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Maximizing the spread of conservation initiatives in social networks

Sean M. Wineland | Thomas M. Neeson

Department of Geography and Environmental Sustainability, University of Oklahoma, Norman, Oklahoma, USA

Correspondence
Sean M. Wineland, Department of Geography and Environmental Sustainability, University of Oklahoma, Norman, OK, USA.
Email: seanwineland@gmail.com

Abstract
Conservation programs and policies can preserve biodiversity and boost ecosystem services, but only when widely adopted. While thousands of conservation initiatives exist globally, most fail to spread beyond a few initial adopters. Here, we use network science to (1) determine the topology and structure of two networks of conservation actors (one regional, one national), (2) identify influential individuals in those networks, and (3) test whether the adoption of a conservation initiative by influential individuals could increase the spread of that initiative across the network. We find that initial adoption by influential individuals results in sharp improvements in the total number of adopters of a conservation initiative network-wide, particularly when a linear threshold diffusion model is used. Under an independent cascade diffusion model, the benefits of targeting influencers are smaller but still substantial. These benefits occurred in both networks despite very different network structures: the regional network resembles a random network comprised mostly of state agencies and local entities, while the national network has a scale-free structure with highly influential hubs of federal agency and NGO entities. Given that many conservation programs fail to reach critical mass, our findings highlight the importance of strategically targeting influential individuals to boost the spread of conservation initiatives.

KEYWORDS
adoption dynamics, conservation initiatives, network science, payment for ecosystem services

1 | INTRODUCTION

Conservation practitioners are grappling with the global challenge of accelerating the adoption of conservation initiatives (Tickner et al., 2020; Leclère et al., 2020; Rilov et al., 2020). The adoption of conservation initiatives varies dramatically: some initiatives spread rapidly among potential adopters, but many fail to spread beyond a few initial participants (Mills et al., 2019). To become widely adopted, conservation initiatives must diffuse through networks of potential adopters from an initial set of seed adopters. The type and scale of each conservation initiative also shapes adoption dynamics. For example, national-scale regulatory (top-down) initiatives can result in rapid, complete adoption. However, local-scale, community-based (bottom-up) initiatives can face initial
slow uptake followed by rapid adoption as the initiative spreads from initial to potential adopters (Jupiter et al., 2014; Meskell et al., 2015; Tafoya et al., 2020; Atisa, 2020). Given this variability and the pressing need to implement timely conservation initiatives to bend the curve on global biodiversity loss, conservation actors are keenly interested in strategies for ensuring that a conservation initiative spreads rapidly and is widely adopted (Butchart et al., 2015; Díaz et al., 2019).

Network science can provide key insights into how and why conservation initiatives spread (Guerrero et al., 2020). Social network analysis (SNA) can reveal stakeholder cooperation, participation, behavior, and barriers to conservation interventions (Cinner, 2018; Barnes et al., 2016; Bodin et al., 2019, Riggs et al., 2020, Wineland et al., 2021). An emerging line of research has focused on identifying key players in conservation networks using centrality-based network metrics (de Lange et al., 2021; Guerrero et al., 2020; Mbaru & Barnes, 2017). This work points to a broader aspect of network science known as the influence maximization problem (Güney, 2019). Influence maximization is the process of selecting initial seed nodes that will maximize the spread of information or innovation throughout a network (Chen et al., 2009). While this line of research has clear applications in marketing, social media, network security, and computer science (Chaoqi et al., 2018; Chen et al., 2010), influence maximization has yet to be applied to conservation networks. We aim to determine if influence maximization approaches can be used to strategically target conservation actors to improve the spread of conservation initiatives.

