SI1. Overview, Design Concepts, Details, and Decision-Making (ODD+D) Description - NarcoLogic

This document follows the ODD+D protocol to describe agent-based models with individual decision-making (1).

1. Overview

1.1. Purpose

The overall purpose of this model is to explore potential explanations, based on 'first principles' of goal-seeking and risk management decisions, of the spatial structure, dynamics, and adaptation of narco-trafficking networks within the transit zones of Central America. The model is designed to test alternative hypotheses of trafficking node 'decision-making' linked to the location and timing of primary and secondary movements of cocaine. In particular, the model strives to reproduce the spatial and temporal dynamics of the 'balloon' and 'cockroach' effects in response to interdiction events. The model is evaluated by comparing model output to a combination of observed and estimated cocaine flows and value dynamics at different points in the trafficking supply chain. This model version is a generalized model of narco-trafficking logic throughout Central America, and is designed for researchers to be used in an exploratory learning (rather than predictive) manner. Future model versions will link narco-trafficking activities to land-use and land-cover change associated with money laundering and territorial control, and will be further refined to account for differences in investment options and transactions costs related to each country's context.

1.2. Entities, state variables, and scales

1.2.1. Agents

Trafficking Network Agents represent the top-down coordination of drug trade organizations (DTOs). In this version of NarcoLogic, two competing DTOs are modeled to explore differential effects of interdiction strategies on each DTO's trafficking network. One network is assigned to each of the DTOs represented in the model. Network agents control the overall volume of cocaine entering a DTO's trafficking network and which trafficking nodes are active at any given time. They respond to supply disruptions from interdiction by expanding or consolidating existing trafficking routes.

Node Agents have a fixed spatial position in two-dimensional space and are connected through a predefined, randomly generated network. Node agents only interact with other node agents with the same DTO membership (Table S1). Node agent locations have several spatially-varying attributes that contribute to their perceived suitability and profitability: proximity to country borders, remoteness, tree cover, market access, slope, protected area status, and suitability of existing land use (Table S1). In addition, each node is described by a set of administrative identifiers (e.g., country, department, and latitude and longitude).

The risk of interdiction has created the need for 1) a semi-decentralized trafficking network structure and 2) social embeddedness of on-the-ground operations to create trust and/or fear among local populaces to allow traffickers to operate with impunity (2–4). *Transportista* groups fulfill these needs, which act like decentralized and franchised operations of larger cartels (5). Nodes agents represent *transportista* groups, which are smaller, domestic organized crime organizations with existing social ties that transnational DTOs (i.e., Network Agents) enroll to navigate spaces within transit countries (3).

Node agents that are 'activated' by a network agent can purchase a shipment of cocaine from another supplying node agent, and decide how to allocate the volume of the shipment among potential buyer nodes as defined by 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). Neighboring nodes are mostly geographically proximate, however long transnational links are also possible via maritime or aerial trafficking modes. Node agents observe prices offered at buying nodes and whether an interdiction event occurred between it and any of its buyer nodes. Over time, node agents learn the relative profitability of potential buyer nodes and allocate among them in proportion to relative perceived profitability.

The ***Interdiction Agent*** is a collective representing coordinated interdiction activities of law enforcement across Central American countries. The interdiction agent decides when and where policing activities will take place. The number of trafficking route segments (i.e., network linkages) that can be policed each time step is constrained by interdiction capacity (Table S1). The interdiction action that is modeled is seizure and loss (S&L), and has the effect of removing all cocaine from the trafficking route segment at the point of interdiction. The interdiction agent attempts to meet an annual interdiction volume target, and deploys S&L effort adaptively responding to shifting cocaine flows and S&L success.

Table S1: Agent attributes. Results of local sensitivity analyses for all calibrated variables are provided in SI2.

Agent	Attribute	Description
Node Agent	*Proximity to Country Border*	Country borders are strategic locations for trafficking nodes. Nodes closer to a country border are more attractive than those further away. Derived in ArcGIS 10.2 from the Global Administrative Boundaries (GADM) dataset (GADM, 2015).
	Proximity to Coast (*Dcoast)*	Interdiction risk increased with distance from coastline. Derived from global coastlines in ArcMap 10.2.
	Population Density (*PDen*)	Probability of detection is positively related to population density. Population density is used as a proxy for and is inversely related to remoteness. Derived from Landscan 2000 data product (6).
	Tree Cover	Greater tree cover reduces the probability of detection and increases attractiveness for money laundering via land improvement through deforestation. Tree cover data in the year 2000 from Hansen et al. (2013).
	Market Access	Travel time along roads to cities of 50,000 or more (8). Market access is another proxy for and is inversely related to remoteness.
	Slope	Contributes to suitability for agriculture. Derived from ASTER GDEM (NASA & METI)
	Protected Area Status	Areas designated as conversation areas or indigenous lands (IUCN)
	Existing Land Use	Some land uses are easier for node establishment (e.g., shrubs, trees, pasture) than others (e.g., built-up areas, row crops). Classified land-use data from (11).
	Salience Coefficient (γ)	‘Local thinker’ coefficient in salience-based risk perception (12). Default value is 0.5.
	Learning Rate (δ)	Coefficient used to weight recent and past information in Bayesian updating of risk information. Default value is 0.5; calibrated value is 0.3558.

