Modeling and Simulating Terrorist Networks in Social and Geospatial Dimensions

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A simple theoretical multiagent model reasons about the criticality of terrorists and regions as terrorist interactions coevolve in geographical and social spaces.

Where we are influences who we know, and vice versa. As we move to new cities or countries, our contacts change. For instance, when a company relocates its employees, they develop new working relations with others while they perform assigned tasks. In theory, these relocations should improve company performance.[1]

However, performance also depends on individuals knowing who to ask about what—that is, on transactive memory.[2] Moving disrupts transactive memory and the social relations by which information flows. So, the question arises whether performance can improve when social and geospatial distributions change simultaneously.

Social and spatial relations evolve over time. Estimating their evolutions is important for management, command and control structures, and intelligence analysis research. By knowing future agent social and spatial distributions, an analyst can identify emergent leaders, hot spots, and organizational vulnerabilities. Historically, such estimations have depended heavily on qualitative data analyses by subject-matter experts.[3] A few researchers approached the issue using multiagent models and simulation. The models addressed the complex nature of the organization and task assignments, resource distributions, or agent locations. The simulations addressed the near-term organizational changes. This research came from two perspectives: the effects of change in the social network[4,5] and the effects of geospatial change.[6,7] Both perspectives can project aspects of emerging organizational structure and future performance, but they can't examine the interaction between physical and social movements.

We've developed a simple theoretical multiagent simulation model to show how changes in the coevolution of social and geospatial dimensions affect group behavior. Our model overcomes the limitations of isolated social and spatial models (see the "Related Work in Social and Geospatial Modeling" sidebar). To illustrate the model's potential for reasoning, we examine its implications here for a real-world terrorist network, using data extracted from open source texts. Although a full validation would require additional field data, the model's output reveals important aspects of complex organizational evolution that apply beyond the counterterrorism domain.

Input data set

The model's input is a network representation of an organizational structure in the social and geospatial dimensions. It includes knowledge and task information: who knows what and who is using that knowledge. For the terrorist network, we extracted relevant data from unclassified documents, using the AutoMap text analysis tool.[8] The documents included newspaper articles and unclassified intelligence reports from subject-matter experts. We hand-coded the corresponding latitudes and longitudes for the relevant data.

Figure 1a is an overall visualization of the resulting network consisting of four node types: agents, knowledge, tasks, and locations; figure 1b is a

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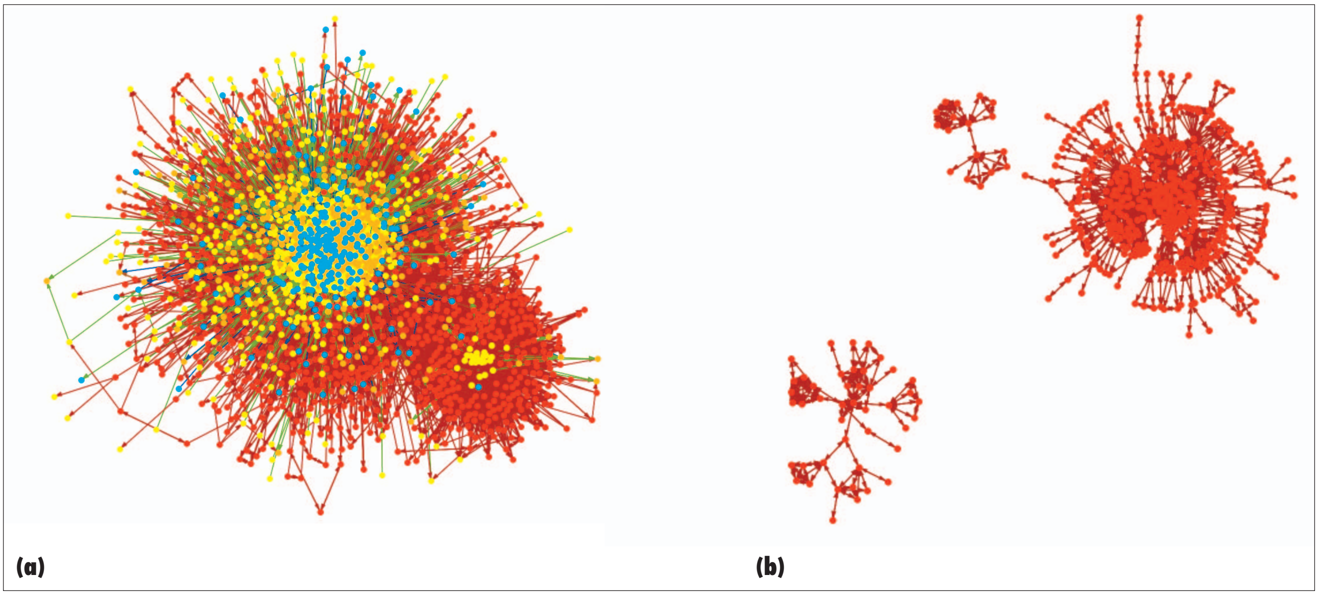

Figure 1. (a) The overall visualization of the example terrorist network represents agents, knowledge bits, tasks, and locations as red, yellow, blue, and orange nodes, respectively. (b) The agent-to-agent network of the data set consists of three disconnected subnetworks.

