future, until seizures returned lower volumes and future interdiction events were discouraged. Trafficking route segments with the highest expected probability of successful interdiction were selected according to interdiction capacity (see below).

The number of routes that could be chosen at any given time step was constrained by the Interdiction Agent's capacity (*SI Appendix*, Table S1), which varied over time based on the success of interdiction efforts. The Interdiction Agent was assumed to have a seizure target, which was the volume of cocaine per time step that interdiction efforts strived to remove from supply. A default value of 30% of total cocaine volume in any given time step was chosen as a conservative assumption. Official Office of National Drug Control Policy seizure targets were set at 40% of suspected total cocaine volume by 2015 (67); however, historic seizure rates have never exceeded 25% (58). Interdiction capacity was adjusted over time based on total seizures relative to the seizure target within minimum and maximum values specified at model initialization. Capacity increased proportionally when seizures exceeded the seizure target volume, or decreased when seizures were less than the seizure target. More details are provided in *SI Appendix*, SI1.3.4.1.

Model Calibration. A pattern-oriented modeling (POM) (68) approach was used to calibrate key parameters. POM is a well-known model evaluation approach for ABMs when confronted with incomplete data and/or process knowledge. POM compares model outcomes with multiple empirical patterns, or target patterns, at different hierarchical system levels. If a model can reproduce all patterns simultaneously, the model's process representation and internal structure are reasonably consistent with those of the real system. Target patterns were derived from select department-level (subnational administrative unit) observations of cocaine shipments delivered in the CCDB.[§] Subnational units selected were Petén in Guatemala, Gracias a Dios in Honduras, Atlántico Norte in Nicaragua, and Colón and Darién in Panama. These departments were selected to include at least one location per country and on the basis of having at least 5 y of continuous observations reported in CCDB. National-level cocaine flows were used for Costa Rica since no department reported 5 y of consecutive observations. The timing and cumulative magnitude of modeled cocaine flows were aggregated to the department level and compared with the target patterns. Following the method used in ref. 69, a genetic algorithm was used to search

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[§]United States Interdiction Coordinator (2015) Data extracted from the Consolidated Counterdrug Database. Accessed December 31, 2014.

the potential parameter space for the combination of parameter values that produced statistically significant correlations with all of the target patterns simultaneously. Sources of model stochasiticity—node location and network configuration—were held constant across all model runs. The resulting calibrated parameter values are provided in *SI Appendix*, Table S1.