	Perceived Risk	Dynamic, subjective perception of interdiction risk among direct neighboring (i.e., one degree) nodes. Bayesian updating using the *Learning rate*.
	Neighbor Preference	Dynamically updated matrix of weights for distributing shipments among direct neighbor nodes based on expected profit and perceived risk of interdiction. When new nodes are activated, initial preference is set equally among neighbors (i.e., 1/# of neighbors).
	Risk premium Threshold	Threshold for perceived risk, above which a 'risk premium' is required to compensate traffickers for increased risk of interdiction. Default value is 0.5; calibrated value is 0.4592.
	Risk Premium Multiplier	Rate of increase of 'risk premium' above the risk premium threshold. Default value is 2.
	DTO Membership	Membership to specific DTO. Default allocation is between two DTOs based on proximity to Atlantic of Pacific coasts. Node agents can interact only with other nodes agents of the same DTO.
Trafficking Network Agent	*Initial Stock* (S_0)	Volume of cocaine produced at the source node at the first time step. Default initialization value is 200 kg.
	Final Stock (S_{max})	Volume of cocaine produced at the source node at the final time step. Default initialization value is 111,500 kg.
	Production Growth Rate (ω)	Annual growth in total volume of cocaine entering trafficking network from producer, and shipped to United States. Estimated based on CCDB data (13).
	Start Value	Default value is $4,500/kg equal to the wholesale price in Panama (14)
	Added Value	Additional price premium for distance cocaine is transported between sending and receiving nodes. Default value is $4.46/kg/km.
	Node Price (P)	Price per kilo of cocaine for each node between Panama wholesale price and end nodes based on distance between nodes and *Added Value*.
	Loss Tolerance (LossTol)	Percent of maximum profit margin that DTO will tolerate as loss to interdiction before restructuring trafficking routes. Default value is 10%; calibrated value is 4.55%.
	Node Expansion Rate (ExpRate)	Maximum number of nodes that can be newly activated per time step. Default value is 10; calibrated value is 8.
Interdiction Agent	*Capacity* (*Cap*)	Number of network links that can be policed per time step. Baseline value minimum and maximum values are 33 and 200, respectively; calibrated values are 21 and 125.
	Learning Rate (δ)	Coefficient used to weight recent and past information in Bayesian updating of interdiction success information. Default value is 0.5; calibrated value is 0.6.
	Seizure Target (R^*)	Target level of total cocaine flows seized through interdiction, expressed as a percent of total trafficked

		volume. Default value is 30%; calibrated value is 34.17%.
	Interdiction Probability	Perceived probability that any given trafficking route segment will be active. Highest perceived probability routes are chosen first for policing subject to *Capacity* constraints.

1.2.2. *By what attributes (i.e. state variables and parameters) are these entities characterized?*

Suitability for nodes. 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 suitability of existing land use (Table S1). Risk of interdiction and increase in cocaine value are highest at border crossings. This makes country border strategic locations for trafficking nodes (i.e., high suitability). Remote locations (using population density and market access as proxies) are more suitable than less remote locations because of reduced risk of detection. Locations with more tree cover are more suitable, because of the lower detection risk and higher potential for money laundering. Slope influences the suitability of the location for a given land-use (licit or illicit) and/or airstrips and is inversely related to node suitability. Protected areas are easily co-opted for trafficking activities because detection risk is low and/or inhabitant have little to no power to enforce land governance. Thus, protected areas are suitable for narco-trafficking but not suitable for legal land-use activities. Finally, existing land uses that are easier targets for node establishment are shrubs, trees, and pasture and rated highly suitable, whereas all other land uses (e.g., built-up areas, row crops, established plantations) are deemed unsuitable.

Trafficking network node locations. Node locations are randomly selected among the top 30% most suitable cells within each department. These locations remain fixed through the simulation. Depending on node characteristics and dynamic interactions within the trafficking network, any given node may or may not be active (i.e., receive shipments).

Trafficking network structure. Links between trafficking nodes are unidirectional (roughly southeast to northwest), exogenously specified, and remain constant throughout the simulation. The producer node represents Columbia (or another producer country) and is not explicitly simulated as a node agent. The producer node is the starting point for all shipments and is connected to all other nodes. The end node represents Mexico and is not explicitly represented as a node agent. All nodes within the trafficking network have a link to the end node, which is the ultimate destination for all shipments that are not seized or lost in transit. All other nodes within the trafficking network are associated with a node agent. Nodes within the trafficking network are linked with a number of other nodes specified as randomly generated number between one and up to ten percent of remaining nodes in the network. In other words, as a node is positioned within the network closer to the end node, there are fewer possible nodes remaining that would provide a profitable movement towards the end node.

Value added. The value of a kilo of cocaine increases every time it changes hands. Thus, the price increases as a shipment moves further along the supply chain towards the end node (generally in the northwest direction) to compensate the traffickers. Based on estimates synthesized from many law enforcement reports and case studies, a default value of $4.46 per kilo per km is assumed (14, 15).

Transaction costs. Movement of cocaine from one node to another incurs a transaction cost, which are partly exogenously and endogenously specified. The *exogenous* portion of transaction costs is based on distance between any two nodes, volume being transported, and mode of transportation. Volume-based transport costs per kilogram were parameterized as: $160/kg by sea, $371/kg by land, and $3,486/kg by air (16). 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 relate to number of people involved in the trafficking and the relative risk of each mode (see Caulkins, Crawford, and Reuter (1993) for more details). The mode of transportation depends on the distance between nodes and/or proximity to the coastline. If both sending and receiving nodes are within 20 km of the coast, maritime transport is possible. Movements that exceed 500 km between nodes are eligible for air transport. Movement over land is possible between all nodes.

The *endogenous* component of cocaine prices is related to perceived risk of interdiction between two nodes. Increased interdiction risk demands a higher 'risk premium' (16), which is included as an additional cost when node agents decide which neighboring node to sell. Risk premiums are based on subjective node risk perceptions of each node, which are independently learned over time through interactions with the interdiction agent.

1.2.3. What are exogenous factors/drivers of the model?

Cocaine price at the first node (Panama wholesale price) is specified exogenously and held constant throughout the simulation at $4,500 per kilo. Increased cocaine production volume over the course of the simulation is estimated from trends observed in the CCDB data for all of the transit countries. A time series of the stock of cocaine, *S*, entering the trafficking network through the production node at time *t* is generated for simulation using the following logistic growth curve:

$$S(t) = \frac{S_{max} S_0 e^{\omega t/_{12}}}{S_{max} + S_0\left(e^{\omega t/_{12}-1}\right)} \qquad [1]$$

where S_0 and S_{max} are the initial and maximum cocaine volumes, ω is the production growth rate, and *t* is the monthly time step.