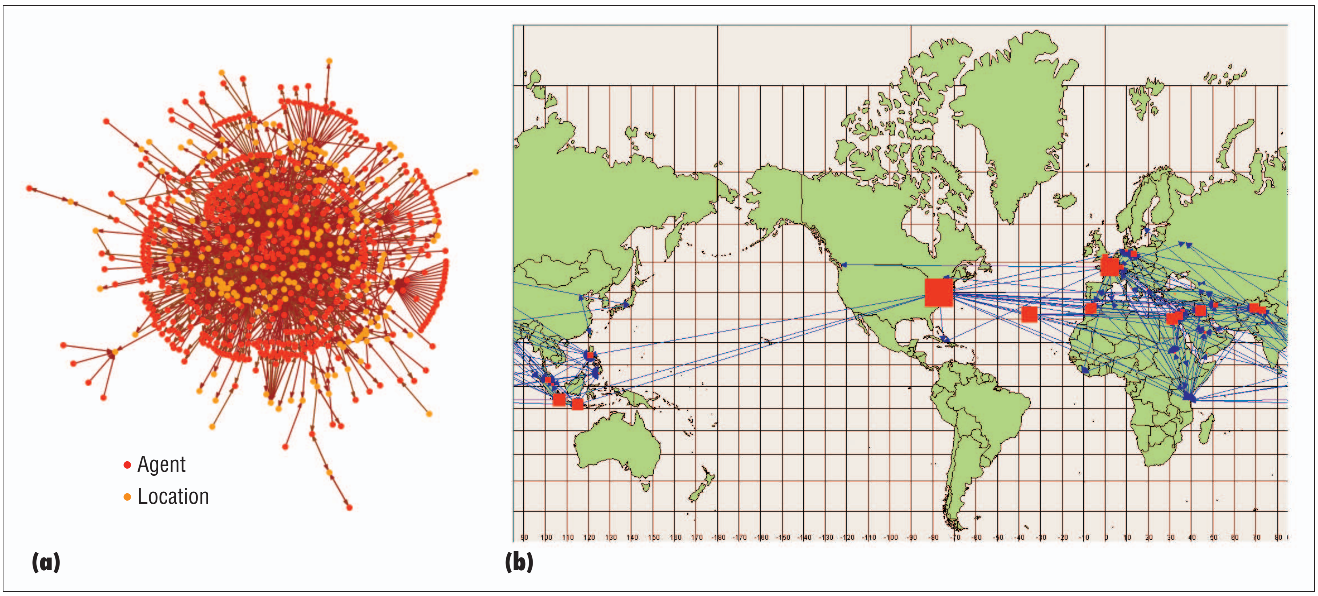

Figure 2. (a) Agent-to-location network. The red nodes represent agents; the orange nodes represent agent locations, which include latitude and longitude coordinates. (b) The AL network overlaid on a world map. To suggest how many agents are clustered at a specific location, the different-sized squares correspond to the number of agents in different regions. The blue edges display the agent-to-agent network links.

visualization of the data set's agent-to-agent (AA) links. Table 1 shows the input network's adjacency matrix, or *metamatrix*, across these nodes. This multimode, multilink network data represents the organization's current structural characteristics in our model.

We model the social dimension by using an algorithm that specifies the interaction probability between two agents. We model the geospatial dimension by using an agent-relocation mechanism that interprets agent movement in a geospatial location network's data set. For instance, if two agents have interactions or formal relations, we assume that an AA link exists between them. Similarly, if an agent possesses a knowledge bit, we assume an agent-to-knowledge (AK) link between the nodes. If two locations appear in the same context, we regard the two locations as related (LL). This topological location network constitutes the agent-relocation dimension. The other subnetworks, such as an agent-to-task network, knowledge-to-location network, and task-to-location network, have their own intuitive meanings based on the connected node types and the data coder's perspective.

Figure 2a shows the agent-to-location (AL) network; figure 2b

Related Work in Social and Geospatial Modeling

Researchers who study people's movements concurrently through social relations and space mainly use two techniques: data mining and simulation. Data mining can uncover patterns such as an organization's network structure, entity properties, and entity clusters. For instance, in a summary of data mining's impact on the counterterrorism community, Jeff Jonas and Jim Harper claim that the 9/11 attack plan was available before the attack.[1] Uncovering the plan would have required extensive data mining on available databases, but the US government might have disrupted the plan by pursuing available leads. Although the authors make a counterterrorism case for data mining, they also note that high false positives, or incorrect predictions, could waste valuable resources.

Link analysis and discovery is another data mining technique applied to counterterrorism. Raymond Mooney and his colleagues use it with an inductive-logic-programming method to discover implied rules in multirelational data.[2] They describe a powerful tool for approximating a complete organizational network from an incomplete one.

