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Research

How social and ecological characteristics shape transaction costs in polycentric wildfire governance: insights from the Sequoia-Kings Canyon Ecosystem, California, USA

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ABSTRACT. Many contemporary social and ecological challenges in forested ecosystems (climate change, invasive species, wildland-urban interface development, and wildfires) span multiple jurisdictions and are characterized by complex patterns of social and ecological interdependencies. Increasing evidence suggests that interdependent risk can best be addressed by working across boundaries (jurisdictional, scalar, and expertise) by sharing information and cooperating in management activities. Polycentric governance has emerged as a framework to understand how multiple and overlapping centers of decision-making authority establish and maintain governance connectivity to solve collective action problems and interdependent risks. Previous studies have examined the collaborative and interorganizational process of polycentric landscape governance, yet most studies rely on qualitative case study data or descriptively employ social network analysis. Understanding the values, beliefs, and motivations of actors (land managers, landowners, researchers, policymakers, and non-governmental organizations) for cooperating is important for improving polycentric governance design, implementation, and operation. How the context and characteristics of social-ecological systems shape polycentric governance remains largely unexplored. On the basis of research in the Sequoia-Kings Canyon Protected Area-Centered Ecosystem, we address this gap by utilizing exponential random graph modeling to analyze the social and ecological drivers of polycentric wildfire governance. This research highlights that even in situations of high stakes (increasing occurrences of high-severity wildfires that escape suppression) actors will collaborate only if the gains from collaboration outweigh the costs. If jurisdictions or other organizations are thought to have low operational capacity or lack useful information, even with a high probability of large wildfire, the actor-to-actor connections are less likely for effective polycentric governance. Our results highlight previously undiscussed mechanisms of network formation in wildfire hazard governance, and we discuss the broader applicability for forest landscape challenges and for polycentric governance design and assessment in other social-ecological contexts.

Key Words: *collaboration; environmental governance; exponential random graph model (ERGM); polycentric governance; social network analysis; wildfire*

INTRODUCTION

Wildfire presents a classic cross-boundary landscape management challenge (Bixler et al. 2016, Scarlett and McKinney 2016, Hamilton et al. 2019, Davis et al. 2021). There is inherent interdependence in wildland fire where wildfire risks can span multiple jurisdictions and social and ecological processes interact across spatial and temporal scales (Abrams et al. 2015, Gillson et al. 2019, Charnley et al. 2020, Barros et al. 2021). In response, systems of governance are necessary to address risk across spatial and temporal scales (Kelly et al. 2019). As Lubell and Morrison (2021:664) note, "most governance is now polycentric...but how [does] polycentric governance var[y] across social-ecological contexts to facilitate cooperation and learning" is the current question. How do actors navigate institutional structures (Lubell and Morrison 2021) to, in our case, plan, mitigate, and respond to wildfire risk, and what social and ecological factors are important for actors to cooperate across jurisdictions? The objective of this study is to examine what social and ecological attributes influence cooperation in polycentric wildfire governance settings.

It is increasingly understood that landscape forest governance that sustains healthy forests, ecosystem processes, and biodiversity and reduces the risk of high-severity fire cannot occur from strictly top-down bureaucratic management or bottom-up decentralized approaches (Bixler 2014, Davis et al. 2021, Nowell et al. 2022). Rather, polycentric governance systems that have multiple and overlapping centers of authority at multiple scales can offer better opportunities for improving the fit between knowledge, action, and specific social-ecological context (Ostrom 2010, Epstein et al. 2015, Lubell and Morrison 2021). Polycentric governance systems provide institutional incentives for monitoring and feedback (Berkes et al. 2002, Morrison 2017), offer a communication infrastructure for actors at different institutional levels and from diverse perspectives to exchange information (Bodin and Prell 2011, Lake et al. 2018), and can contribute expertise and resources where and when needed (Armitage et al. 2009). Because polycentric systems distribute decision-making authority across space and scales, a broader range of actors are empowered because they retain power and options for self-governance (Morrison et al. 2017, Bixler et al. 2018, Kelly et al. 2019). However, polycentric governance systems are also challenged by high transaction costs (Gallemore 2017), lack of transparency (Morrison et al. 2019), and implementation failures (Sunderlin et al. 2015). How actors navigate institutional structures to develop trusting and cooperative linkages so that

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the positive features, rather than challenges, are manifest is an important yet understudied domain of polycentric governance. Understanding what underlying network properties and what actor attributes drive network tie formation can advance the scholarship and design of polycentric hazard governance.