1.2.3. How is space included in the model?

NarcoLogic is a spatially-explicit model built using country and department level administrative boundaries for Panama, Costa Rica, Nicaragua, El Salvador, Honduras, and Guatemala from the GADM dataset (GADM, 2015). Trafficking nodes are georeferenced with latitude and longitude to the GADM dataset using the WGS 1984 projection. Node agent attributes related to node suitability are specified from a series of raster layers georeferenced to the forest cover data layer (7).

Trafficking nodes occupy specific locations in two-dimensional space at the centroid of raster cells. Each edge in the trafficking network has an associated geodesic distance on which transportation costs are based. Node attributes are also defined in relation to geographic features, such as country borders, transportation infrastructure, population centers, and landscape features.

1.2.4. What are the temporal and spatial resolutions and extents of the model?

The time step of the model is one month, which is assumed to be the amount of time required of shipments to pass through the trafficking network to Mexico and the time scale at which S&L events occur. Node agents and the interdiction agents update their perceived risk and probability of S&L, respectively, for each trafficking network link at this frequency. The temporal extent of the model is from 2001-2015, or 180 months.

The spatial extent of the model covers the countries of Panama, Costa Rica, Nicaragua, El Salvador, Honduras, and Guatemala. Administrative boundaries are specified with vector data. Landscape features are specified with raster data harmonized (i.e., down-sampled or aggregated) to 30 meter resolution.

1.3. Process overview and scheduling

The following provides a simplified version of the process overview and scheduling. For more detail regarding each process or agent attribute involved (*italics*), please see the Submodels section below. At initialization, administrative boundary data layers and suitability rasters are imported as exogenous inputs. Trafficking nodes are assigned spatial locations based on suitability and associated with a single node agent. Nodes membership to a DTO is assigned based on user-specified criteria (see *Collectives*). Trafficking network edges are randomly generated among DTO members, and the initial stock of 200 kilos is added to the producer node. *Risk Premium* is zero for all nodes and *Price* is calculated for each node based only on distance between nodes and *Value Added*. For producer node, initial shipment from producer node is split evenly (i.e., *Neighbor Preference* is equal) among at least one node from each DTO.

The following sequence of processes repeat every time step.

- **Specify trafficking route segments for policing**. Interdiction agent specifies number of trafficking route segments to be policed based on *SLCapacity*. Policed routes are selected based on perceived suitability of node for trafficking and past success of interdiction (see Submodels).
- **Move cocaine shipments through trafficking network**. Beginning with the producer node and repeated for every node that receives a shipment, the perceived profitability is calculated for all neighboring nodes one link away and of the same DTO. Volume of shipment is allocated among neighboring nodes with positive profitability and in relative proportion to perceived profitability (see Submodels). Shipments moving along unpoliced routes are transported in full to receiving node.
- **Interdiction events**. If shipments move along policed routes, the entire volume is seized. Affected nodes (both sending and receiving) update *Risk Perception* and *Neighbor Preference* to reflect updated risk information.
- **Update Interdiction Agent's perceptions**. Based on results of interdiction events, Interdiction agent updates *Interdiction Probability* for each policed route, and updates overall *Capacity* based on cumulative interdiction success relative to *Seizure Target*.
- **Route selection**. Route selection is performed be each DTO. If total losses from interdiction events are less than *Loss Tolerance*, the Network Agent consolidates trafficking routes by discounting shipments to the highest risk and lowest profit (in that order) nodes and associated route segments. If total losses from interdiction events are greater than *Loss Tolerance*, the Network Agent expands existing trafficking routes by adding nodes and associated route segments that were inactive (at least) in the previous time step. See Submodels for a description of the rate of route consolidation and expansion.
- **Update Node and Network Agents**. Individual Nodes Agents calculate *Risk Premium* for next time step based on updated *Risk Perception*. Final shipment volume at end node is removed from the trafficking network, and initial shipment volume at producer node for the next time step is updated according to Equation 1.

2. Design concepts

2.1. Theoretical and empirical background

2.1.1. Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) (apart from the decision model)? What is the link to complexity and the purpose of the model?

At the micro-level, node agent decision-making is based on transaction cost theory (17). Nodes agents perceive and form expectations of future risks of interdiction and making decisions of how to allocate shipments to risk-minimizing and profit-maximizing neighboring nodes. Risk perception is grounded in socio-psychological theories of risk, specifically availability bias and salience theory. Availability bias reflects the tendency to place more weigh on recent risk information than past information (18), and is simulated with a time-weighting factor (see Submodels) (19, 20). Salience theory (12) is similar to Prospect Theory in that there is risk aversion relative to a reference point, but it goes beyond Prospect Theory to also address risk-seeking behavior.

The model's network structure was also informed by supply and value chain literatures, which address questions about optimum network configurations for reducing costs and delivery time and increasing resilience to shocks such as supply disruptions or infrastructure damage (e.g., Kaihara, 2003; Akanle and Zhang, 2008; Giannakis and Louis, 2011). The supply chain literature often assumes profit-maximizing rationale in network configuration, which is partially applicable in this context.

