Quantitative methods of identifying the key nodes in the illegal wildlife trade network

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Edited by Susan Hanson, Clark University, Worcester, MA, and approved May 15, 2015 (received for review January 15, 2015)

Innovative approaches are needed to combat the illegal trade in wildlife. Here, we used network analysis and a new database, HealthMap Wildlife Trade, to identify the key nodes (countries) that support the illegal wildlife trade. We identified key exporters and importers from the number of shipments a country sent and received and from the number of connections a country had to other countries over a given time period. We used flow betweenness centrality measurements to identify key intermediary countries. We found the set of nodes whose removal from the network would cause the maximum disruption to the network. Selecting six nodes would fragment 89.5% of the network for elephants, 92.3% for rhinoceros, and 98.1% for tigers. We then found sets of nodes that would best disseminate an educational message via direct connections through the network. We would need to select 18 nodes to reach 100% of the elephant trade network, 16 nodes for rhinoceros, and 10 for tigers. Although the choice of locations for interventions should be customized for the animal and the goal of the intervention, China was the most frequently selected country for network fragmentation and information dissemination. Identification of key countries will help strategize illegal wildlife trade interventions.

wildlife trade | network analysis | key player | elephant | rhinoceros

The illegal wildlife trade is an industry in which thousands of wild animals and associated products are shipped daily around the globe as food, pets, medicines, clothing, trophies, and religious amulets (1, 2). The complex illegal wildlife trade network structure often involves important intermediate stops for bulking or breaking down shipments, switching modes of transport, and manufacturing wildlife byproducts (3–5). Despite advances in wildlife detection technology and general descriptive work on the illegal trade (3, 6–17), current prevention and control approaches are failing (5, 18). More quantitative research has been called for (4, 17, 19). Accordingly, we take a more analytical approach to identify the key countries involved in the illegal wildlife trade network. Specifically, we use a new database of illegal wildlife trade reports, HealthMap Wildlife Trade (www.healthmap.org/wildlifetrade/), to identify (*i*) the key exporter, intermediary, and importer countries and (*ii*) the countries where enforcement activities and educational campaigns might most effectively disrupt the networks. Identifying these key countries can provide useful information on how to allocate resources to combat the illegal trade in wildlife.

Results

We analyzed a total of 232 international shipments of elephants, 165 shipments of rhinoceros, and 108 shipments of tigers for the period August 2010 to December 2013 after the exclusion of reports due to being duplicates, not providing the countries of origin and destination, or not involving international trading. We excluded 153 shipments for elephants, 170 for rhinoceros, and 197 for tigers (Table S1). Details regarding the sources of the data and how they were coded are included in *Materials and Methods*.

The networks, mapped in Circos (*Materials and Methods*), provided a visualization of the differences in the size and topology of the networks (Fig. 1 *A–C*). Table 1 quantified what we saw in the visualized networks. The elephant trade had more nodes (59) than the rhinoceros trade (39), which had more nodes than the tiger trade (21).

For countries that engaged in elephant trading, there was an average of 3.9 shipments to 2.3 countries for the time period August 1, 2010 to December 31, 2013. Countries trading in rhinoceros products averaged 4.2 shipments to 2.2 countries, and countries trading in tiger products averaged 5.1 shipments to 1.8 countries. Although the median number of shipments exported by a country was 2 for all animals, the total number of shipments was as high as 40 for elephants, 51 for rhinoceros, and 29 for tigers. Similarly the median number of countries exported to, by any country, was 1–2, but the total number of shipments was as high as 13 for elephants, 9 for rhinoceros, and 7 for tigers. The median number of shipments imported by a country was 1, but the total number of shipments was as high as 50 for elephants, 50 for rhinoceros, and 45 for tigers. The median number of countries imported from was 1, but the total number of shipments was as high as 27 for elephants, 23 for rhinoceros, and 9 for tigers (Table 1).