We set out to identify factors that predict the formation of relationships between actors from different jurisdictions or organizations. We hypothesized that the probability of tie formation between actors would be positively correlated with: (1) similarity in actor characteristics (i.e., homophily); (2) fire risk within those actors' jurisdictions; (3) confidence in operational capacity; and (4) the perception among actors that a cooperator can provide useful information. We tested these hypotheses by using a survey distributed to organizations that administer land and/or provide management services within and around Sequoia and Kings Canyon National Parks in California. To define our study area we employed a protected area–centered ecosystem approach (Hansen et al. 2011, Belote and Wilson 2020) and thus included multiple jurisdictions beyond the national park. We refer to this area as the Sequoia–Kings Canyon Protected Area–Centered Ecosystem (SEKI PACE). Our findings, though specific to our study site, may lend insight to planners from a range of systems and help them identify opportunities and barriers to cooperation when addressing natural hazard risks in multi-ownership land- and seascapes.

Background: environmental challenges and management across boundaries

Drivers of global environmental change impact patterns and processes across wide landscapes and regions via changes in climate, fire and other disturbance regimes, land use, and species assemblages. Faced with these challenges, an increasing literature examines the role of cross-boundary collaboration in sustainable resource management and conservation (Wyborn and Bixler 2013, Guerrero et al. 2015, Kark et al. 2015, Aslan et al. 2021, Steen-Adams et al. 2022). Regional and landscape-scale responses to environmental change affect public and private entities, governmental agencies at multiple scales, and stakeholders varying in management concerns and objectives (Bergmann and Bliss 2004, Epanchin-Niell et al. 2010, Guerrero et al. 2015, Barros et al. 2021), and the ways in which actors "respond" through coordination often differ from the ways in which "policy" responds (Abrams et al. 2018). Coordination of responses among multiple players requires communication, collaboration, and cooperation, but lack of such coordination can result in lack of success because efforts are spatially limited by jurisdictional boundaries (Bergmann and Bliss 2004, Ferranto et al. 2013, Fischer and Charnley 2012).

In addition, coordination can allow entities to pool resources, learn from one another's experiences, and respond rapidly to events such as wildfires (Epanchin-Niell et al. 2010, Guerrero et al. 2015, Aslan et al. 2021, Tait and Brunson 2021). When multiple neighbors bring resources to bear to address a wildfire ignition, for example, the probability that the fire will grow enough to cross multiple boundaries is diminished (Palaiologou et al. 2019, Charnley et al. 2020). Communication and cooperation between neighboring jurisdictions can also allow managers to work together to prepare for future fires and reduce landscape-scale fire risk by managing fuels and identifying and combating factors that increase fire risk, such as invasive species infestations (Fischer and Charnley 2012, Schultz and Moseley 2019). Finally, restoration of landscapes following fire may rely on cross-boundary cooperation wherein resources are shared and restoration plantings are spatially distributed to maximize habitat connectivity (Schultz et al. 2018). Considering these potential benefits, research aiming to understand the conditions under which cooperation occurs and the factors that facilitate or impede it can inform managers and help them plan and carry out more effective polycentric landscape governance for healthy forests and ecosystems and biodiversity conservation.

Polycentric governance and network-analytical frameworks offer important insights into understanding coordination across boundaries (Bodin and Crona 2009, Guerrero et al. 2015, Scarlett and McKinney 2016, Bodin 2017, Scott and Ulibarri 2019, Kluger et al. 2020). Polycentric governance acknowledges that solving today's resource management challenges will require working across legal, jurisdictional, and institutional boundaries (Sternlieb et al. 2013) and is necessary because the capacity (e.g., leadership, staff, legal authority, technology, funding, etc.) for addressing large-scale problems varies significantly across spatial and temporal scales (Guerrero et al. 2013). The network of interactions that underpins polycentric governance provides the means for actors to make collective decisions, establish shared priorities, improve coordination, and identify ways to work together productively (Provan and Kenis 2007). Research on how and why policy actors and practitioners engage in collaborative behavior has seen significant growth of late (Kapucu et al. 2017, Siciliano et al. 2021) and significant contributions have been made to landscape-scale ecological issues and polycentric governance systems (Guerrero et al. 2015, Fischer and Jasny 2017, Hamilton et al. 2019, Bodin et al. 2020) and polycentric governance systems (Berardo and Lubell 2016, Morrison 2017, Bixler et al. 2018, Lubell et al. 2020, Angst et al. 2021).