2.1.2. On what assumptions is/are the agents' decision model(s) based?

Agent decision models in NarcoLogic rely on the following assumptions:

- While trafficking networks are coordinated by a DTO, individual trafficking nodes have some autonomy in decision-making, because they have better knowledge of local conditions (2). Node agent decision-making is boundedly rational such that risk and profit perceptions are based only on individual experience (24).
    - Node agents are best described as having some autonomy in the day-to-day operations of narco-trafficking, but ultimately their participation in the cocaine supply chain is at the discretion of the DTO (i.e., Network Agent). This is represented in the model as multi-level decision-making between Network and Node Agents. This design choice was based on limited evidence in the literature and references to DTO structure in U.S. Joint Interagency Task Force – South congressional testimony. For example, Dell (4) suggests that local cells make day-to-day operational decisions to minimize risks that information about routes and strategies will be compromised if one member or cell is captured. Profiles of the Sinaloa cartel, Mexico's most powerful, by Insight Crime describes as DTO as operating as a federation independent organizations that further outsource transport to local groups (25). Insight crime describes one of the major Honduran DTOs, the Cachiros, as intermediaries who "contracting out much of their work to locals, to whom they owed little allegiance and with whom they had little contact; this minimized their risk if any individual cell were to have been compromised" (26). Finally, recent congressional testimony from then Commander of the U.S. Southern Command, Admiral Kurt W. Tidd, described the evolution of modern DTOs: "As this [Senate Armed Services] Committee knows, thirty years ago we focused on large cartels with designated leaders and relatively straightforward operations. Today, those cartels have diversified, decentralized, and franchised their operations" (p. 4) (5). However, perhaps the strongest support for this model design choice is from the authors' collective interview experiences. The actual actors on the ground at individual nodes are not representatives

of major DTOs but local actors who act more like franchises who can make independent decisions.

- Trafficking routes are selected to minimize interdiction risk and then to maximize profit, in that order. Because profit margins are so large, traffickers are assumed to prioritize risk minimization even if it leads to less than profit-maximizing outcomes (2, 27).
    - This assumption directly influences the choice of trafficking route, its length, and associated spatial adjustments. More details are provided in *Submodels* section 3.4.2.
- Tolerance for losses to interdiction is based on the value rather than volume of cocaine seized. This assumption is based on personal communications and CCDB seizure and loss data (13).
- Interdiction capacity increases with interdiction success and vice versa. Field interview and individual country case study evidence suggests that successful interdiction brings attention to the drug trafficking problem, which prompts more resources to be contributed to future interdiction efforts.

2.1.3. Why is/are certain decision model(s) chosen?

The decision models of each agent have been chosen so that the timing and location of active trafficking nodes can emerge from 'first principles' of objective-seeking behavior in the context of dynamic interactions between interdiction events and traffickers' adaptive responses.

2.1.4. If the model/submodel (e.g. the decision model) is based on empirical data, where do the data come from?

No systematic, primary data is available to inform agent decision models. Model design is informed by fragmented evidence in field interviews, case studies, expert opinion, and system-level observations, such as national statistics.

2.1.5. At which level of aggregation were the data available?

See answer to 2.1.4.

2.2. Individual decision-making

2.2.1. What are the subjects and objects of the decision-making? On which level of aggregation is decision-making modeled? Are multiple levels of decision making included?

Individual Node Agents make decisions of how to allocate a shipment among neighboring, receiving Node Agents in order to minimize risk of interdiction and maximize profit in the transaction given their location and the locations of their neighbors in the trafficking network. The Network Agent for each DTO makes a network-level decision to expand or consolidate current trafficking routes to reduce interdiction risk. The Interdiction Agent decides which specific route segments to police based on expected probability of successful interdiction.

2.2.2. What is the basic rationality behind agent decision-making in the model? Do agents pursue an explicit objective or have other success criteria?

Node and Network Agents pursue a strategy of risk minimization and profit maximization over time. Node Agents use the expected payoff in the event of no interdiction nor risk premium as their profit target. The Interdiction Agent attempts to meet the *Seizure Target*.

2.2.3. How do agents make their decisions?

For each neighboring node, Nodes Agents calculate expected profit given perceived risk of interdiction, transportation costs, and risk premiums (if applicable) and proportion their current cocaine shipment accordingly to maximize profit (see Submodels).

Depending on total losses relative to *Loss Tolerance*, the Network Agent consolidates trafficking routes by eliminating the highest risk nodes and/or route segments, or expands trafficking routes by adding new, low risk nodes and associated segments (see Submodels).

The Interdiction Agent selects the route segments with the highest perceived success of interdiction based on node characteristics and/or past experiences.

2.2.4. Do the agents adapt their behavior to changing endogenous and exogenous state variables? And if yes, how?

Agents maintain a record of time-weighted past observations, so that as the trafficking network changes and experience with interdiction events increase, they learn successful locations/strategies and modify their evaluations of risk/profit/success over time.

2.2.5. Do social norms or cultural values play a role in the decision-making process?

Not in the version of NarcoLogic presented here.

2.2.6. Do spatial aspects play a role in the decision process?

Transportation costs between georeferenced nodes influence expected profits and risks of trafficking decisions.

2.2.7. Do temporal aspects play a role in the decision process?

Agents use past experiences to update perceptions of current conditions and form expectations of future conditions. All agents learn at specified rates by weighting current and past information by *Learning Rate*.

2.2.8 To which extent and how is uncertainty included in the agents' decision rules?

Uncertainty enters into Node Agents' decisions only by incomplete knowledge of network-level conditions and no knowledge of other agents' future actions. Similarly, the Interdiction Agent does not know which routes will be active in a given time step, and must select routes to police based on rough heuristics and reinforcement learning.

2.3. Learning

2.3.1. Is individual learning included in the decision process? How do individuals change their decision rules over time as consequence of their experience?

The Interdiction Agent uses reinforcement learning to select trafficking route segments believed to be active. When information about successful interdiction locations is limited, the Interdiction Agent forms expected probabilities of interdiction success based on the node suitability data layers. However, when a successful interdiction occurs, the Interdiction Agent will prioritize that location for future interdiction. Thus, the choice of interdiction locations depends on information and learning from past successful attempts.

Node Agents are able to reallocate shipments among neighboring Nodes Agents, including reducing shipments to zero if deemed too risky and/or unprofitable. Network Agents decide whether to consolidate or expand trafficking routes based on experiences with interdiction losses. For both agents, these decisions are informed by risk perceptions, which are updated over time, however decision rules do not change.