Vandana P. Janeja, Vijayalakshmi Atluri, and Nabil R. Adam focus a modeling and simulation approach to detecting anomalous geospatial trajectories on the basis of spatiosemantic associations.[3] They create basic spatial analysis units, or *spatial units*, and cluster them into a microneighborhood that shares similar characteristics across subspatial units. Their analysis of spatial and social characteristics at the same time is similar to our correlation between spatial and social dimensions.

Hsinchun Chen, Fei-Yue Wang, and David Zeng describe the development of an intelligence and informatics security model that depends heavily on network and link analysis.[4] They examine three interesting uses of the model: cross-jurisdiction information sharing, terrorism information collection, and smart-border and bioterrorism applications. One of their applications, the West Nile Virus-Botulism Portal, includes hot-spot analysis and a prediction function.

Organizational-behavior research has benefited from agent-based modeling techniques. For instance, Kathleen Carley has made the efforts to model sociotechnical systems as networked multiagent structures.[5] She introduces exemplary multiagent models such as OrgaHead[6] and Construct.[7] These models take networked organizational structures as an input and generate the estimated performance of task accuracy and information diffusion over time as well as the evolved structures after simulation. This approach might be difficult to validate, but it represents an effort to create more complex, realistic models that can automatically generate hypotheses forecasting organizational behavior.[8] Researchers could then use these hypotheses to estimate domain features or trends of interest and subsequently use other statistical analysis tools, such as data mining, to validate the hypotheses.

References

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Table 1. A metamatrix of the input data set for a terrorist network organizational structure.*

Nodes	Agent	Knowledge	Task	Location
Agent (916)	Social network (AA, 0.0024)	Knowledge network (AK, 0.0093)	Assignment network (AT, 0.0070)	Deploy network (AL, 0.0026)
Knowledge (614 bits)	—	Not used	Needs network (KT, 0.0961)	Regional knowledge network (KL, 0.0692)
Task (258)	—	—	Not used	Regional task network (TL, 0.1042)
Location (387)	—	—	—	Proximity network (LL, 0.0799)

*The number of nodes and network densities are in parentheses.

overlays it on a geographic map. Details on the coding process are available elsewhere.[9]

Model summary

The model simulates each agent and its interaction with others to estimate changes over time in organizational performance and structure. As agents interact and learn, their behavior eventually changes the performance and structure. The following algorithm outlines the interaction and relocation mechanisms for agent *A*'s behavior:

1. *A* searches for locations within its vision range (VR), looking for unknown

Table 2. Model input, output, parameters, and internal variables.*

Type	Name	Implication
Input	A networked organizational structure	A network including agents, knowledge bits, tasks, and locations. The network represents the target domain's complex organizational structure.
Output	An evolved network organization	A network organization with a recreated agent-to-agent (AA) network and an agent-to-location (AL) network, both of which reflect interactions and relocations.
	Knowledge diffusion	A performance metric showing how fast information can diffuse across the network.
	Energy task accuracy	A performance metric showing how accurately information is distributed to agents who require it to complete their tasks.
	Gini coefficient for AA and AL	Coefficients indicating the extent of unequal distribution of AA and AL network criticalities.
Parameters	Simulation runtime step (default = 30 steps)	The total simulation runtime.
	Number of replications (default = 3)	The number of model runs (required because the model is stochastic, not deterministic).
	Move radius (MR)	The radius on the spatial-route network specifying the maximum distance an agent can move in one time step.
	Vision range (VR) (default = 1)	The range on the spatial-route network specifying an agent's ability to gather a knowledge bit or interact with another agent.
	Sphere of influence (SI) (default = 2)	The number of social links that an agent can cross for an interaction.
	Relative-similarity (RS) weight, w_1; relative-expertise (RE) weight, w_2; social-distance (SD) weight, w_3 (default = 0.5); and spatial-proximity (SP) weight, w_4 (default = 0.5)	The weights to calculate four interaction probabilities.
	Learning rate from an agent (default = 0.05)	The possibility that an agent can learn a knowledge bit from an interaction with another agent.
	Learning rate from a location (default = 0.025)	The possibility that an agent can gather a knowledge bit by observing a knowledge node within vision range.
Internal variables	Relative similarity (RS_{ij})	The likelihood of interactions caused by homophily between *i* and *j* (passive information seeking).
	Relative expertise (RE_{ij})	The likelihood of interactions caused by expertise between *i* and *j* (active information seeking).
	Social distance (SD_{ij})	The likelihood of interactions over multiple social links.
	Spatial proximity (SP_{ij})	The likelihood of interactions from spatial distance.
	Interaction candidate set (ICS_i)	The agent set with which agent *i* can interact.
	Probability of interaction ($P_{ij}^{Interaction}$)	The likelihood of agent *i*'s interaction with agent *j*, calculated as the weighted linear sum of RS, RE, SD, and SP.
	Probability of relocation ($P_{il}^{Relocation}$)	The likelihood of agent *i*'s moving to location l, determined by the number of available knowledge bits required to perform the agent's assigned tasks.

* We use model default values here except for the move radius (MR), relative-similarity weight (w_1), and relative-expertise weight (w_2).

but necessary knowledge bits.