There are two primary information diffusion models that are used to test whether seeds selected using influence maximization improve spread: the Independent Cascade (IC) and Linear Threshold (LT) models (Kempe et al., 2003). Both models consider a graph \( G = (V,E) \) where \( V \) is a set of nodes and \( E \) is a set of edges, and nodes can be either active (i.e., an adopter of the initiative) \( V_a \) or inactive \( V_i \) (either initially or after interacting with another active node). Under the IC model, an inactive node \( v \) can activate after interacting with its active neighbor node \( u \) based on the probability \( P_{u,v} \), which indicates the probability of \( u \) activating \( v \). Under the LT model, an inactive node \( v \) examines all neighboring nodes, and if the number of active neighbors exceeds a threshold (either absolute or fractional), then node \( v \) becomes activated (Shakarian et al., 2015). Because both models take an initial set of active seed nodes as input, influence maximization can be used to select highly influential individuals as these seed nodes. Both models could be useful for understanding conservation initiative adoption dynamics, as stakeholders’ and decision-makers’ willingness to adopt an initiative widely varies (Knight et al., 2010; Prinbeck et al., 2011). For example, individuals and organizations in conservation networks exhibit different values and perspectives on conservation initiatives, which can represent a range of activation probabilities under IC (Thompson et al., 2015; Wineland et al., 2021). Many conservation initiatives need time to achieve critical mass; stakeholders may need time to consider or better understand the intervention and may avoid adoption until a critical mass of other stakeholders have also adopted (Rogers et al., 2014).

Quantifying and classifying the topology of a network of conservation actors is central to the influence maximization problem (Guerrero et al., 2020; Mihara et al., 2015). Network structural features like node degree distributions and centrality-based metrics are important to contextualize the connectedness and importance of individuals and organization types (Bodin et al., 2006). Network topology is an emergent property that affects influence maximization because the entire network topological structure is used to detect seed nodes and propagate information through the network (Delre et al., 2010; Mihara et al., 2015; Shakarian et al., 2015). Real-world networks can be typically classified as one of three main types: random, small-world, or scale-free (Solé & Valverde, 2004). In random networks, the degree distribution follows a binomial or Poisson distribution. This means that most of the nodes in the network are equally likely to be connected with any other node (Erdős & Rényi, 1959). Small-world networks are defined by the presence of cliques, or highly connected sub-networks, that result in a defining characteristic of a high clustering coefficient (Watts & Strogatz, 1998). Small-world networks also tend to have right-skewed degree distributions because of the abundance of hubs; however, their degree distribution does not typically follow a power law. Scale-free networks have degree distributions that follow a power law, where the fraction of nodes with degree \( k \) follows a power-law distribution \( k^{-\alpha} \), where typically \( \alpha \geq 1 \) (Barabási & Albert, 1999). Scale-free networks also operate under a “preferential attachment” mechanism (i.e., rich get richer, or existing hubs become more highly connected) that can be either linear or non-linear.

Here, we investigate influence maximization on two networks of freshwater conservation actors. The first is a regional \((n = 24)\) network of freshwater decision-makers from the Oklahoma and Texas portions of the Red River (Wineland et al., 2021). The second is a national \((n = 426)\) network of workshop participants from The Nature Conservancy (TNC) and U.S. Army Corps of Engineers’ (USACE) Sustainable Rivers Program (SRP). These two networks contain key hallmarks of conservation networks worldwide: nodes derived from a diverse
and representative group of actors, and network ties derived from social processes within the socio-ecological system (Ostrom, 2009; Matous & Todo, 2015; Bodin, 2017). Thus, while we focus on networks derived from freshwater conservation actors, our approaches will be transferable to terrestrial and marine ecosystems. This study was motivated by current efforts to accelerate the implementation of environmental flows (e-flows; Arthington, 2021, Tickner et al., 2020). E-flows describe a broad range of conservation initiatives to restore or design ecologically relevant flow regimes to sustain the structure and function of flowing freshwater systems (Arthington et al., 2018). While there have been some small inroads into understanding freshwater research collaborations and networks (Bixler et al., 2019; Kuehne et al., 2020), practical applications that can inform strategic planning for freshwater conservation initiatives are still poorly studied and underdeveloped.