2.3.2. Is collective learning implemented in the model?

There is collective learning in the sense that the Network Agent learns the perceived interdiction risk at each individual node within a DTO's network.

2.4. Individual sensing

2.4.1. What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?

Agents consider and learn from their past experiences, particularly to inform risk perceptions. Risk perception is subjective and based on individual experience, so individual risk perception of interdiction can diverge from actual probability of interdiction, for example. Node and Network Agents are also assumed to know prices at each node in their neighborhood (i.e., one degree of separation) and throughout the DTO's entire network, respectively. Prices are endogenously updated to reflect changing risk of interdiction. Transportation costs, including risk premiums, are known among neighboring Node Agents.

2.4.2. What state variables of which other individuals can an individual perceive? Is the sensing process erroneous?

Node Agents know the location of neighboring Node Agents, but no others. Network Agents know the location of all Node Agents within their DTO. This process is not erroneous.

In future versions, Node and Network Agents will also know the locations of adjacent nodes from other DTOs to simulate territorial competition.

2.4.3. What is the spatial scale of the sensing?

Network Agents can sense the location of all nodes within their DTO, which span the extent of Central America. The spatial scale of sensing by Node Agents varies with network structure, from within country to cross-border.

2.4.4. Are the mechanisms by which agents obtain information modeled explicitly, or are individuals simply assumed to know these variables?

Node and Network Agents are assumed know risk, price, and cost information. The Interdiction Agent must police a given trafficking route segment to know whether or not it is active.

2.4.5. Are the costs for cognition and the costs for gathering information explicitly included in the model?

There are no explicit information acquisition costs.

2.5. Individual Prediction

2.5.1. Which data do the agents use to predict future conditions?

Agents use their knowledge of past interactions, profits, cost, success/failure, and risk, in different places and times, to predict future conditions.

2.5.2. What internal models are agents assumed to use to estimate future conditions or consequences of their decisions?

Node and Network Agents implement subject risk and expected profit models to assess potential outcomes of trafficking choices. The Interdiction Agent uses reinforcement learning and/or suitability models to estimate probability of interdiction success.

2.5.3. Might agents be erroneous in the prediction process, and how is it implemented?

Agents are only erroneous to the extent that past performance (and their incomplete knowledge of it) is an imperfect prediction of the future.

2.6. Interactions

2.6.1. Are interactions among agents and entities assumed as direct or indirect?

Agents interact directly through trafficking transactions and interdiction events. In future versions, DTOs will interact directly to compete for territory.

DTOs also interact indirectly with one another. Since interdiction capacity is limited and the Interdiction Agent attempts to maximize volume seized, successful interdiction of routes of one DTO will draw additional interdiction assets in subsequent time steps and indirectly ease interdiction pressure on the other DTO.

2.6.2. On what do the interactions depend?

Interactions depend on a) the structure of one-way linkages within the trafficking network; b) potential revenues and costs between nodes; and c) the probability of interdiction for a given trafficking route segment in a given time step.

2.6.3. If the interactions involve communication, how are such communications represented?

Communication of interdiction risk among Node Agents is implicit and assumed to be coordinated by the Network Agent.

2.6.4. If a coordination network exists, how does it affect the agent behavior? Is the structure of the network imposed or emergent?

The structure of the trafficking network is imposed at initialization. Cocaine flows between Node Agents are initially evenly distributed, but are endogenously adjusted over time. Trafficking network structure is also endogenously modified by Network Agent decisions over time.

2.7. Collectives

2.7.1. Do the individuals form or belong to aggregations that affect and are affected by the individuals? Are these aggregations imposed by the modeler or do they emerge during the simulation?

Individual Node Agents belong to a single DTO. Smuggling success of individual Node Agents cumulatively affects the wealth of the DTO, and the DTO's Network Agent affect which nodes and routes are active at any given time step.

2.7.2. How are collectives represented?

DTOs are represented by member Node Agents and trafficking network connections among them.

2.8. Heterogeneity

2.8.1. Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?

Nodes Agents are heterogeneous in all node suitability attributes listed in Table S1. Nodes Agents also vary in DOT membership, and endogenous variables such as *Risk Perception*, *Risk Premium*, and *Neighbor Preference*. Other variables, such as *Learning Rate* and *Salience Coefficient* are homogenous due to lack of data for alternative parameterization.

2.8.2. Are the agents heterogeneous in their decision-making? If yes, which decision models or decision objects differ between the agents?

Agents do not differ in the structure of their decision-making, only in the decision-related parameters outlined above.

2.9. Stochasticity

2.9.1. What processes (including initialization) are modeled by assuming they are random or partly random?

Nodes locations and trafficking network linkages are randomly created at initialization. However, using the Matlab default random number generator ('twisted'), network structure was held constant across all model executions with the same random number seed. Thus, only trafficking node location was allowed to vary stochastically. Node locations were randomly selected among the top 30% most suitable cells within each department, and their locations remain fixed throughout individual simulations. This choice was based on our current knowledge and available data. Past observations of narco-activity allow us to generally describe characteristics that make areas vulnerable to node establishment, whereas network routes are unknown and dynamic. Allowing network structure to vary across runs may have provided insight into the range of possible outcomes the model could produce. However, due to a lack of information, we would not have a way of judging model variation as realistic versus an artefact of model design.

Depending on node characteristics and dynamic interactions within the trafficking network, any given node may or may not be 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.

2.10. Observation

2.10.1. What data are collected from the ABM for testing, understanding and analyzing it, and how and when are they collected?

System-level outcomes, such as number of active route segments, interdiction events, and volume of cocaine seized by interdiction, are collected at each time step. Cocaine flow volumes and values are measured for specific administrative departments to compare to CCDB data.

2.10.2. What key results, outputs or characteristics of the model are emerging from the individuals? (Emergence)

In addition to the data described in 2.10.1, node-specific outcomes, such as time of first shipment and time-varying risk premiums, are also collected at each time step, and are the emergent results of interactions with other Node Agents, coordination by the Network Agent, and interactions with the Interdiction Agent.