2. *A* moves to a found location.
3. *A* learns the unknown knowledge at its location.
4. *A* selects an agent from those that qualify as communication candidates.
5. *A* exchanges the unknown knowledge with the selected agent.

Basically, agents can interact and relocate at each simulation time step. They select a location to move to and an agent to interact with according to probabilistic values for each interaction and relocation opportunity. Exactly which agents interact with which, when they interact, what choices they make, and what they communicate and learn are defined probabilistically. Consequently, the model is stochastic and, as such, requires multiple replications to generate stable results and to define the space of outcomes.

Table 2 lists several factors that drive an agent's behavior and so the network's evolution and organization's structure. For example, agent behavior depends on the given input data set, which sets the initial environment. The input determines the initial probability of interaction among agents according to what they know and where they are located. The model's parameters include the relocation (move) radius in the geospatial dimension, the interaction (sphere of influence) radius in the social dimension, and the probability of learning after a knowledge exchange with an agent or a knowledge gathering at a certain location. Finally, the internal variables reflect behaviors calculated from the defined inputs and parameters, according to various model formulas.

We tested this model by varying important parameters in the agent interactions and relocations. First, we changed the agent move radius (MR) by 0, 1, and 2. If an agent's MR is 0, it's stationary to its initial location. If its MR is 2, the agent can search locations linked by two LL links from its initial location. Next, we varied the weight of relative similarity (RS) and relative expertise (RE) contributing to the probability interaction. If the RS weight is high, the agents interact mainly with agents sharing similar backgrounds, beliefs, and knowledge. This imitates agents as passive information receivers. In contrast, a higher RE weight makes the agents active information seekers. Finally, we tested the input data's sensitivity by randomly dropping or adding links in the AA or LL networks.

Agent-interaction mechanism

Agents have the opportunity to interact during each time period. They select an agent to interact with according to a probability of interaction, *P*, that's a weighted sum of four different factors: RS, RE, social distance (SD), and spatial proximity (SP). The theory for these factors comes from sociology, communication theory, and counterterrorism analysis.

Because the model is stochastic, an agent will usually interact with agents that it has a higher probability of choosing but will occasionally end up with a less likely choice. Like humans, these simulated agents can't always talk to their first choice. The model thus captures interactions that reflect less-than-optimal connections between intention and action as well as the rare unexpected interaction.

After an agent chooses another agent to interact with, the two agents will exchange knowledge bits. For each exchanged knowledge bit, the model draws a number from a uniform distribution ranging from 0 to 1. If the number is within the receiving agent's learning rate, that agent will have a new link to the communicated knowledge piece in the AK network.

Agents have the opportunity to interact during each time period. They select an agent to interact with according to a probability of interaction that's a weighted sum of four different factors.

Relative similarity and relative expertise. RS is a ratio reflecting similarity in the choosing and chosen agents' knowledge. It's based on the sociological principle of *homophily*,[10] which describes the increased likelihood of a person interacting with another person who shares similar education, beliefs, or race. RS represents the probability of a terrorist interacting with other terrorists that share the same religion or nationality. RE is a ratio reflecting the amount of knowledge the chosen agent has that the chooser doesn't have, and it's based on transactive memory.[2] RE captures why a Middle Eastern terrorist interacts with a South American drug cartel to exchange weapons expertise or information about funding sources. At first glimpse, the two factors might seem contradictory, but they're just two metrics capturing different aspects of terrorist knowledge-acquisition attitudes:

$$RS_{ij} = \frac{\sum_{k=0}^{K} AK_{ik} AK_{jk}}{\sum_{k=0}^{K} AK_{ik}}, \quad RE_{ij} = \frac{\sum_{k=0}^{K} AK_{jk}\left(1 - AK_{ik}\right)}{\sum_{k=0}^{K} AK_{ik}} \tag{1}$$

where K is the number of knowledge bits.

Social distance. SD is another factor affecting agents' probability of interaction—if two agents must cross many social links, then the probability should be low, and vice versa.[11] We compute it by finding the shortest path between two agents and then dividing one by the number of links in that path.

$$SD_{ij} = \frac{1}{\left|AA_{ij}\right|}$$
$$\left|AA_{ij}\right| = \begin{cases} \text{No. of links on shortest path from } i \text{ to } j \\ \qquad (\text{no. of links} \le \text{SI}) \\ \text{SI} + 1 \ (\text{no. of links} > \text{SI}) \end{cases} \tag{2}$$

If SD is larger than the maximum number of links in the sphere of influence, SI, then SD is set to one plus the maximum for social-interaction perimeter modeling. An agent can recognize and distinguish the closeness of other agents within the SI perimeter, but it can't differentiate the closeness when the interacting agent is outside the perimeter. In this case, an agent regards the interacting agents as just SI + 1 links away, though the real SD might differ.