Interactions among entities within governance systems are well suited for representation as networks, which are interdependent structures involving a number of "nodes" (typically individuals, organizations, or agencies, but can be ecological characteristics) with multiple linkages or "edges" (ties between two nodes representing connections). As such, network-analytic approaches are increasingly being used to model social-ecological systems (Bodin et al. 2019a, Sayles et al. 2019, Felipe-Lucia et al. 2021). For example, Sayles and Baggio (2017) modeled scale mismatches in estuary conservation by building a social-ecological network using local and regional conservation actors and biophysical hydrological units as network nodes. Others have advanced reef fishery conservation by modeling the network communication patterns between individual fishers and trophic interactions among target species (Barnes et al. 2019). Social-ecological network approaches have also been used to understand wildfire hazard governance (Bodin and Nohrstedt 2016, Fischer and Jasny 2017, Hamilton et al. 2019).

Clustering is one frequently cited structural aspect for why actors cooperate (Henry et al. 2011). Clustering refers to choosing to partner with a "friend of a friend," which provides quick signals of trust, shared norms, and goal alignment, all of which can reduce transaction costs. Clustering in networks is captured by triadic-level network properties (three-node configurations), and is an important consideration when examining properties of polycentric governance (Lusher et al. 2013).

Within the wildfire risk setting, Fischer and Jasny (2017) demonstrated that organizational homophily, geographic proximity, and shared management goals have significant influence on network ties. In addition, Hamilton et al. (2019) examined risk interdependence archetypes by asking if coordination had been increased by social-ecological characteristics, such as a fire igniting and burning in land jointly managed or fire igniting in one jurisdiction and burning within another. They found that actors form partnerships to help reduce wildfire exposure on lands they jointly manage or lands that share a boundary and could present risks to other jurisdictions (Hamilton et al. 2019). These studies identified important indicators of the social and ecological characteristics that shape wildfire hazard governance. However, additional factors may shape cooperation in these contexts. We extended this prior work with the following three sets of hypotheses:

- Homophily hypothesis (hypothesis 1): actors more similar in characteristics (e.g., agency type, objectives, ecosystem type) are more likely to cooperate. Such homophily can reduce the costs of collaboration by streamlining communication, aligning collaboration objectives, and building trust (Krueger 2005, Kark et al. 2015, Vosick 2016, Hamilton et al. 2021). Shared traits among entities may lead to faster tie formation by increasing the likelihood that they will come into contact and the likelihood that they share perception of threats and needs (Gallemore et al. 2015, Olivier and Berardo 2022).
- Ecological hypothesis (hypothesis 2): the probability of a fire igniting in one jurisdiction and becoming a large wildfire event across the landscape, as predicted by current biophysical condition, will increase the likelihood of partnering with the actor in that jurisdiction. Hamilton et al. (2019) specifically examine social selection effects of two actors because of exposure to fires that ignite and burn within land jointly managed. They put forth a hypothesis that goes beyond geographic proximity to suggest that the likelihood of a partnership increases as a function of exposure to wildfire on jointly managed lands (Hamilton et al. 2019). Because an actor can influence another jurisdiction's forest management practices (Fischer and Jasny 2017), and known collaboration occurs when private lands are at risk of fires transmitted from public lands (Fischer and Charnley 2012), we extended these considerations to look at the effect of exposure to wildfire risk from any jurisdiction within a given large landscape.
- Governance hypothesis (hypothesis 3a): actors are more likely to work with others that are perceived to have the operational capacity to achieve shared goals and/or provide useful information. That is, actors are more likely to engage in cooperation, which can be costly (Berardo and Scholz 2010), if they believe other actors are likely to bring successful tactics, tools, and strategies to the table. Along similar lines, we hypothesized (hypothesis 3b) that actors are more likely to form ties with those they consider to be sources of useful information (Fleishman 2008). Again, the likelihood of an actor to invest in coordination will increase if the value of a collaborator is perceived as higher.