We use these two freshwater decision-maker networks to achieve three goals: (1) determine the network topology and structural features, (2) identify influential individuals in those networks, and (3) test whether the adoption of a conservation initiative by influential individuals could increase the spread of that initiative across the network. We use two different-sized networks to represent the different spatial scales (i.e., local, regional, national) at which conservation initiatives operate. The first goal aims to provide much-needed data on what conservation networks look like, how their structure might influence adoption dynamics, and how the relative influence of different organization types varies at different spatial scales. The second and third goals aim to provide a practical framework to conservation practitioners so that they can target influential individuals and organizations in conservation networks to help boost the spread of conservation initiatives.

2 | METHODS

2.1 | Network descriptions

We used two networks of freshwater conservation actors. The first network (hereafter, the Red River network) was derived from a survey of n = 24 freshwater decision-makers from Texas and Oklahoma in the Red River basin in the south-central USA (Wineland et al., 2021). The survey targeted freshwater decision-makers, which are defined as “individuals that have the authority to inform, influence, or make decisions that impact water resource management or aquatic natural resource management” in this region. The goal of the survey was to identify data needs and barriers to e-flows implementation. This network was derived from a survey question that asked individual respondents how frequently they communicate with each other. Thus, in Wineland et al. (2021), network ties were weighted and undirected (i.e., two nodes were connected if one or both respondents indicated that they communicate with each other) based on social relations (frequency of communication). For the purposes of this paper, we use an unweighted version of the Red River network to allow comparison with the other network.

The second network (hereafter, the SRP network) was derived from lists of participants in e-flows workshop reports from the SRP. The SRP is arguably the largest e-flows initiative in the United States that functions through dam re-operation and adaptive reservoir management (Hickey & Warner, 2006; Warner et al., 2014). As of 2021, the program is active at 24 federal dams on 13 rivers, with 71 additional sites advancing through the program's process that follows a propose-advance-implement-incorporate progression (John Hickey, personal communication, April 23, 2021). The e-flows workshops are part of the advance phase of the program, where regional water managers, scientists, stakeholders, etc. gather to compile information and identify flow-ecology needs prior to an e-flows recommendation workshop, where modeling and scenario testing occurs. We used the available lists of workshops (n = 9, USACE, 2021) and their participants (n = 426) to create a network for the SRP. We assumed that all workshop participants had unweighted, undirected ties (i.e., each individual workshop is a complete network, and two nodes were connected if they participated in a workshop together), which is a grounded assumption given that each workshop was split into working groups organized by either topic or expertise and that each group subsequently presented findings and fielded questions from other groups (John Hickey, pers. comm. April 23, 2021). For both networks, we identified the organization type (e.g., federal, state, university, NGO, local, other) of individuals to provide context to the relative influence of these groups.

2.2 | Network topology and structural features

To determine which network topology the Red River and SRP networks resemble (Goal 1), we performed a Monte Carlo simulation (n = 1000) where each network was compared against randomly generated networks of each of the three topologies. For the random network topology, we used the G(n, M) variation of the Erdős and Rényi (1959) model to generate networks, where graphs (G) are generated randomly with a uniform probability of
edge generation given \( n \) nodes and \( M \) edges. We used the values of \( n \) and \( M \) from both the Red River and SRP networks as input for this model. For the small-world network topology, we used the Watts and Strogatz (1998) network model to generate networks with rewiring probabilities that ranged from 0.1 to 0.9 in 0.1 increments. The rewiring probability describes the probability that an edge is rewired or disconnected from a node and subsequently randomly connected to another anywhere in the network. This network model begins with networks of random lattice topology and then uses the rewiring probability to create shortcuts across the network to reach farther than the original ties, facilitating faster diffusion through fewer steps (Centola, 2018; Watts & Strogatz, 1998). For the scale-free network topology, we used the Barabási and Albert (1999) model to generate networks with different preferential attachment powers. While most scale-free networks exhibit linear preferential attachment (i.e., \( \alpha = 1 \)), some can exhibit non-linear preferential attachment that can be either sublinear (i.e., \( 0 < \alpha < 1 \)) or superlinear (i.e. \( \alpha > 1 \)). Sublinear preferential attachment can limit the size of hubs, and superlinear preferential attachment can lead to large hubs (Barabási, 2013). We tested values for \( \alpha \) ranging from 0.1 to 3. All networks were generated using the igraph package in R version 4.1.0 (Csardi & Nepusz, 2006; R Core Team, 2021).