Spatial proximity. Intuitively, two persons at the same location are more likely to talk than are two at different locations.[12–14] Some might argue that SP isn't significantly correlated with interaction frequency in the Internet age. However, in the terrorism domain, attending the same training camp or the same mosque is a critical interaction indicator.[14] The SP model is similar to SD but indicates the probability of being at the same location, rather than having a social link:

$$SP_{ij} = \frac{1}{\sum_{l_1=0}^{L} \sum_{l_2=0}^{L} \left(\left|LL_{l_1 l_2}\right| + 1\right) AL_{il_1} AL_{jl_2}}$$
$$\left|LL_{l_1 l_2}\right| = \begin{cases} \text{No. of links on shortest path from } l_1 \text{ to } l_2 \\ \qquad (\text{no. of links} \le \text{VR}) \\ \text{VR} + 1 \ (\text{no. of links} > \text{VR}) \end{cases} \tag{3}$$

As with SD, if SP is greater than VR, which is a maximum communication range across the geospatial dimension, and chosen by the user, the model sets SP to one plus the maximum for computing convenience. The rationale for using VR in the geospatial-domain calculation is the same as the rationale for using SI in the social dimension.

Probability of interaction. Using the four different factors we've described, we can express the probability that agents will select another agent to interact with as a weighted sum:

$$P_{ij}^{Interaction} = w_1 RS_{ij} + w_2 RE_{ij} + w_3 SD_{ij} + w_4 SP_{ij} \tag{4}$$

Although the model can calculate the probability for any pair of agents, we limit the number of possible interaction candidate agents according to two distances, SD and SP. This restriction assumes that

Table 3. Virtual-experiment design: Sensitivity analysis and parameter-space exploration.

Input parameters	Value	Implication
Move radius (MR)	0, 1, or 2 (3 cases)	Parameter-space exploration, examining the results' sensitivity according to the agent-movement perimeter (MR parameter)
Weights for RS (w_1)/RE (w_2)	0/1, 0.25/0.75, 0.6/0.4, 0.75/0.25, 1/0 (5 cases)	Parameter-space exploration, examining the agent-interaction attitudes and their affect on the results, from passive information gathering to active information gathering
Density of the organizational-structure network (AA and LL densities)	75%, 100%, 125% (3 cases)	Sensitivity analysis, examining the sensitivity of results according to the density changes of the AA and LL networks corresponding to the social and geospatial dimensions, respectively
Total virtual experiment cells	45 cells (3 × 5 × 3 cases)	—

a person will interact with others in his or her neighborhood—either social or geographic. Formally, the model defines the interaction candidate set as

$$ICS_i = \left\{ A_j \middle| \left(\left| AA_{ij} \right| \le SI \right) \vee \left(\left| LL_{l_1 l_2} \right| AL_{il_1} AL_{jl_2} \le VR \right) \right\} \tag{5}$$

An agent can communicate only with its candidate agents, so the probability of interaction is calculated between each agent and its candidate agents.

Agent-relocation mechanism

Our model lets agents relocate themselves to adjacent locations. The MR parameter defines the sphere of relocation, but the probability of choosing a certain location is more complicated:

$$P_{il}^{Relocation} = \frac{1}{\sum_{t=0}^{T}\sum_{k=0}^{K} AT_{it} \times KT_{kt} \times \left| KL_{kl} \right|}$$
$$\left| KL_{kl} \right| = \begin{cases} \text{No. of links on shortest path from } l \text{ to } k \\ \qquad (\text{no. of links} \le \text{VR}) \\ \text{VR} + 1 \ (\text{no. of links} > \text{VR}) \end{cases} \tag{6}$$

In essence, the agents choose a location that, on average, guarantees the shortest path to their required knowledge bits. In other words, the agents try to put themselves at the optimal location to collect the knowledge they want. However, like the AA interaction model, this is a stochastic model that determines location choices probabilistically. So, it's possible to choose a nonpreferred location with lower probability.

After selecting a location, the model changes the AL network by removing the edge from the agent to the old location and adding an edge to the new location. Additionally, the agent will gather knowledge bits linked to locations in its VR. This knowledge gathering is similar to the knowledge exchange between agents, except it uses a different learning rate. Some might argue that this regional knowledge acquisition isn't necessarily true, especially in the real world where terrorists can learn new knowledge from Web sites. However, many terrorists go to training sites and organization headquarters to receive specific, detailed training. These relocations are an important issue in the counterterrorism field,[14] and we're specifically examining them in this example.

Output measures

We use two performance metrics to evaluate an evolving organization over time: *knowledge diffusion* and *energy task accuracy*. KD gauges the dispersion of the knowledge bits across the agents as follows:

$$KD = \frac{\sum_{i=0}^{A}\sum_{j=0}^{K} AK_{ij}}{K \times A} \tag{7}$$

But KD considers only who knows what. ETA calculates the extent to which the agents have the knowledge they need to do their assigned tasks. This calculation introduces the agent-to-task (AT) and knowledge-to-task (KT) networks:

$$ETA = \frac{100}{T}\sum_{t=0}^{T} \frac{\sum_{k=0}^{K}\left(KT_{kt} \times \sum_{a=0}^{A} AK_{ak} \right)}{\sum_{a=0}^{A} AT_{at} \times \sum_{k=0}^{K} KT_{kt}} \tag{8}$$

Furthermore, we define two criticality metrics for the agents and locations. For agents, we count the number of agents that an agent interacts with during the simulation. This represents the number of agents that the agent knows and influences. For locations, we count the number of agents in a location at the end time. If the location harbors more agents, it might have higher terrorist activities.