1. Allen CM (2005) *An Industrial Geography of Cocaine* (Routledge, New York).
2. Bagley B (2013) The evolution of drug trafficking and organized crime in Latin America. *Sociol Probl e Práticas* 71:99–123.
3. Dudley SS (2010) *Drug Trafficking Organizations in Central America: Transportistas, Mexican Cartels and Maras* (Woodrow Wilson International Center for Scholars, Washington, DC).
4. Mejia D, Restrepo P (2016) The economics of the war on illegal drug production and trafficking. *J Econ Behav Organ* 126:255–275.
5. Caulkins JP, Crawford G, Reuter P (1993) Simulation of adaptive response: A model of drug interdiction. *Math Comput Model* 17:37–52.
6. US Government Accountability Office (2005) Drug control: Agencies need to plan for likely declines in drug interdiction assets and develop better performance measures for transit zone operations (US Government Accountability Office, Washington, DC), GAO-06-200.
7. Paterson P, Robinson K (2014) *Measuring Success in the War on Drugs* (William J. Perry Center for Hemispheric Defense Studies, Washington, DC).
8. Caulkins J, Reuter P (2006) Reorienting U.S. drug policy. *Issues Sci Technol* 23:79–85.
9. Pollack HA, Reuter P (2014) Does tougher enforcement make drugs more expensive? *Addiction* 109:1959–1966.
10. Rydell CP, Caulkins JP, Everingham SS (1996) Enforcement or treatment? Modeling the relative efficacy of alternatives for controlling cocaine. *Oper Res* 44:687–695.
11. Office of National Drug Control Policy (2001) Measuring the deterrent effect of enforcement operations on drug smuggling, 1991–1999 (Office of National Drug Control Policy, Washington, DC).
12. Frankt A (March 5, 2018) Overshadowed by the opioid crisis: A comeback by cocaine. *NY Times*. Available at https://www.nytimes.com/2018/03/05/upshot/overshadowed-by-the-opioid-crisis-a-comeback-by-cocaine.html. Accessed April 29, 2018.
13. Office of the Inspector General (2018) Independent auditor's report on the FY 2017 DoD performance summary report for the funds obligated for national drug control program activities (Office of the Inspector General, Washington, DC), DODIG-2018-066.
14. Executive Office of the President of the United States (2017) National drug control budget: FY 2018 funding highlights (Executive Office of the President of the United States, Washington, DC).
15. Office of Management and Budget (OMB) (2018) An American budget–President's budget FY 2019 (Office of Management and Budget, Washington, DC).
16. McSweeney K, Wrathall DJ, Nielsen EA, Pearson Z (2018) Grounding traffic: The cocaine commodity chain and land grabbing in eastern Honduras. *Geoforum* 95: 122–132.
17. US Government Accountability Office (2017) Counternarcotics: Overview of U.S. efforts in the Western hemisphere (US Government Accountability Office, Washington, DC), GAO-18-10.
18. US General Accounting Office (1996) Drug control: U.S. interdiction efforts in the Caribbean decline (US General Accounting Office, Washington, DC), GAO-NSIAD-96-119.
19. Reuter P, Crawford G, Cave J (1988) Sealing the borders: The effects of increased military participation in drug interdiction. Available at https://apps.dtic.mil/docs/citations/ADA213737. Accessed February 14, 2018.
20. Bunck JM, Fowler MR (2012) *Bribes*, Bullets, *and* Intimidation: *Drug* Trafficking *and the Law in Central America* (Penn State Press, State College, PA).
21. McSweeney K, et al. (2014) Conservation. Drug policy as conservation policy: Narco-deforestation. *Science* 343:489–490.
22. McSweeney K, Richani N, Pearson Z, Devine J, Wrathall DJ (2017) Why do narcos invest in rural land? *J Lat Am Geogr* 16:3–29.
23. Sesnie SE, et al. (2017) A spatio-temporal analysis of forest loss related to cocaine trafficking in Central America. *Environ Res Lett* 12:054015.
24. Tree S (March 26, 2018) Opinion: The war on drugs breeds crafty traffickers. *NY Times*. Available at https://www.nytimes.com/2018/03/26/opinion/war-on-drugs-trafficking.html. Accessed July 18, 2018.
25. Kelly JF (2016) Statement of General John F. Kelly, United States Marine Corps (Ret) Former Combatant Commander, United States Southern Command (USSOUTHCOM) before the Senate Committee on Homeland Security and Governmental Affairs. April 13. Available at https://www.hsgac.senate.gov/imo/media/doc/Testimony-Kelly-2016-04-131.pdf. Accessed April 24, 2018.
26. Maguire E, Slattery B (2017) The Coast Guard is seizing record amounts of drugs. Why more funding is needed for the fight. *Dly Signal*. Available at https://www.dailysignal.com/2017/04/11/the-coast-guard-is-busting-record-amounts-of-drugs-why-more-funding-is-needed-for-the-fight/. Accessed February 20, 2018.
27. Reuter P (1988) Quality illusions and paradoxes of drug interdiction federal interdiction: Federal intervention into vice policy. *Law Contemp Probl* 51:235–244.
28. Anthony RW, Crane BD, Hanson SF (2000) Deterrence effects and Peru's force-down/shoot-down policy: Lessons learned for counter-cocaine interdiction operations. Available at https://apps.dtic.mil/docs/citations/ADA381193. Accessed February 16, 2018.
29. Crane BD, Rivolo AR (1997) An empirical examination of counterdrug interdiction program effectiveness. Available at https://apps.dtic.mil/docs/citations/ADA320737. Accessed December 21, 2017.
30. US General Accounting Office (1994) Drug control: U.S. drug interdiction issues in Latin America (US General Accounting Office, Washington, DC), GAO/T-NSIAD-95-32.
31. Kelly JF (2015) Posture statement of General John F. Kelly, United States Marine Corps Commander, United States Southern Command, before the 114th Congress (Senate Armed Services Committee, Washington, DC).