To better understand the overall and sub-network structural features of each network (Goal 1), we calculated common network metrics (degree, clustering coefficient [global and local], shortest path distance, betweenness centrality, and eigenvector centrality). These network metrics represent a range of centrality measures that indicate the level of influence a group of nodes have in the network (Mbaru & Barnes, 2017). We describe these network metrics for the overall network and each organization type sub-network (e.g., federal, state, university, NGO, local, other) to contextualize the organizational makeup of the networks and relative influence of these groups so that practitioners aiming to maximize the spread of an e-flows initiative might target individuals within the most influential organization types (Kuehne et al., 2020).

To compare both the Red River and SRP networks to randomly generated networks of all three network topologies, we used two commonly used network comparison methods, Graphlet Degree Distribution Agreement (GDDA) and the Jaccard similarity index (Tantardini et al., 2019). The first, GDDA, uses graphlets (i.e., small non-isomorphic subgraphs) to measure the number of nodes touching \( k \) graphlets (like degree distribution which measures the number of nodes touching \( k \) edges). The GDDA measure uses 73 graphlet degree distributions to compare graphlet degree distributions between networks. GDDA ranges between 0 and 1, where values closer to 1 indicate identical distributions and values closer to 0 indicate disparate distributions (Pržulj, 2007). The second method, the Jaccard index, is a commonly used similarity/diversity statistic in ecology but has been extended to network science where graphs are transformed into binary adjacency matrices where 0 indicates no connection and 1 indicates a connection (Bass et al., 2013; Simpson et al., 2013). Here, we used the Jaccard similarity index where values closer to 1 indicate identical networks and values closer to 0 indicate disparate networks. We used the mean across \( n = 1000 \) MC simulations to determine which of the three network topologies both the Red River and SRP networks most closely resemble.

If the GDDA and Jaccard indices provided ambiguous results (i.e., identical support for one of our networks resembling more than one network topology), we conducted a post-hoc analysis to determine if the degree distribution of the network followed a power law. If there was equal support for a network resembling both random and scale-free or small-world and scale-free, this analysis would allow us to determine whether the network was scale-free, because the degree distributions of scale-free networks follow a power law. To test whether a network followed a power law, we used the combined maximum-likelihood fitting and goodness-of-fit test (Kolmogorov-Smirnov, KS) method described in Clauset et al. (2009). This method hypothesizes that the observed data follow a power-law distribution and quantifies the distance between the distribution of the observed data and comparable synthetic datasets derived from the same model. If \( p > 0.05 \), then this difference between distributions suggests a plausible fit to the hypothesized power-law distribution.

### 2.3 Influence maximization

To identify influential individuals in each network (Goal 2), we used three methods: Integrated Value of Influence (IVI), Cost-Effective Lazy Forward (CELF++) and a “brute force” Monte-Carlo (MC) simulation. The IVI approach combines local, neighborhood, and global centrality measures of a network to determine the most influential nodes (Salavaty et al., 2020). The CELF++ approach uses lazy-forward optimization to identify the most influential nodes in a network by exploiting submodularity (i.e., the marginal gain of a node in the current iteration cannot be better than its marginal gain in previous iterations, Goyal et al., 2011), and is one of the most widely used seed selection algorithms in influence maximization. The MC approach simulated diffusion using randomly selected seeds on each network 1000 times. Then, the seed node sets that resulted in the
maximum number of total activated nodes were identified as influential seed node sets. All three seed selection methods were run on both networks using both the IC and LT diffusion models to produce 26 sets of influential seed nodes that varied in the total number of seed nodes. For both the IVI and CELF++ seed selection methods, influential seed node set sizes were 1,2,3,4,5 seeds in the Red River network, and 18,36,53,71,88 seeds in the SRP network to match the relative % of total nodes of the five seed node sets in the Red River network. For the MC seed selection method, influential seed node set sizes were 1,2,3,4,5 seeds in the Red River network, and 1,5,10,15,20,25 seeds in the SRP network.