We next identified individual key nodes. For key exporters, Kenya and Tanzania had the highest number of exported shipments and connections to other nodes for elephants, South Africa for rhinoceros, and India for tigers (Tables S2–S4). For key intermediaries, Kenya, Thailand, China, and Hong Kong had the highest influence on the flow of the trade in the network (based on the flow betweenness centrality measurement) for elephants, China and Vietnam for rhinoceros, and India and Myanmar for

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Significance

Despite advances in technology and general descriptive work, current approaches at reducing the illegal wildlife trade are failing. We take a more analytical approach to identify the key countries involved in the illegal wildlife trade network by using a new database of illegal wildlife trade reports, HealthMap Wildlife Trade, to identify (*i*) the key exporter, intermediary, and importer countries and (*ii*) the countries where enforcement activities and educational campaigns might most effectively disrupt the networks. Identifying these key countries can provide useful information on how to allocate resources to combat the illegal trade in wildlife, a major focus for conservation and public health agendas.

Author contributions: N.G.P., D.O.J., and G.S. designed research; N.G.P. performed research; D.O.J., J.S.B., R.B., and M.Z.L. contributed new reagents/analytic tools; N.G.P. analyzed data; and N.G.P., C.R., and G.S. wrote the paper.

The authors declare no conflict of interest.

This article is a PNAS Direct Submission.

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This article contains supporting information online at www.pnas.org/lookup/suppl/doi:10.1073/pnas.1500862112/-/DCSupplemental.