Across the three sets of hypotheses, we compared two networks from our case study ecosystem. One network includes only land management entities (i.e., "jurisdictional" network). The second network includes both land managing entitites and non-land managing science and policy agencies and non-governmental organizations (NGOs; i.e., "cross-sector" network). Comparing the two networks offers insights into the differences between networks with management authority and networks that include broader scopes and missions.

METHODS

We investigated the three sets of hypotheses by estimating exponential random graph models (ERGM) using data collected through ecological models and by surveying organizational actors in the Sequoia–Kings Canyon Protected Area–Centered Ecosystem (SEKI PACE).

Study area

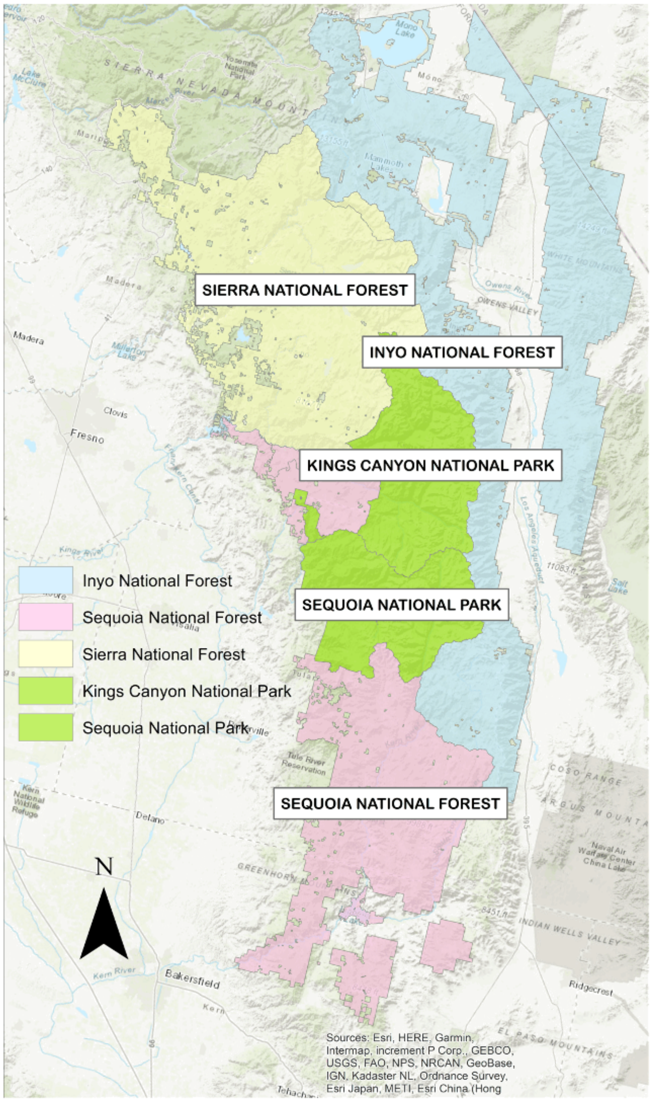
Sequoia National Park was established in 1890 and Kings Canyon National Park in 1940; the two parks have been jointly managed since 1943. The protection of the parks' unique stands of giant sequoia (*Sequoiadendron giganteum*) trees was the primary driving force behind the creation of the parks, but the parks additionally protect a combined landscape of 865,964 acres, 93.3% of which is wilderness. The broader protected area–centered ecosystem in which the parks are located includes U.S. Forest Service tracts, both wilderness and non-wilderness, and Bureau of Land Management units, in addition to state, private, and tribal lands (Fig. 1).

Historical and current land management objectives represented within the PACE include conservation, forestry, recreation, livestock grazing, resource extraction, settlement, and others. Since the PACE encompasses a connected and continuous ecosystem, centered around the paired national parks of Sequoia and Kings Canyon, large-scale disturbances occurring within the PACE have the potential to impact most or all of the mosaic of management units occupying the PACE. Coordination of actors within the PACE, specifically with relation to landscape-scale disturbances such as fire, is likely to require certain conditions that both enable actors to overcome the costs of collaboration and elevate the value they will receive from the collaboration.