To test whether the IVI, and CELF++, and MC seed selection approaches result in a higher total number of adopters in each network over arbitrarily selected seeds, we used a paired MC simulation approach (Goal 3). First, seed node sets that match the influential seed node set sizes were selected arbitrarily using a random number generator \((n = 1000)\). Second, both the influential and arbitrarily selected seed node sets were fed into both the IC and LT diffusion models using a MC approach \((n = 1000)\) to test the spread of a hypothetical e-flows conservation initiative in each network. We tested each seed set size scenario across a range \((0.1–0.9\) for IVI and CELF++, \(0.01, 0.05, 0.1–0.9\) for MC) of activation probabilities (IC) and thresholds (LT). Seed selection methods and information diffusion models were employed using the influential and influence.mining packages in R version 4.1.0 (R Core Team, 2021; Salavaty et al., 2020).

3 | RESULTS

3.1 | Network topology and structural features

Network maps highlight the differences in topology, structure, and organizational makeup of each network (Figure 1). Nodes in the Red River network, for example,
are all moderately well-connected, as the average degree, shortest path distance, and centrality metrics do not vary much between the overall network and organization-type sub-networks (Figure 1a, Table 1). However, the high degree, betweenness, and eigenvector centrality of the single federal actor in this network highlights the influence of this individual. The SRP network exhibits a series of complete networks connected by hubs (Figure 1b). Among these high degree hubs are an individual at a federal agency and several NGO actors, which supports the Sustainable Rivers Program being a partnership between the USACE and TNC. Some of the lower degree hubs include other federal actors, a few state actors, and one university individual (Figure 1b). The SRP network exhibits a range of connectedness among the different organizational sub-groups. For example, federal and NGO actors are well-connected based on their high degree and centrality metrics (Table 1). However, the local organization type sub-network had the highest degree (Table 1), and one workshop group that is comprised of many local actors is well-connected with other workshop groups through NGO actor bridging ties (Figure 1b).

We found that the Red River network resembles a random topology, and the SRP network resembles a scale-free topology. While the node degree histogram for the Red River network is slightly skewed, it fits within the random topologies’ typical characteristic of having a Poisson distribution; there are relatively few nodes with

| Network   | Metric                  | Scale     |
|-----------|-------------------------|-----------|
|           | Whole network | Federal    | University | NGO | Other | Local | State |
| Red river | Degree         | 10.66      | 14.00      | –   | 10.25 | 10.14 | 10.83 |
|           | Global clustering coefficient | 0.54      | –          | –   | –     | –     | –     |
|           | Local clustering coefficient | 0.63      | 0.63       | –   | 0.70  | 0.68  | 0.57  |
|           | Shortest path distance | 3.93      | 3.17       | –   | 3.93  | 4.23  | 3.81  |
|           | Betweenness centrality | 8.19      | 20.17      | –   | 9.56  | 2.75  | 9.90  |
|           | Eigenvector centrality | 0.53      | 0.58       | –   | 0.49  | 0.60  | 0.49  |

| Sustainable Rivers Program | Degree | 60.09 | 60.21 | 56.79 | 62.65 | 40.33 | 72.49 | 51.67 |
|                           | Global clustering coefficient | 0.86 | –    | –    | –    | –    | –    | –    |
|                           | Local clustering coefficient | 0.97 | 0.94 | 0.99 | 0.94 | 1.00 | 1.00 | 0.99 |
|                           | Shortest path distance | 1.99 | 1.96 | 1.98 | 1.97 | 2.10 | 2.08 | 1.99 |
|                           | Betweenness centrality | 212.27 | 413.24 | 7.10 | 645.84 | 0.00 | 0.00 | 11.41 |
|                           | Eigenvector centrality | 0.22 | 0.22 | 0.20 | 0.21 | 0.01 | 0.55 | 0.10 |