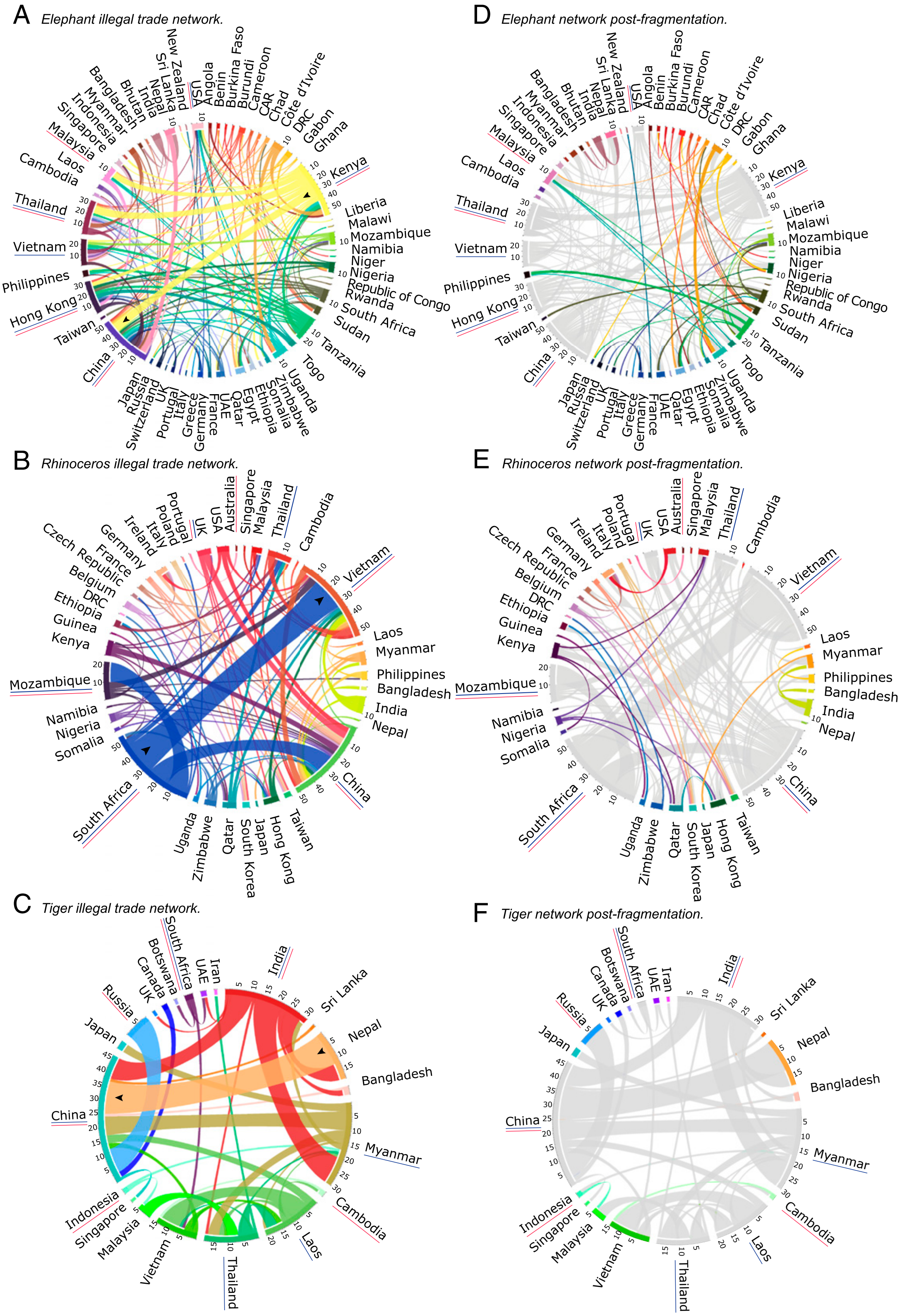

Fig. 1. Illegal wildlife trade flows from August 2010 to December 2013 for elephants (*A*), rhinoceros (*B*), and tigers (*C*). Networks before (*A*–*C*) and after removal (*D*–*F*) of trading by the six fragmentation key player countries (underlined in blue) shown here. Tick marks indicate the number of shipments. Trade flow ribbons adjacent to a country indicate outflow and ribbons with a gap next to a country indicate inflow (see arrows). Information dissemination key players are underlined in red.

tigers. For key importers, China, Hong Kong, Thailand, and Vietnam had the highest number of imported shipments and connections arriving from other nodes for elephants, China and Vietnam for rhinoceros, and China for tigers.

Table 1. Elephant, rhinoceros, and tiger network characteristics for internationally illegally trading countries

Statistic	Elephant	Rhinoceros	Tiger
Size (total number of countries)	59	39	21
Mean number of shipments	3.9	4.2	5.1
Median (range) of exported shipments	2 (0–40)	2 (0–51)	2 (0–29)
Median (range) of imported shipments	1 (0–50)	1 (0–50)	1 (0–45)
Mean number of connections	2.3	2.2	1.8
Median (range) of exported connections	2 (0–13)	2 (0–9)	1 (0–7)
Median (range) of imported connections	1 (0–27)	1 (0–23)	1 (0–9)

Information based on HealthMap Wildlife trade reports from August 2010 to December 2013.

We found the set of nodes whose removal from the network (by isolating the node and effectively stopping trade in and out of the node) would cause the maximum disruption to the network. If we assume that we only have enough resources to completely remove or isolate the six nodes that would result in the most disruption to the network, we find that we can fragment 89.5% of the network for elephants, 92.3% for rhinoceros, and 98.1% for tigers (Table 2). In other words, 89.5% of potential elephant trading partners cannot reach one another, and so on. The mapped networks provided a visualization of the effect of removing these six key player countries (Fig. 1 *A–F*). China was selected as a key country for fragmenting the networks in 96.7% of bootstrapped samples for elephants and 100% for rhinoceros and tigers (Table S5).

We then found sets of one to six nodes that would disseminate information to the most nodes through connections in the network. These selected nodes would hypothetically share educational information on the perils or evils of the wildlife trade with all of the nodes to which it is directly connected to in the network. Table 3 shows the percentage of the network reached by selecting the optimal set of one to six nodes. We found that we would need to select at least 18 nodes for an educational campaign to be able to reach 100% of the elephant trade network via direct connections from these nodes. Sixteen nodes would be needed for rhinoceros, and 10 would be needed for tigers; however, only 5 nodes for elephants and tigers and 6 nodes for rhinoceros would be needed to reach 80% of the network via direct connections. China was the most frequently selected key country, with 93.3% of all bootstrap samples selecting China as a key country for information dissemination, 95.0% for rhinoceros, and 80% for tigers (Table S6). The countries best identified for fragmenting the networks were not always the same as those best suited for disseminating information (although at least half are).