Data

A survey was designed to better understand how social and ecological factors may shape wildfire risk collaboration patterns in the SEKI PACE. We designed and administered the survey using the online platform Qualtrics. We sent the survey to individuals representing 38 federal, state, and local agencies and nonprofits who either operate within the SEKI PACE boundaries or who have a stake in forest and fire management in the region. This list was generated by using geographic information system (GIS) analysis of administrative units in the SEKI PACE as well as from preliminary interviews with agency personnel in the region. Prior to launching our survey in the study area, we pilot-tested the survey with personnel from outside the region to ensure that language and terminology were appropriate. The initial invitation to participate in the survey was sent on 3 February 2021. A reminder was sent on 9 February, 24 February, and a final

Fig. 1. Map of the Sequoia-Kings Canyon Protected Area-Centered Ecosystem (SEKI PACE), with boundaries among major land management units defined.



reminder on 5 March was sent by a well-known member of the SEKI fire community. The survey was closed on 12 March 2021. We received responses from 23 organizations for an overall response rate of 61%. We analyzed the data in two separate ways, providing relative response rates for two different approaches to bounding the network:

- Network 1 (jurisdiction network) includes only land-managing entities within the study area boundaries. There are 14 land management agencies and we received responses from 11 of those organizations for a response rate of 79%.
- Network 2 (cross-sector network) includes the cross-section of all 38 land management entities, non-land management entities, and NGOs. Our response rate for network 2 was 61%.

The survey instrument included three primary sections. In part one, we collected general information about the respondent (either agency or NGO), including the fire management issues they work on and budget allocation towards reported issues.

Network data

Section two collected network information. We used a list-recognition method that included a list of the 14 land management agencies within the study boundaries and a second list that included other organizations that do not manage land and are therefore decoupled from defined jurisdictional areas. We asked each respondent to select from the list by considering "with whom you go to fire-related meetings, receive or share advice or information, or implement projects within or across the PACE." Respondents could select all that apply. By selecting an agency or NGO from the list in the survey, the respondent was indicating a network tie between the two organizations. We treated these ties as directional for the analysis with the survey responder as the sender and nominated organization as the receiver.

Governance data

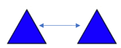
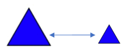
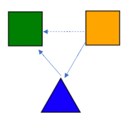
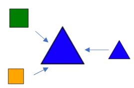
The third section of the survey collected additional information on each connection reported. Following Tait and Brunson (2021), we asked respondents to rate the purpose of the tie as either communication ("we make sure partnering entities know what we're doing"), coordination ("we make sure partnering entities know what we're doing, consult them in planning, and try to schedule our independent activities to achieve synergies"), or collaboration ("we communicate and plan together, and try to share resources where possible, within constraints imposed by laws or regulations"). We used this information to descriptively describe the different types of relationships in the two networks under study, but for the purposes of the exponential random graph model (ERGM) analysis a reported tie between two actors was a non-valued, binary (0/1) value where 1 indicates that a communication, coordination, or collaboration tie exists and 0 indicates no actor-to-actor linkage.

If a respondent reported a tie with another organization, we asked them to "rate your level of satisfaction with the joint activities to increase the capacity to prepare for and respond to fire" and noted that responses are kept confidential; asked about the usefulness of the information provided by each partner (from 1 [not useful] to 4 [extremely useful]); asked each respondent to "estimate the likelihood of fire spreading to other jurisdictions" from each of the 14 jurisdictions (from 1 [low] to 4 [extreme]); and asked about confidence in the "planning and operational capacity of the jurisdiction to prevent ignition or limit the spread of a large fire" (from 1 [not confident at all] to 4 [completely confident]). For each of these questions the mean of the responses was calculated and each organization was assigned their respective mean score. Figure 2 shows the descriptive statistics of the continuous variables (fire probability, operational capacity, and useful information).

Ecological data

In addition to survey data, we constructed ecological variables related to probability of a large fire, fire occurrences, and land cover. Land cover data include the percentage of forest cover and the classification of ecoregion type. Ecoregion types, categorical variables based on the EPA classification of ecoregion type with greatest coverage by area, include: Central Basin and Range, Central California Valley, Mojave Basin and Range, and Sierra

Fig. 2. Descriptive statistics of continuous variables.