Note: Values for each metric indicate the mean value for that metric at each scale (number of nodes for that organization type).
both small and large degrees, and many nodes with an average degree of 10.66 (Figure 2a, Table 1). The SRP network, by contrast, exhibits a highly skewed node degree histogram that clearly shows the few high degree hubs and low-degree nodes typical of scale-free networks (Figure 2b). The network topology simulation results further support these findings. For the Red River network, the random topology exhibited the highest mean GDDA (0.49) and Jaccard (0.30) values. For the SRP network, mean GDDA values were identical for both the random and scale-free (power = 0.1, 0.3, 0.5, 0.8, 1, 1.5, 2) topologies (0.55), however mean Jaccard values for the scale-free topology (0.11–0.16, power = 0.1, 0.3, 0.5, 0.8, 1, 1.5, 2, 2.5) were higher than random (0.08). The equal support for the SRP network being of both the random and scale-free topology under GDDA could be due to the $G(n, M)$ model variation we used to generate random networks where the exact number of nodes and edges are specified. For the small-world and scale-free topologies, the number of nodes and edges will vary around those of

![Graph showing total activated nodes for Regional Red River Basin Network (n=24) and National Sustainable Rivers Program Network (N=426).](image)

**FIGURE 3** Mean total activated nodes from the Monte-Carlo simulation using arbitrarily selected (left column—“Arbitrarily Selected Seeds”). Maximum total activation from the Monte-Carlo simulation using arbitrarily (right column—“Maximum Activation”). Y-axis includes seed set size.
the Red River and SRP networks. Our post-hoc analysis indicates that the SRP network degree distribution follows a power law where $\alpha = 1.57$ given the KS test ($p = 0.35$). This finding indicates that the SRP network exhibits super-linear preferential attachment, which, given the high node degree of a few of the hubs, further supports our characterization that the SRP network exhibits a scale-free topology (Barabási, 2013).

### 3.2 Influence maximization

We find that initial adoption of a conservation initiative by the most influential individuals results in widespread adoption by others in the network (Figure 3). This outcome is consistent across both networks and both diffusion models. However, influential individuals produce more total adopters under LT than IC. For example, in the Red River network under the IC diffusion model at an activation probability of 0.5, 5 arbitrarily selected seeds resulted in a total activation of 13 nodes, whereas 5 influential seeds resulted in a total activation of 20 nodes, a 53% increase (Figure 3a). In the SRP network under the LT diffusion model at a threshold of 0.05, 20 arbitrarily selected seeds resulted in a total activation of 74 nodes, whereas 20 influential seeds resulted in a total activation of 349 nodes, a 372% increase (Figure 3b).

Although IVI and CELF++ are common seed selection methods, we found that they did not consistently identify the conservation actors with the greatest
influence on the spread of an initiative (Figure 4). For example, influential seeds selected using IVI seed selection method performed better than arbitrarily selected seeds in the small, regional Red River network under the LT and IC model, except when only using 1 seed under IC (Figure 4a). However, influential seeds selected using IVI failed to initiate any significant diffusion in the SRP network under LT (Figure 4b). The CELF++ seed selection method performed slightly better than arbitrarily selected seeds in the Red River network, but only at higher (3–5) seed set sizes under IC and at low (0.1–0.3) activation thresholds under LT (Figure 4a). In the SRP network, CELF++ failed to perform better than arbitrarily selected seeds at low (0.1–0.2) activation thresholds but outperformed arbitrarily selected seeds at higher (0.3–0.6) thresholds under LT (Figure 4b). In the SRP network, both IVI and CELF++ seed selection methods slightly outperformed arbitrarily selected seeds under the IC model across all seed set sizes and activation probabilities.

4 | DISCUSSION

Overall, our results show that targeting influential individuals as initial adopters of a conservation initiative improves the total spread of the initiative. This result is robust across the different network spatial scales, topologies, and mechanisms of spread we considered: influencers improved initiative spread in a large, scale-free network (SRP) and in a small, random network (Red River), regardless of whether the initiative diffused via Independent Cascade (IC) or Linear Threshold (LT). Our result that influencers improve total adoption regardless of this variation then has clear implications for improving the spread and adoption of conservation initiatives in conservation networks globally (de Lange et al., 2021; Guerrero et al., 2020; Mbaru & Barnes, 2017). Our work is timely, as governments involved in the Convention on Biological Diversity (CBD) are negotiating an effective post-2020 global biodiversity framework focused on facilitating urgent implementation of conservation initiatives (CBD 2021).