3. Details

3.1. Implementation details

3.1.1. How has the model been implemented?

The current version of NarcoLogic is implemented in Matlab, compatible at least up to version 2017a.

3.1.2. Is the model accessible, and if so where?

Model code and documentation is available at Github, https://github.com/nickmags13/NarcoABM.

3.2. Initialization

3.2.1. What is the initial state of the model world, i.e. at time t = 0 of a simulation run?

At initialization, administrative boundary data layers and suitability rasters are imported as exogenous inputs. Trafficking nodes are assigned spatial locations based on suitability and associated with a single node agent. Nodes membership to a DTO is assigned based on user-specified criteria (see *Collectives*). Trafficking network edges are randomly generated among DTO members, and the initial stock of 200 kilos is added to the producer node. *Risk Premium* is zero for all nodes and *Price* is calculated for each node based only on distance between nodes and *Value Added*. For producer node, initial shipment from producer node is split evenly (i.e., *Neighbor Preference* is equal) among at least one node from each DTO.

3.2.2. Is the initialization always the same, or is it allowed to vary among simulations?

Matlab's random number generator can be seeded to reproduce identical results; otherwise, each new simulation run will have a different initial node placements and trafficking network linkages.

3.2.3. Are the initial values chosen arbitrarily or based on data?

Node locations are based on suitability layers described as node attributes in Table S1.

3.3. Input data

3.3.1. Does the model use input from external sources such as data files or other models to represent processes that change over time?

Initial cocaine price, or wholesale price in Panama, and added value per kilometer transported are estimated based on reports by the United Nations Office on Drugs and Crime (14). These prices represent the floor, because price at each node (other than producer) can be adjusted upwards as the result of risk premiums. Finally, a time series of cocaine flow volumes is estimated from CCDB data (13) using Equation 1.

3.4. Submodels

3.4.1. Selecting trafficking route segments for policing

The Interdiction Agent uses two decision rules for selecting which trafficking routes to police subject to the level of available information about the success of past interdiction events. At initialization, when all trafficking route segments lack information about past trafficking activity, the Interdiction Agent must rely on estimates of node suitability to select the route segments between nodes that will most likely result in successful interdiction. Three factors are used to estimate the success of interdiction (and thus probability of policing a given route segment): remoteness, proximity to the coast, and transportation distance.

The *remoteness factor*, F_R, uses population density as a proxy for remoteness, and probability of successful interdiction is positively related to population density, *PDen*, and is expressed with the following piecewise function:

$$F_R = \begin{cases} 1, & PDen > PDen_{Q_3} \\ \frac{PDen}{PDen_{Q_3}}, & PDen \leq PDen_{Q_3} \end{cases} \quad [2]$$

where P_{Q_3} is the 75th percentile of population density values, such that risk of interdiction (from the perspective of traffickers) is 1 at population densities above P_{Q_3}. Choice of the 75th percentile, specifically, is arbitrary, but it effectively deters traffickers from high population density locations (due to their visibility) and produces (in combination with the other two factors below) spatial patterns consistent with historical observations of narco-trafficking areas.

The *coast factor*, F_C, specifies the probability of successful interdiction as a positive relationship with distance from the coastline, D_{coast}:

$$F_c = \frac{D_{coast}}{\max(D_{coast})} \quad [3]$$

The rationale for this factor is based on field interview evidence and government agency reports (28–30) that suggests that trafficking activities associated with maritime shipments are more dispersed and thus more difficult to detect.

The *transportation distance factor*, F_D, specifies the probability of successful interdiction as a positive relationship with the length of the trafficking route between nodes, D_{route}:

$$F_D = \frac{D_{route}}{\max(D_{route})} \quad [4]$$

The rationale for this factor is that longer cocaine movements are risky with more chances for detection.

Thus, the probability of successful intervention is given as the mean of these three factors, which takes into account the setting of each nodes and trafficking routes between them.

The alternative rule for selecting trafficking routes to police uses information about past successful (or not) policing and interdiction efforts. In this case, the probability of successful interdiction is calculated using a reinforcement learning algorithm. The probability of a trafficking route segment being selected for policing varies proportionally with the normalized volume of cocaine seized (i.e., trafficking route segment with the largest seizure receives a weight of 1). Trafficking route segments from which large volume seizures occurred are more likely to experience additional interdiction events in the future, until seizures return lower volumes and future interdiction events are gradually discouraged. Additionally, because resources for undertaking interdictions are finite, the probability of selecting any route segment is conservative across the entire trafficking network. In other words, if the probability of selecting a segment increases somewhere in the trafficking network, then it is simultaneously and equally decreased elsewhere in the network.

The application of each of these decision rules depends on the Interdiction Agent's *Capacity* at any given time step (Table S1). *Capacity* constrains how many trafficking route segments can be policed during one time step. Initial *Capacity* is specified by the modeler with a default minimum and maximum values of 67 and 400, respectively. Over time, *Capacity* (*Cap*) can increase above the minimum value if the *Seizure Target* (*R**) volume is exceeded, or decrease in seizure volume, *Q*, is less than the *Seizure Target*. The baseline value for *Seizure Target* is 30% of the total cocaine volume trafficked each time step, whichwas 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 (31), however historic seizure rates have never exceeded 25% (32). *Capacity* is updated at the *Learning Rate* (δ, default value is 0.5) given the following equation:

$$Cap(t+1) = (1-\delta)Cap(t) + \delta\frac{Q}{R^*} \quad [5]$$

If information about past successful interdiction is available, trafficking route segments will be selected using the reinforcement learning decision rule described above. If there is *Capacity* remaining and all route segments for which interdiction information exists have been selected, then the suitability-based decision rule is used to select additional route segments until *Capacity* is exhausted.