Visual	ERGM Term	Statistical notation	Hypothesis
	Agency, Org Type, Ecoregion, Shared Boundary	$\sum_{i,j} x_{ij}\, y_i y_j$	1
	Fire probability, Fire probability (difference), Operational confidence, Operational confidence (difference), useful information, useful information (difference)	$\sum_{i,j} \lvert y_i - y_j \rvert\, x_{i,j}$	2, 3a, 3b
	Triangle (GWESP)	$w = e^{\alpha} \sum_{i=1}^{n-2} [1-(1-e^{\alpha})^{i}]\, p_i$	Structural parameter
	Popularity (GWIDEG)	NA	Structural parameter

Nevada. Probability of a large fire was computed by using weather, climate, and land-surface dynamics at multiple time scales to predict individual fire occurrence (Gray et al. 2018). The variable is a continuous value from 0 to 1 that represents the mean conditional burn probability of each pixel (Gray et al. 2018). The data have a 250 m resolution and were calculated from the most recent 5-year period available (2014–2018) averaging the fire season months (May to October). We computed one score that represented the mean value within each jurisdiction in the SEKI PACE.

Analytical approach

We analyzed the network data using methods that are structurally descriptive and structurally explicit (Scott and Ulibarri 2019). Structurally descriptive network studies seek to characterize an entity (in this case an organization) or network in terms of aggregate structural features (e.g., what actor or organization is most central in a network or whether one network is denser than another). In contrast, structurally explicit network studies seek to draw inferences about what gives rise to specific ties or tie arrangements. For the former, we included visualizations and network statistics on the jurisdictional (network 1) and cross-sector network (network 2). We report measures of density, centralization, and transitivity for both networks. These measures were calculated in R 3.4.1 (R Core Team 2022) using statnet package v2016.9 (Handcock et al. 2008). For the latter, we employed exponential random graph models (ERGMs). ERGMs are a class of network statistical techniques for understanding network structure and social selection effects, i.e., how actor covariates and forms of relational dependence underpin the likelihood that two actors are connected. In general, ERGMs are used to test whether certain configurations or tendencies are more prevalent than would occur by chance (Lusher et al. 2013). The most basic test compares the random graph to the observed graph where the random graph serves as a null hypothesis, or Bernoulli model, to ask whether the observed density of a given network is more probable than could occur randomly (Wang et al. 2009). Increasingly, ERG models use the observed network as a single realization of a multivariate distribution, removing the assumption of independence and allowing hypothesis testing similar to regression specification (i.e., covariate x is expected to affect the outcome y) while also utilizing network dependence as covariates (Cranmer et al. 2017). Our ERGM application treats the network tie as the dependent variable, and the probability of occurrence of that tie is modeled similarly to logistic regression using network structure and nodal attribute covariates such as organizational type, perceived operational capacity, and fire probability.

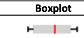
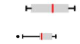
In ERG models, coefficients represent the change in the (log-odds) likelihood of a tie for a unit change in a predictor. However, different from logistic regression network dependence means that some ties are likely to depend on others (Lusher et al. 2013). Specifically, an ERGM (Hunter and Handcock 2006, Handcock et al. 2008, Lusher et al. 2013) models the probability of a tie between i and j given the observed network, G, as:

$$odds(G_{ij}=1) = \frac{p(G_{ij}=1|G^c_{ij})}{1-p(G_{ij}=1|G^c_{ij})} = \frac{p(G_{ij}=1|G^c_{ij})}{p(G_{ij}=0|G^c_{ij})} \qquad (1)$$

where the odds of a link between nodes i and j are conditional on the structure of the network before a link between i and j is created (G^c_{ij}).

In an ERGM there are two kinds of explanatory variables: structural and node-level variables. In our study, we use structural variables as controls to better understand the effect of node-level variables that were measured in the survey. Four primary node-level ERGM functions in R were used: *nodematch*, *nodecov*, *edgecov*, and *absdiff* (Handcock et al. 2008). *Nodematch* is used to test categorical variables, *edgecov* is used to test categorical variables where the edge attribute is being tested; *nodecov* is used to test the effect of the continuous node characteristics (e.g., perception of operational confidence) on the likelihood of an organization having a network tie; and *absdiff* is used to test the role of the absolute difference between two organizations' scores on a continuous variable. For an *absdiff* test, a negative parameter estimate indicates that the more similar two organizations are the more likely they have a network tie. A positive parameter estimate indicates that the more different two organizations are the more likely they are to have a network tie. The diagram visual in Figure 3 illustrates the "difference" with a large and small triangle (i.e., a high fire probability score and a low fire probability score). Finally, the *edge* parameter is akin to an intercept term in a linear regression model and is a count of how many edges there are in the network where the coefficient is interpreted as the probability of an edge being in the graph (Lusher et al. 2013).