32. US Government Accountability Office (2008) Drug control: Cooperation with many major drug transit countries has improved, but better performance reporting and sustainability plans are needed (US Government Accountability Office, Washington, DC), GAO-08-784.
33. Ribando Seelke CLS, Wyler LS, Beittel JS, Sullivan MP (2011) Latin America and the Caribbean: Illicit drug trafficking and U.S. counterdrug programs (Congressional Research Service, Washington, DC). Available at https://fas.org/sgp/crs/row/R41215.pdf. Accessed July 5, 2018.
34. Office of the Inspector General (2016) *DHS Drug Interdiction Efforts Need Improvement* (Office of the Inspector General, Washington, DC).
35. Santos CP (2016) Disrupting cocaine trafficking networks: Interdicting a combined social-functional network model. Available at https://apps.dtic.mil/docs/citations/AD1027593. Accessed February 16, 2018.
36. Wood RK (1993) Deterministic network interdiction. *Math Comput Model* 17:1–18.
37. Gift Philip D (2010) Planning for an adaptive evader with application to drug interdiction operations. Available at https://calhoun.nps.edu/handle/10945/5161. Accessed April 25, 2018.
38. Fowler TB (1996) The international narcotics trade: Can it be stopped by interdiction? *J Policy Model* 18:233–270.
39. Atkinson MP, Kress M, Szechtman R (2017) Maritime transportation of illegal drugs from South America. *Int J Drug Policy* 39:43–51.
40. Levin SA (1998) Ecosystems and the biosphere as complex adaptive systems. *Ecosystems (N Y)* 1:431–436.
41. Malleson N (2012) Using agent-based models to simulate crime. *Agent-Based Models of Geographical Systems* (Springer, Dordrecht, The Netherlands), pp 411–434.
42. Devine J (2014) Counterinsurgency ecotourism in Guatemala's maya biosphere reserve. *Environ Plann D Soc Space* 32:984–1001.
43. Devine JA, Wrathall DJ, Currit N, Langarcia YR, Tellman B (November 26, 2018) Narco-cattle ranching in political forests. *Antipode*, 10.1111/anti.12469.
44. Hall T (2013) Geographies of the illicit: Globalization and organized crime. *Prog Hum Geogr* 37:366–385.
45. Taylor JS, Jasparro C, Mattson K (2013) Geographers and drugs: A survey of the literature. *Geogr Rev* 103:415–430.
46. Bright DA, Delaney JJ (2013) Evolution of a drug trafficking network: Mapping changes in network structure and function across time. *Glob Crime* 14:238–260.
47. Morselli C, Petit K (2007) Law-enforcement disruption of a drug importation network. *Glob Crime* 8:109–130.
48. Kenney M (2007) The architecture of drug trafficking: Network forms of organisation in the Colombian cocaine trade. *Glob Crime* 8:233–259.
49. Basu G (2014) Concealment, corruption, and evasion: A transaction cost and case analysis of illicit supply chain activity. *J Transp Secur* 7:209–226.
50. Magliocca NR (2017) Data from "NarcoABM." GitHub. Available at https://github.com/nickmags13/NarcoABM. Deposited January 12, 2017.
51. United Nations Office on Drugs and Crime (2010) *World Drug Report 2010* (NY United Nations Publ, New York).
52. United Nations Office on Drugs and Crime (2018) *World Drug Report 2018* (NY United Nations Publ, New York). Available at https://www.unodc.org/wdr2018/en/maps-and-graphs.html. Accessed July 4, 2018.
53. US Government Accountability Office (2010) Coast Guard: Observation on the requested fiscal year 2011 budget, past performance, and current challenges (US Government Accountability Office, Washington, DC), GAO-10-411T.
54. United Nations Office on Drugs and Crime (2012) *Transnational Organized Crime in Central America and the Caribbean: A Threat Assessment* (NY United Nations Publ, New York).
55. Office of National Drug Control Policy (2018) Cocaine. Available at https://www.whitehouse.gov/ondcp/key-issues/cocaine/. Accessed February 20, 2018.
56. Brown DG, Pontius RG, Lange MD (2013) Opportunities to improve impact, integration, and evaluation of land change models. *Curr Opin Environ Sustain* 5:452–457.
57. Decker SH, Chapman MT (2008) *Drug Smugglers on Drug Smuggling: Lessons from the Inside* (Temple Univ Press, Philadelphia).
58. Bailey JW, Heurin TC, Roberts B (2016) Assessing Southern Border Security (Institute for Defense Analyses, Alexandria, VA), NS P-5304.
59. Reuter P (2014) The mobility of drug trafficking. *Ending the Drug Wars* (London School of Economics and Political Science, London), pp 33–40.
60. Bartilow HA, Eom K (2009) Busting drugs while paying with crime: The collateral damage of U.S. drug enforcement in foreign countries. *Foreign Policy Anal* 5: 93–116.
61. Organization of American States (2013) The drug problem in the Americas: Studies/scenarios for the drug problem in the Americas 2013–2025 (Organization of American States, Washington, DC).

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62. Tversky A, Kahneman D (1974) Judgment under uncertainty: Heuristics and biases. *Science* 185:1124–1131.

63. Camerer C, Hua Ho T (1999) Experience-weighted attraction learning in normal form games. *Econometrica* 67:827–874.

64. Gallagher J (2014) Learning about an infrequent event: Evidence from flood insurance take-up in the United States. *Am Econ J Appl Econ* 6:206–233.

65. Bordalo P, Gennaioli N, Shleifer A (2012) Salience theory of choice under risk. *Q J Econ* 127:1243–1285.

66. Tversky A, Kahneman D (1981) The framing of decisions and the psychology of choice. *Science* 211:453–458.

67. Department of Defense (2011) DASD counternarcotics and global threats (Department of Defense, Washington, DC).

68. Grimm V, et al. (2005) Pattern-oriented modeling of agent-based complex systems: Lessons from ecology. *Science* 310:987–991.

69. Magliocca NR, Ellis EC (2013) Using pattern-oriented modeling (pom) to cope with uncertainty in multi-scale agent-based models of land change. *Trans GIS* 17:883–900.

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