Assumptions about this overall reactive interdiction strategy are based on evidence gathered during interviews with USJIATF-S personnel and unclassified documents describing broad interdiction goals and strategies. All evidence suggests that interdiction agents are reactive. Interdiction efforts are a multi-agency, multi-country coordinated effort that must locate and intercept traffickers in a transit area larger than the lower 48 states. In addition, the entity responsible for coordinating interdiction resources, the USJIATF-S is housed under the Dept. of Defense, and as such does not have law enforcement authority. This fact in itself means that USJIATF-S can gather intelligence about, detect, and monitor suspected drug shipments, but has to rely on partner agencies (e.g., U.S. Coast Guard) to undertake the actual interdiction action [32]. Added to the slow interdiction response necessitated by interagency coordination, funding approvals and bureaucratic processes pose additional obstacles. Because of this, interdiction has thus far only been reactive. A good recent source describing this reactiveness is GAO 2014 report: "Coast Guard: Resources provided for drug interdiction operations in the transit zone, Puerto Rico, and the U.S. Virgin Islands." [92].

This logic is a simplification, because interdiction responses are not purely reactive in response to changes in trafficking activities. For example, USJIATF-S has recently focused on countering 'threat networks', which shifts interdiction strategy to focusing on dismantling organized crime networks and concentrating resources on apprehending and prosecuting organizational leaders (i.e., 'kingpins'). In addition, Operation Martillo was launched in 2012 as part of the White House Strategy to Combat Transnational Organized Crime and the U.S. Central America Regional Security Initiative. The operation was a concerted effort to force maritime trafficking routes away from coastlines and into areas of international jurisdiction (i.e., the high seas) in response to ineffectiveness/under capacity of Latin American partners (http://www.southcom.mil/Media/Special-Coverage/Operation-Martillo/). We gathered this information from personal communications with the Strategic Initiatives Office at USJIATF-S and from unclassified documents, such as the 2018 Posture Statement to Congress by Admiral Kurt W. Tidd (http://www.southcom.mil/Portals/7/Documents/Posture%20Statements/SOUTHCOM_2018_Posture_Statement_FINAL.PDF?ver=2018-02-15-090330-243). Both of these are examples of USJIATF-S attempting to be proactive or adapting the interdiction strategy to changes in narco-trafficking activities.

However, such specific initiatives are consistent in their implementation or effects with the basic interdiction logic and assumptions represented in the model. For example, Operation Martillo made long maritime transits, from Ecuador to the Guatemalan coast for example, increasingly risky, which prompted narco-traffickers to choose shorter coastal routes and/or inland routes. The effects of Operation Martillo are encoded into the route selection logic for both traffickers and the Interdiction Agent based on choosing the routes with the highest risk-profit payoffs and highest probability of successful interdiction, respectively.

3.4.2. Dynamic subjective risk perception and trafficking route choice by Node Agents

Node Agents distribute cocaine through the trafficking network by passing shipments along unidirectional network linkages. Allocation of shipment volume among neighboring nodes is decided by a benefit-cost calculation that considers profit maximization and risk minimization. Expected profit, π_{ij}, is calculated as the net of the price at the receiving node j, P_j, and the cost of transporting the shipment between nodes i and j, C_{ij}^{trans}, given the shipment volume, Q_{ij}.

Perception of interdiction risk for each route segment is modeled using a dynamic subjective risk function. A common Bayesian learning model provides a formalization of dynamic subjective risk perception in which individual Node Agents observe the occurrence of an interdiction event among them and their neighbors, and update their expected probability of future interdiction events (33, 34). However, additional empirical evidence demonstrates that not only does risk perception diverge from objective levels over time, but also the rate at which it diverges varies in relation to time since an event (e.g., Atreya, Ferreira, & Kriesel, 2013; Bin & Landry, 2013; Gallagher, 2014). This is modeled by modifying the Bayesian updating model with a weighting parameter that discounts past information (19, 37).

Following the formalization of Gallagher (2014), the expected probability of an interdiction event $E(p_{ij})$ between nodes i and j, or subjective risk perception, at time t is formalized as:

$$E\left(p_{ij}|I'_t, t'\right) = \frac{I'_t + \alpha}{t' + \alpha + \beta} \qquad [6]$$

where α = 2 and β = 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.

Profit maximization and risk minimization are then combined in the same objective function using Salience Theory (ST; Bordalo et al., 2012). ST formalizes cognitive biases of risk aversion and risk-seeking behavior by modifying perception of the probability of a given event given its expected payoff. Each outcome is valued based on the relative salience of its payoffs (i.e., magnitude of change relative to one another), and perceived probabilities of each outcome are thus increased (decreased) for more (less) salient outcomes.

ST frames decisions under risk as a choice problem between payoffs from two or more 'lotteries'. In this context, lotteries are analogous to choosing among alternative trafficking routes given each routes' perceived an interdiction event or no event. This is formalized as a set of possible states (S) where each state $s \in S$ occurs with a probability $E(p_{ij})$ and has payoffs of x_s^k for the behavioral options L_k. With these dimensions of the choice problem, a salience function is calculated as:

$$v\left(x_s^k, x_s^{-k}\right) = \frac{|x_s^k - x_s^{-k}|}{|x_s^k| + |x_s^{-k}| + \theta} \qquad [7]$$

where θ=1. The salience of a state for L_k increases in the distance between its payoff (x_s^k) and the payoff x_s^{-k} of the alternative lottery.