Discussion

Many wildlife species are facing imminent extinction. Targeted strategies and operational approaches to disrupt the illegal wildlife trade can benefit conservation and public health agendas (20). Here, we quantified parameters to identify key nodes with major influence in the network to help develop strategies to combat the illegal wildlife trade. Key export nodes had large numbers of export shipments and connections; clearly the focus in these countries should be legislation and interdiction activities to decrease the supply. South Africa, the major exporter of rhinoceros products, should ramp up current efforts of drones and other security measures, as well as integrate other novel tools to track the animals and products in the event of poaching. Key intermediary countries were transit points, which had a high influence on the flow of the trade. Key import nodes had large numbers of import shipments and connections. China, Vietnam, and Thailand have been identified in this and other studies as major intermediary and import nodes (17). The emphasis in these countries should be on improving baggage screenings at ports and airports to apprehend traders. Import countries can also work on reducing demand through educational campaigns and by increasing conviction rate of and penalties for consumers. Multinational organizations can allocate resources based on the set of nodes whose removal from the network would cause the maximum disruption. It was interesting to see that the key players at best fragmenting the network were not always the countries that ranked high in import or betweenness centrality measures; the United States was selected as a key player over Malaysia in the elephant network, and the United Kingdom was selected over Hong Kong, Qatar, and Kenya in the rhinoceros network. By visually examining these nodes in the networks, the importance of the distance from other key players and the diversity of the connections of the

Table 2. Key sets of nodes for best fragmenting the illegal wildlife trade network

Animal	Group size	Key players	Fragmentation index*
Elephant	1	Kenya	0.620
	2	China, Kenya	0.673
	3	China, Thailand, Vietnam	0.735
	4	China, Kenya, Thailand, Vietnam	0.809
	5	China, Hong Kong, Kenya, Thailand, Vietnam	0.847
	6	China, Hong Kong, Kenya, Thailand, United States, Vietnam	0.895
Rhinoceros	1	China	0.670
	2	China, Vietnam	0.750
	3	China, South Africa, Vietnam	0.810
	4	China, South Africa, United Kingdom, Vietnam	0.850
	5	China, South Africa, Thailand, United Kingdom, Vietnam	0.895
	6	China, Mozambique, South Africa, Thailand, United Kingdom, Vietnam	0.923
Tigers	1	China	0.685
	2	China, India	0.799
	3	China, India, Vietnam	0.870
	4	China, India, Myanmar, Thailand	0.920
	5	China, India, Myanmar, South Africa, Thailand	0.967
	6	China, India, Laos, Myanmar, South Africa, Thailand	0.981

Information based on HealthMap Wildlife trade reports from August 2010 to December 2013.
*The fragmentation measure represents the proportion of the network that would be isolated based on the removal of the key players.

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Table 3. Key Nodes for Optimal Information Dissemination

Animal	Group size	Key players	Reciprocal distance reach index*
Elephant	1	China	61.4%
	2	China, Thailand	68.8%
	3	China, Kenya, Thailand	74.4%
	4	China, Kenya, Malaysia, Thailand	79.5%
	5	China, Hong Kong, Kenya, Malaysia, Thailand	82.3%
	6	China, Hong Kong, Kenya, Malaysia, Thailand, United States	85.0%
Rhinoceros	1	China	53.6%
	2	China, Vietnam	62.6%
	3	China, Hong Kong, Vietnam	70.3%
	4	Australia, China, Hong Kong, Vietnam	75.4%
	5	Belgium, China, Hong Kong, Portugal, Vietnam	79.3%
	6	Australia, China, Mozambique, South Africa, United Kingdom, Vietnam	83.1%
Tigers	1	India	41.1%
	2	China, India	57.0%
	3	China, India, Indonesia	69.2%
	4	China, India, Indonesia, Vietnam	78.7%
	5	China, India, Indonesia, Laos, South Africa	83.5%
	6	Cambodia, China, India, Indonesia, Russia, South Africa	87.7%

Information based on HealthMap Wildlife trade reports from August 2010 to December 2013.

*The reciprocal distance index represents the weighted distance, in terms of connections, of the non-key countries to the key countries.

United States and the United Kingdom are seen. Finally, we identified key countries where educational campaigns explaining illegal wildlife trade risks would likely be most effective. Again, China, Vietnam, Thailand, and India are important countries for educational programs. It is interesting to note that almost all key intermediary nodes, key import nodes, key nodes for network disruption, and key nodes for dissemination of information included China as one of its targets. With its increasing global economic importance, China has to be a major focus for wildlife trade reduction programs to make a real impact (21).