Conservation practitioners seeking to use influence maximization to boost the adoption of conservation initiatives should consider key network characteristics. Our network descriptions can help conservation actors better understand network variation at different spatial scales (i.e., local, regional, national) as they attempt to integrate social factors into conservation initiative designs (Harper et al., 2021; Tickner et al., 2020). Indeed, previous work from other disciplines underscores the importance of network topology and structural features for successful diffusion (Minor & Urban, 2008; Ma et al., 2013; Mihara et al., 2015; Sizemore et al., 2019; Edge & Fortin, 2020). In the two real-world networks we focused on, network size was an important feature. Our results suggest that the small, regional-scale Red River network resembles a random network topology, where most actors in the network are equally connected. Conservation initiatives that operate at the local or regional scale are most likely to resemble random or small-world networks because actors already know or work with each other. In these networks, conservation practitioners often rely on local or regional community leaders that can be easily identified to diffuse conservation initiatives (Bodin & Crona, 2009; Pretty & Smith, 2004). In these networks, it may not be cost-effective or practical to employ influence maximization approaches when influencers or community leaders can be identified either by using centrality-based network metrics or manually (i.e., local knowledge, or “eye-bal-ling” from network maps; Mbaru & Barnes, 2017).

On the other hand, our results suggested that the large, national-scale SRP network resembled a scale-free topology, where there are a few actors that are well-connected that act as bridges between sub-networks. Conservation initiatives that operate at the national or global level may resemble scale-free networks because they are often comprised of different disciplinary groups with individuals or organizations that act as bridges between them (Nita et al., 2016). In these networks, conservation practitioners might use influence maximization approaches to identify influencers because it may not be feasible to rely on manual or centrality-based metrics. In conservation science, efforts to quantify topology and structural features of social conservation networks are lacking (Guerrero et al., 2020; Kuehne et al., 2020). Our findings support that investigating conservation network structure and features can reveal a wealth of social information that can be obtained without collecting extensive sociometric data (e.g., SRP network method).

Our work also highlights the importance of organizational makeup and the relative influence of different organization types that conservation practitioners should account for as they seek to maximize the spread of conservation initiatives. For example, in the regional-scale Red River network, while state agencies and local entities form almost 80% of the network, NGO and federal entities had the highest sub-network connectivity metrics (Figure 1, Table 1). In the national SRP network, federal entities comprise most of the network and, along with NGO entities formed important bridges between sub-networks Figure 1, Table 1). Indeed, another study that examined a network of freshwater assessment authors found that federal agency and NGO actors were the most well connected among different organization types and provided important bonding (within-group) and bridging
(between-group) ties (Kuehne et al., 2020). Our findings reinforce existing research that highlights the critical role of government agencies and NGOs in facilitating connections and adoption in conservation networks, regardless of network size (Hauck et al., 2016; Kuehne et al., 2020; Rozylowicz et al., 2017). Additionally, we found that state and local entities are important in facilitating the adoption of conservation initiatives. In both the Red River and SRP network, these two groups comprised most of the network and exhibited high sub-network connectivity metrics. These findings have important practical and ethical applications to the implementation and design of conservation initiatives. Practitioners should target the most influential individuals or organizations, but should also avoid excluding smaller organizations, which could inhibit the adoption of conservation initiatives (Mbaru & Barnes, 2017).