Results

We used the model to analyze the terrorist network in the meta-matrix format (see table 1) and to generate estimates on agent relocation, geospatial clustering, agent interaction, and social-network evolution. We performed a sensitivity analysis first, then visualized and analyzed the model output in two dimensions.

We replicated the simulation three times for 30 simulation time steps. The sensitivity analysis showed significant p-values for some independent factors. Specifically, MR is a significant predicting factor for ETA, KD and the Gini coefficient are significant for location-criticality distribution, and RS is important for explaining the Gini coefficient of the agent-criticality distribution. (The Gini coefficient comes from economics and describes a property's distribution across a population.) These p-values indicate that three replications are sufficient for identifying the critical factors for each performance metric. The stabilized distribution of the results requires further examination, but that work is outside this article's scope.

Sensitivity analysis

We analyzed the model's sensitivity by varying the input parameters in table 3. After running the model with varied parameters, we performed a regression analysis. The independent variables are the varied parameters of a *virtual-experiment cell*—for example, a com-

Table 4. Regression for sensitivity analysis.

Dependent variable	Energy task accuracy	Knowledge diffusion	Gini coefficient of location-criticality distribution	Gini coefficient of agent-criticality distribution
Standardized coefficients				
Move radius	0.748*	0.780*	–0.956*	–0.088
Relative similarity	0.008	0.004	0.020	0.131†
Possible density	0.010	0.009	–0.114*	–0.865*
Adjusted R-square	0.506	0.555	0.925	0.765

*p-value < 0.001
†p-value < 0.01

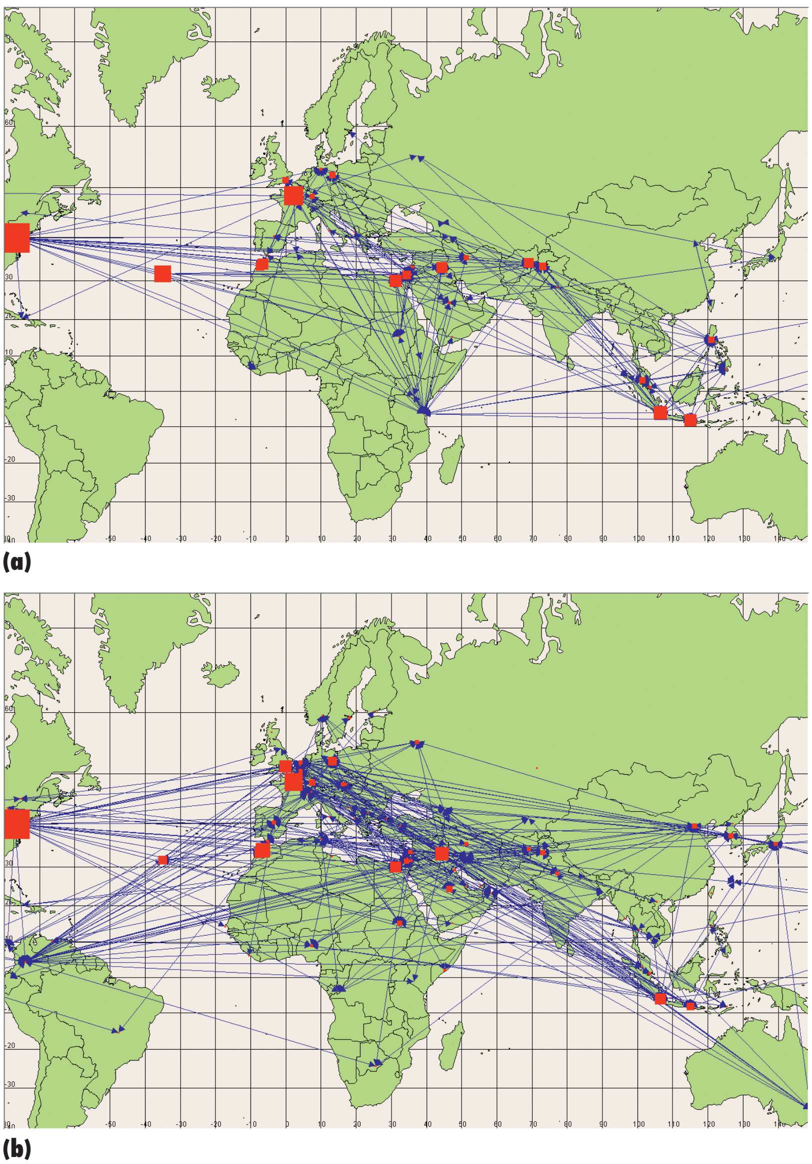

Figure 3. The agent geospatial distribution changes over time with a move radius of 1: (a) the distribution at time 0, (b) the distribution at time 30. The size of the squares corresponds to the number of agents in the region, and the lines are the interlocation agent-to-agent communication links.

bination of 0 MR, 0/1 RS/RE ratio, and 75 percent density rate. The dependent variables are the two performance metrics and the Gini coefficients of the agent- and location-criticality distributions.