There are some limitations to this work. We analyzed transnational rather than domestic smuggling here; looking into trade within a country could also be beneficial. The current approach yields 'culprit' countries; however, there are forces at play exploiting wildlife in each country that are not so black and white. Thus, understanding the cultural and economic backdrop within these countries could improve our ability to devise better interventions. In addition, HealthMap data will have missing data due to variability in media coverage, media censorship, and the language of the curated reports (22). However, HealthMap has tried to minimize bias through a systematic approach to collecting data, as well as sourcing data in other languages like Japanese. As the Internet continues to expand and access increases by non-English users, Internet-based surveillance will grow more powerful, although algorithms and assessment tools will need to continually adapt.

The key player program used an undirected (no direction for shipments between two countries) and unweighted (no frequency of shipments between two countries) network, and within-country trade was ignored. It may be possible to extend the key player algorithm to account for the direction and weight of the various routes in the future. However, for the purposes of dissemination of information, the locations of the connections between countries of the network are the most important, and not the direction or the weight, so results presented here will be of great value regardless of future studies.

Strategies for isolating nodes and dismantling the network could fail from short-term or variable enforcement efforts or nonresilient procedures (3, 13). Disrupting the trade could push the trade to be even more underground (23, 24). To elaborate, we can think of networks as being on a spectrum from provincial (networks having mainly strong ties) to cosmopolitan (networks having mainly weak ties). Somewhere in between (a suburban network) is the most efficient dark network (23). When removing key nodes, we are pushing networks toward the cosmopolitan end of the spectrum. Though not a concern in the cosmopolitan wildlife trade networks we studied here, we need to be careful not to make provincial networks more efficient in this process. Furthermore, there are only a few ways that a shipment can make its way to international destinations, so the routes may not change too fundamentally. We recommend conducting regular analyses using this database of near real-time reports to stay abreast of shifting trade routes. It would also be beneficial to expand this work to other animals heavily traded illegally, like pangolins and birds, as part of a varied toolkit of strategies to fight wildlife smuggling.

Materials and Methods

As no comprehensive data on the volume, frequency, composition, and routes of the illegal wildlife trade are publicly available, we relied on the formal and informal reports in global digital media as described by Sonricker Hansen et al. (22) to summarize the network and composition of the illegal wildlife trade. These reports are contained in the HealthMap Wildlife Trade database (www.healthmap.org/wildlifetrade/). The HealthMap Wildlife Trade database combines official data with informal real-time media stories and reports from the public on illegal wildlife trade seizures. It is an automated web-crawling surveillance system of the wildlife trade similar to those used for infectious disease events (e.g., GPHIN, HealthMap). Official sources include TRAFFIC, WildAid, The Coalition Against Wildlife Trafficking, World Wildlife Fund, and the International Fund for Animal Welfare. Unofficial sources include free and publicly available websites, discussion forums, mailing lists, news media outlets, and blogs. The database uses a text-mining algorithm based on keyword search strings, which uses news indexers that draw from more than 50,000 possible English and Japanese Web-based sources (22).

We focused on the period between August 1, 2010 and December 31, 2013 and limited the scope of our wildlife trade analysis to elephants, rhinoceros, and tigers, which are the most frequently cited animals in the database (22). From each report of a trade interception of an elephant, rhinoceros, and tiger listed in the wildlife trade database, we extracted the type of product(s) traded, country of origin of the product, and the actual or intended country of destination of the product. A report that listed a trade interception involving multiple types of products, multiple origins, or multiple destinations was parsed so that each product type, origin, and destination was entered separately into our own database. For example, a report with an interception of tiger skins, a tiger cub, and elephant tusks resulted in three corresponding separate entries. We delineated by product type to reflect the distinctive market demands. If these items were traveling from India to Nepal to China, they were entered separately for traveling from India to Nepal and from Nepal to China. If they were sourced in India and being sent to China and Vietnam, they were entered as traveling from India to China and India to Vietnam. Each entry in our database, hereafter referred to as a shipment, corresponded to an animal product transported between two countries; this shipment was the unit of analysis. Duplicate shipments were identified based on the identification of an identical shipment route reported within a 30-d period with the same combination of products.