Our results reinforce existing work that finds that targeting influential individuals in conservation networks can improve the adoption of a conservation initiative (de Lange et al., 2021; Mbaru & Barnes, 2017). Our approach used a range of activation probabilities and thresholds, which allowed us to explore scenarios where individuals in conservation networks are either willing or resistant to adopt a conservation initiative based on their own individual perspectives or values (IC) or peer pressure (LT). While it is impossible to determine whether a conservation initiative will diffuse in a probabilistic (IC) or threshold manner (LT) in the real-world without extensive surveys that gather sociometric data (i.e., data about social or communication ties, Banerjee et al., 2020), data on willingness to participate in an initiative (Knight et al., 2010) or data mining (Lu et al., 2012), we speculate on the differences in diffusion models and their practical implications for conservation network science. For example, we assumed that all nodes have the same probability (IC) or threshold (LT) of activation, but in the real-world this is unlikely to be true. For example, lessons learned from the behavior change literature suggest that individuals and organizations in conservation networks may have different levels of communication or social status, perspectives on the conservation initiative, or feelings of being sidelined, which could result in varying levels of willingness or resistance to adopting the initiative (Haas et al., 2019; Manfredo et al., 2017; Schultz, 2011). Thus, we recommend determining individual node probabilities/thresholds of activation as a future research avenue to further understanding of the adoption dynamics and diffusion of conservation initiatives within conservation networks.

While IVI and CELF++ are common influential seed selection methods, they did not consistently identify the most influential individuals across the different network spatial scales, topologies, and mechanisms of spread we considered (Figure 4). In general, both IVI and CELF++ seed selection methods performed poorly with the large, national-scale Sustainable Rivers Program network under the LT model, and with the small, regional-scale Red River network under the IC model. Because these heuristic estimates of the influence of each node are designed to be used on large-scale networks, they aim to provide a result in a reasonable amount of time at the sacrifice of a sub-optimal solution (Arora et al., 2017; Goyal et al., 2011; Yuan et al., 2019). Our results suggest a brute-force MC simulation approach identified the most influential seed nodes that resulted in the highest adoption outcomes more effectively than IVI and CELF++ that require additional computational time. Given the modest size of most conservation networks (Barnes et al., 2016; Kuehne et al., 2020; Mbaru & Barnes, 2017), Monte Carlo simulations provide more consistent results at a reduced computational cost.

We tested if conservation influencers could increase adoption of a simulated environmental flows initiative in two networks of freshwater conservation actors. We found that one seed selection method results in robust improvements in adoption across different conservation network scales, topologies, and diffusion models. The brute force Monte-Carlo (MC) simulation approach provides improved outcomes and is more computationally feasible than traditional heuristic-based seed selection approaches. In practice, our study suggests that practitioners should seek to employ information diffusion models using a MC simulation approach to identify and target influencers as initial adopters in the design of conservation initiatives. By describing the topological, structural features, and organizational makeup of a regional and national conservation network, we found that the regional network resembles a network with a random topology, while the national network resembles a network with a scale-free topology. We suggest that small, local, or regional-scale conservation initiatives around the world will likely resemble random networks because of the high connectivity of actors, while national or global-scale conservation initiatives will likely resemble scale-free networks because of the subnetwork like structure facilitated by groups. We suggest that influence maximization approaches might only be practical in large conservation networks, while small conservation networks might benefit most from centrality-based methods to identify influencers. We highlight that federal and NGO actors are critical to facilitating diffusion in both networks, but that state and local entities also play a key role. These findings should help inform conservation practitioners as they seek to employ influence maximization approaches to help boost the adoption of conservation initiatives.
AUTHOR CONTRIBUTIONS
Sean M. Wineland: Conceptualization, Methodology, Software, Validation, Formal Analysis, Data Acquisition, Writing – Original Draft, Writing – Review & Editing, Visualization. Thomas M. Neeson: Conceptualization, Methodology, Project Administration, Supervision, Writing – Review & Editing.

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DATA AVAILABILITY STATEMENT
Network ties for the Red River network were derived from survey data from Wineland et al. (2021). Due to the nature of this research, participants of this study did not agree for their data to be shared publicly, so supporting data are not available. Data on network ties for the Sustainable Rivers Program were derived from workshop participant lists available at: https://www.hec.usace.army.mil/sustainablerivers/publications/.

ORCID
Sean M. Wineland https://orcid.org/0000-0003-3548-1927

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