Table 4 is the regression-analysis result. First, as MR increases, the network's performance improves. The terrorists in the model tend to relocate to regions where they can collect more information, rather than stay in their current location. Furthermore, these relocations increase task performance by increasing the information feed. Next, higher MR and higher possible density decreases the Gini coefficient of location criticalities. This indicates that terrorists will disperse more if they can relocate more easily and the input network is denser. Finally, lower RS will induce a more centralized terrorist network. Particularly, the input network density has a great impact on the agent-criticality distribution compared with its impact on the location-criticality distribution.

Location-criticality analysis

Agent movement creates segregation patterns over time (see figure 3). Figure 4 shows an accumulated agent distribution across the locations. The distribution implies that agents will disperse more if we increase MR: the fewer places harboring terrorists, the greater the MR, which should help the terrorists find the places to cluster. However, our model indicates the opposite scenario: the terrorists in our model can't find the places to cluster densely. Rather than gathering in a few regions, the terrorists will disperse around the world.

Table 5 lists the top 10 locations harboring terrorists after the simulations. Although the accumulated distribution and its Gini coefficient in figure 4 showed terrorist dispersion, the top 10 locations are fairly consistent across three different MR levels. This implies that the hot regions with frequent terrorist activity will remain at the top after the relocations, even though some terrorists in those regions move to regions with less activity. In detail, the northwest African regions—that is, Morocco and Casablanca—become important locations as well as some European regions, such as France. The south Asian regions of Indonesia and Bali and the areas of frequent activity—US and Israel—will remain the same.

Agent-criticality analysis

We analyzed the important agents after the simulation. According to the sensitivity analysis, RS changes impact the distribution of the agent criticality. Figure 5 visualizes the accumulated agents' social link coverage across the RS levels. It shows some slight differences in terms of Gini coefficients, but the link-coverage distribution doesn't change much. This implies that the terrorist social network's evolution is stable regardless of the parameter change. In spite of the small changes, the increase in Gini coefficient with higher RS suggests that fewer terrorists will control the social links if the terrorists gather information more passively. For instance, one terrorist group often has different backgrounds from another group. In that case, under a strong RS interaction weight, only terrorists with backgrounds similar to both groups will be able to communicate with the groups' members. A strong homophily trend means that agents will have fewer possible agents within their ICS and that fewer agents will control more social links.

As with location-criticality analysis, we identified the top 10 terrorists who control the most links after simulation. Table 6 shows that the top terrorists, such as Bin Laden and Riduan Isamuddin, have similar power after simulations in spite of varying parameters. This is because they're already the center of terrorist social networks, so they appear frequently in ICSs. Additionally, they have fairly comprehensive backgrounds and knowledge, so most agents can find high RS and RE with the top-ranking agents. On the other hand, Mohammad Atta shows higher ranks under the passive-information-gathering assumption, because his background was common across the agents.

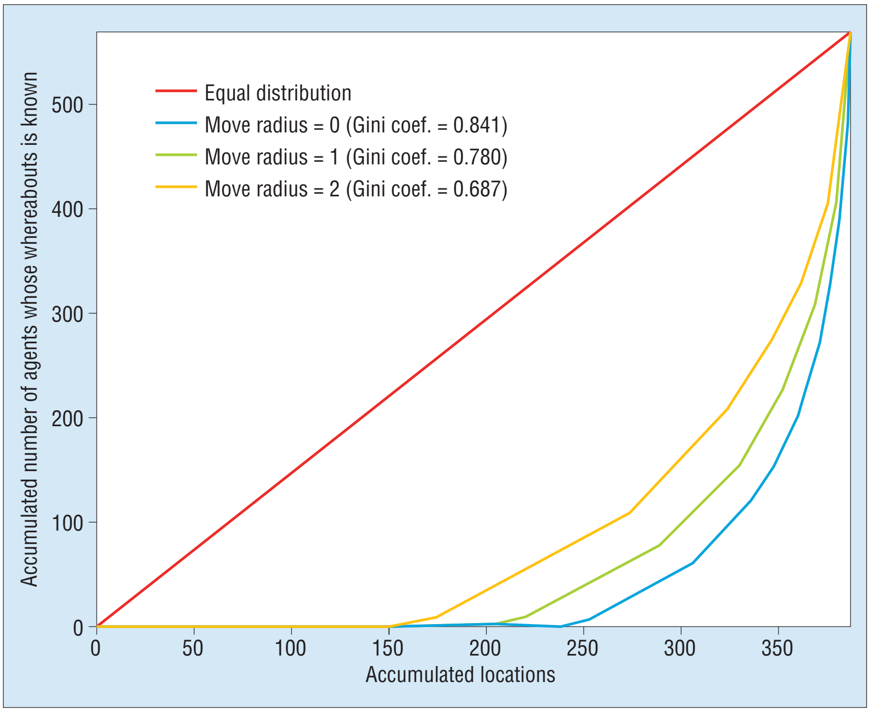

Figure 4. An accumulated distribution of agents across the locations. The whereabouts of 570 agents are known, and there are 387 locations.