Trade networks for elephants, rhinoceros, and tigers were mapped using Circos (mkweb.bcgsc.ca/tableviewer), software more widely used in genetics (25). Networks consisted of nodes joined by directed connections. The nodes in the network represented the countries of origin and destination of shipments based on the HealthMap Wildlife Trade database. Each connection was characterized by the direction of the shipment and its corresponding number of reported shipments. A pair of nodes could have two connections if trade was occurring in both directions. A connection that began and ended at the same node was not included in the analyses.

We generated basic demographics for each animal network including network size, average number of exported and imported shipments per country, and the average number of exporting and importing connections per country from August 1, 2010 to December 31, 2013 (26, 27). Network size was defined as the total number of countries, or nodes, in the network. The number of exported and imported shipments per country was defined as the total number of shipments that were sent from and received by a particular country, respectively, in a given time period. The number of exporting and importing connections per country was defined as the total number of countries to which a particular country exports and imports, respectively. For each animal, we analyzed countries that reported illegal export(s) or import(s) of that animal.

As described below, we identified (*i*) the key exporter, intermediary, and importer countries and (*ii*) the key countries where enforcement activities and educational campaigns might most efficiently disrupt the activities of the network. We identified the key exporter and importer countries based on (*i*) the number of shipments and (*ii*) the number of connections departing from and arriving at a node. Key intermediary countries were identified from flow betweenness centrality, a measure of the extent to which the overall trade flow must pass through a particular node, or in other words, a node's gate keeping role (26, 28, 29). Identifying these key nodes helped pinpoint key transit points where the trade could be stopped from moving from the source to consumers (17, 30–32). Further details on flow betweenness calculations are provided in *SI Materials and Methods* and Fig. S1. Flow betweenness was calculated using the sna package in R (33, 34).

We identified sets of key countries using criteria Borgatti defined in the key player problem (35, 36). We first found the set of countries whose removal from the network would maximize the fragmentation in the trade network. Fragmentation was defined as increasing the number of connections it takes to go from one node to another with an end point of having all of the nodes be disconnected or isolated from one another, effectively preventing consumers from connecting with illegal wildlife products sources (35). A fragmentation index was calculated representing the proportion of the countries that are isolated after the removal of the key countries. We then found the set of nodes that act as the best seeds to disseminate information, via an educational campaign, most efficiently through the network. A reciprocal distance weighted reach index was calculated representing the weighted distance, in terms of connections, of the non-key countries to the key countries. Key countries and their associated fragmentation and reach indices were calculated using the key player program (Analytic Technologies) version 1.45 (35, 36). Further details on the key player program are provided in *SI Materials and Methods*. To examine the probability of a country being chosen as a key country, we conducted a Poisson parametric bootstrap. Although methods for understanding a range of processes on networks has been described, we focused on examining each directed connection in the network as a random variable based on Poisson distribution. We assumed independence among network connections. Methods involving more relaxed homogeneity assumptions and modeling clustering and star configurations (propensity for a country to have connections with multiple network partners) have been proposed but are not examined here (37).

Borgatti's methodology was chosen because it explicitly selects the optimal set of nodes to fragment or disseminate information through the network. Because interventions are not always based on just one node, examining sets of nodes will provide more optimal results than selecting the top-ranked individual nodes in prioritizing locations for interventions (35). The key player problem was developed as a general model that can be applied to public health and criminal justice problems (35). Examples include selecting a subset of people in a population to immunize to contain an epidemic and selecting players to dismantle a criminal or terrorist network (35, 38, 39). Examples of selecting the best seeds to transmit information through the network include the selection of people to promote law-abiding practices or healthy behaviors (35, 40–43). The key player problem method lends itself well to the illegal movement of wildlife because of its criminal justice and indirect public health implications.

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ACKNOWLEDGMENTS. We thank Annie Li, Amy Hansen Sonricker, and Sumiko Mekaru from HealthMap for assistance with the data, E. Paul Wileyto and A. Russel Localio for assistance with the analysis, and Neelendu Dey for assistance with graphics. This research was supported by the University of Pennsylvania School of Veterinary Medicine VMD/PhD program.

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