In this case, *k*=1,2 corresponding to route *i,j* and the average expected payoff from all other routes (*i*,-*j*), and *s*=1,2 corresponding to no interdiction event and the occurrence of an interdiction event, respectively. Payoffs from these outcomes are enumerated as follows:

$$x_1^1 = Q_{ij}(P_j - C_{ij}^{trans}) \quad [8]$$

$$x_2^1 = Q_{ij}(P_j - C_{ij}^{trans}) - P_j Q_{ij} \quad [9]$$

$$x_1^2 = Q_{i,-j}(P_{-j} - C_{i,-j}^{trans}) \quad [10]$$

$$x_2^2 = Q_{i,-j}(P_{-j} - C_{i,-j}^{trans}) - P_{-j} Q_{i,-j} \quad [11]$$

The decision-maker then ranks the salience σ of each state *s* for L_k. This is expressed as $z_s^k \in \{1, \ldots, S\}$, with a lower z_s^k indicating higher salience. Given this ranking, decision weights are defined:

$$\omega_s^k = \frac{\delta^{z_s^k}}{\left(\sum_{r=1:S} \gamma^{z_r^k} \cdot \pi_r\right)} \quad [12]$$

where $\gamma \in (0,1)$ represents a 'local thinker' coefficient that controls the distortion of perceived probabilities of each outcome given its salience (Bordalo et al., 2012). Decision weights ω_s^j then modify the perceived probability of an interdiction event, $E(p_{ij})$, of outcomes by:

$$\pi_s^k = E(p_{ij}) \cdot \omega_s^k \quad [13]$$

The salience function is then expressed as a salience value for each outcome $v(x_s^k)$, which is used to calculate the perceived value (*V*) of each behavioral option *j* given the perceived salience of lottery:

$$V(L_k) = \sum_{s \in S} \pi_s^k v(x_s^k) \quad [14]$$

The Node Agent then chooses the set of routes that maximize *V* across all available routes.

3.4.3. Dynamic pricing with risk premiums

Cocaine prices per kilo begin at $4,500 when entering the trafficking network from the first transport node (Panama). The minimum price at each subsequent node en route to the end node is given as the product of the transportation distance between nodes and the *Added Value*, which is assumed to be $4.6/kg/km and accounts for increased value as the shipment nears the retail market. Node prices can also be updated endogenously with the *Risk Premium*, *Y*, to reflect dynamic risk of interdiction along a given trafficking route. For the route between nodes *i* and *j* at time *t*, the risk premium modifies the price, *P*, at node *j*:

$$P(j,t) = P(j,t-1)\left[(1-\delta)Y_{i,j,t-1} + \delta \frac{E(p_{ij})}{I^*}\right] \quad [15]$$

where I^* is the *Risk Premium Threshold* and δ is the *Learning Rate*.

3.4.4. Trafficking route selection by the Network Agent

The Network Agent for each DTO the selection of trafficking routes with the dual objectives of maximizing profits while minimizing risk of interdiction. Prioritization of profit or risk is the main adaptive decision made by Node and Network agents, which results in different transit distances per single shipment and associated spatial shifts. Regardless of the transit distance for any given shipment, the inherent value of a cocaine shipment increases as it moves through the supply network closer to the retail market (i.e., towards Mexico for retail sale in the US) due to increased risk of seizure and loss and/or interdiction (i.e., *Value Added*). Higher profits will be captured by minimizing the number of nodes and supply chain actors (i.e., local traffickers) through which the shipments flow. Conversely, interdiction risks are higher the longer the cocaine is in transit, because longer maritime or aerial movements (i.e., bulk primary movements) are easier to detect and intercept (3, 38, 39). When primary movements come to land, bulk shipments are typically disaggregated into many smaller shipments to be trafficked among multiple over-land routes (3, 38, 40). Further, long maritime or aerial movements tend to be bulk primary shipments, and are thus the focus of interdiction forces as they present an opportunity to seize large volumes in a single operation (32). Thus, the fewer the intermediaries, the higher the overall profits captured by the DTO but at an increased risk of interdiction events. Management of this trade-off in response to interdiction events is the main adaptive behavior driving trafficking network evolution.

The network agent (i.e., cartel) decides when and where to supplement or eliminate current trafficking routes based on the value of cocaine shipments being delivered to the end node during each time step. The decision to either expand or consolidate trafficking routes depends on the losses experienced to interdiction relative to a *Loss Tolerance*. To be consistent with the authors' field interview and case study evidence, Network Agents are 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* is set to 10% of the maximum profit margin obtained during a given time step. This value is compared against the total losses (*TotLoss*) from nodes experiencing an interdiction event, N_I:

$$LossTol = 0.1 * \max[Q_{ij}\left(P_j - P_i - C_{ij}^{trans}\right)] \quad [16]$$

$$TotLoss = \sum_{j=1:N_I} Q_{ij}(P_j - P_i - C_{ij}^{trans}) \quad [17]$$

If losses to interdiction exceed this value (*TotLoss* > *LossTol*), the Network Agent responds by expanding trafficking routes to new nodes in an effort to direct shipments away from a susceptible location. The number of new nodes, N^*, to be activated and their associated network linkages is given by the ratio of total losses to *Loss Tolerance* (rounded to the nearest integer), constrained by the *Expansion Rate* (*ExpRate*):

$$N^* = \min\left(\frac{TotLoss}{LossTol}, ExpRate\right) \quad [18]$$

If losses are below or equal to this value (*TotLoss* ≤ *Loss Tol*), the Network Agent will consolidate current trafficking routes by discontinuing shipments to the highest risk nodes. The number of nodes to be eliminated, N^{-*}, is a proportion of currently active nodes, N^{act} (rounded to the nearest integer):

$$N^{-*} = N^{act}\frac{TotLoss}{TotLoss+LossTol} \quad [19]$$

The differences in route selection between Node and Network Agents is what creates a resilient trafficking network even if individual trafficking nodes face repeated and/or debilitating interdiction. Node Agents calculate expected profit and interdiction risk along routes between themselves and other Node Agent to which they are directly connected, and select the highest expected payoff among their neighboring nodes. Network Agents consider the cumulative value delivered and lost across the trafficking network, and decide how many nodes to (de)activate given the network's overall performance. The difference in 'global' versus 'local' route selection decisions gives rise to stable trafficking networks that experience seizures of large volumes but low values – a state that is not ideal for nodes experiencing interdiction but ensures continued profits at the DTO level.

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