Table 5. The top 10 critical locations.

Rank	MR = 0 (stationary)	MR = 1 (adjacent move)	MR = 2 (farther move)
1	US	US	US
2	Israel	France	France
3	France	Morocco	Morocco
4	Bali	Israel	Casablanca
5	Morocco	Bali	Bali
6	Egypt	Casablanca	Egypt
7	Afghanistan	Egypt	Israel
8	Casablanca	Iraq	Strasbourg
9	Iraq	Indonesia	Gaza
10	Indonesia	Strasbourg	Indonesia

Our analysis indicates that the agents become more dispersed around the world but that critical agents themselves don't change much. Obviously, the analysis method has its limitations. First, validating the simulation model is very challenging and involves open research questions, such as matching the simulated time step to the real-time flow. Also, incorrect input data sets can misdirect the model's output. Complete and correct real-world data sets are rare, but we expect to resolve some concerns by adding more realistic agent-behavior mechanisms. As the subjects' behaviors become more complex, adding more salient features to the model will increase its usability. A recent book addresses defense modeling, simulation, and analysis issues further.[15]

Despite some concerns, this complex multiagent model generates several estimates that are useful for policy making and theory building. Furthermore, the formula-based, agent-behavior design can be updated easily as findings from other disciplines become available. These two points provide incentives for using the model in the real world and for updating and developing it on the basis of future findings. ■

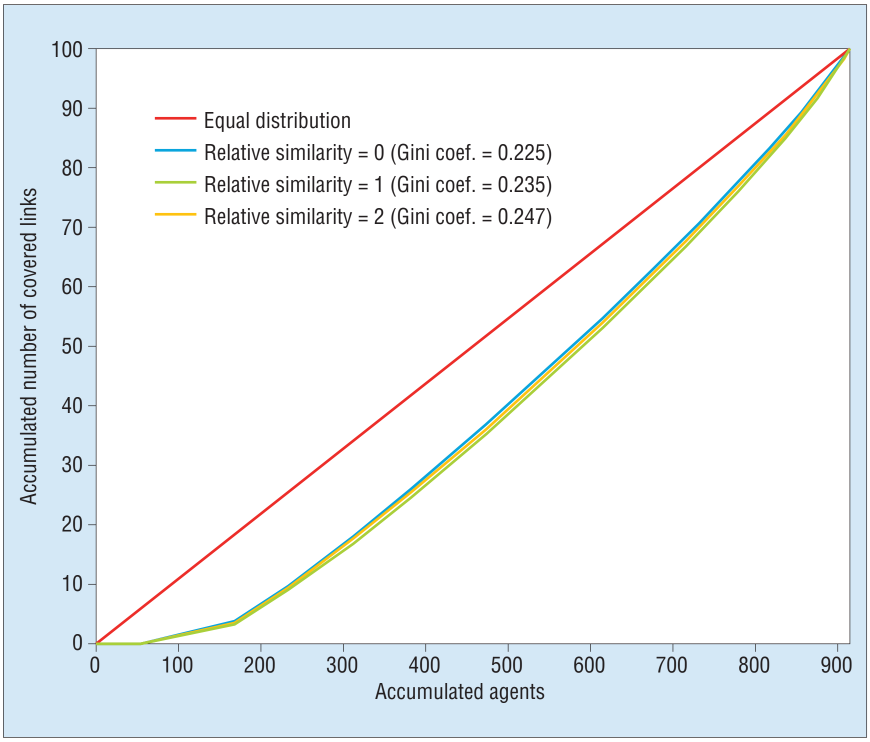

Figure 5. The accumulated distribution of the percentage of covered social links across the agents.

Table 6. The top-10 critical agents.

Rank	RS = 0.0 (active information gathering)	RS = 0.6	RS = 1.0 (passive information gathering)
1	Bin Laden	Bin Laden	Bin Laden
2	Riduan Isamuddin	Riduan Isamuddin	Riduan Isamuddin
3	Abdul Aziz	Abdul Aziz	Mohammed Atta
4	Yasser Arafat	Yasser Arafat	Bakar Bashir
5	Bakar Bashir	Yaacov Perry	Yasser Arafat
6	Mohammed Atta	Mohammed Atta	Zacarias Moussaoi
7	Yaacov Perry	Bakar Bashir	Yaacov Perry
8	Imam Samudra	Zacarias Moussaoui	Abdul Aziz
9	Zacarias Moussaoui	Mohambedou Slah	Yazid Sufaat
10	Abdullah Sungkar	Abdullah Sungkar	Mohambedou Slah

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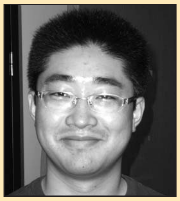

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