Fig. 3. Exponential random graph models employed in hypothesis testing. * Where α is the GWESP decay parameter, and p_i is the number of actor pairs who have exactly i shared (edgewise) partners. n is the number of nodes in the network; the maximum number of edgewise-shared partners for any pair of nodes in the network is n-2.

Variable	Range	Mean	SD	Boxplot
Fire Probability (mean)	0-1	.23	0.17	
Operational Capacity	1-4	2.77	0.06	
Useful information	1-4	3.37	0.18	

Using these R functions we tested the hypotheses in the following ways. For hypothesis 1, we conducted the following tests:

- Homophily effect of similar organization types using *nodematch*. For the jurisdictional network we tested the matching effect of being from the same agency and in the cross-sector network we tested the effect of being the same organizational type (local, non-governmental, or federal agency: land manager; federal agency: science/policy/regulatory).
- Homophily effect of having the same ecoregion designation using *nodematch* (jurisdiction network). For this, we used the EPA classification of the ecoregion type with the greatest coverage by area. These included Central Basin and Range, Central California Valley, Mojave Basin and Range, and Sierra Nevada.
- A geographic proximity effect of sharing a boundary using *edgecov*. This only applied to the jurisdiction network analysis (1 = shared boundary, 0 = no shared boundary).

For hypothesis 2, we conducted the following tests:

- The effect of "fire probability" measured the effect of increasing fire probability of a jurisdiction on the likelihood of being connected to partners (*nodecov*) and the effect of being similar or different in terms of the fire probability of a jurisdiction (*absdiff*).

For hypothesis 3, we conducted the following tests:

- The effect of "operational capacity," estimated as the mean of perceived confidence "in the planning and operational capacity of the jurisdiction to prevent ignition or limit the spread of a large fire" (a four-point scale from completely confident to not confident at all), on the likelihood of network ties (*nodecov*) and the effect of being similar or different in average operational capacity confidence in driving a tie between two organizations (*absdiff*).
- The effect of "useful information," estimated as the effect of mean perception of an organization providing useful information (*nodecov*) and the effect of being similar or different in the perception of useful information in driving a tie between two organizations (*absdiff*).

Structural explanatory variables frequently reported as important drivers of network tie formation include a network closure parameter (or triangle) and a preferential attachment (or popularity) parameter. In statnet, the geometrically weighted edgewise shared partnership (GWESP) statistic models triad closure, and the GWIDEG parameter is used to test the likelihood that new ties go to actors that already have many ties (Snijders et al. 2006, Hunter 2007). A significantly positive coefficient for *gwidegree* implies that nodes with low indegree are more likely to form a link with those with high indegree in the network (i.e., the presence of the popularity effect). Alternatively, a significantly negative coefficient indicates a preference toward the homogeneity of nodes' indegree. A non-significant coefficient suggests all indegree distributions are equally preferred (Lusher et al. 2013).

RESULTS

Since the ERGM is based on the social network of our governance actors, our analysis produced both network descriptive and network predictive results. Structurally descriptive network analysis focused on how particular network structures relate to management outcomes. This included summarizing the structure and function of governance networks, such as whether a network is centralized or decentralized, dense or not, and whether it includes sub-groups and/or clustering.

Network description

The jurisdictional network has 14 actors and 50 connections (3.6 connections per actor) and the cross-sector network has 38 actors and 254 connections (6.7 connections per actor). Land management agencies' connections to other land management agencies are more frequently reported as collaboration (72%) in the jurisdiction network than in the cross-sector network (55%), whereas cross-sector connections report more coordination (11%) than in the jurisdictional network (2%). Because network 1 is based across the case study geography, we could map the network to the jurisdictions (Fig. 4) and the cross-sector network is not spatially explicit but visualized as a network in Figure 5.

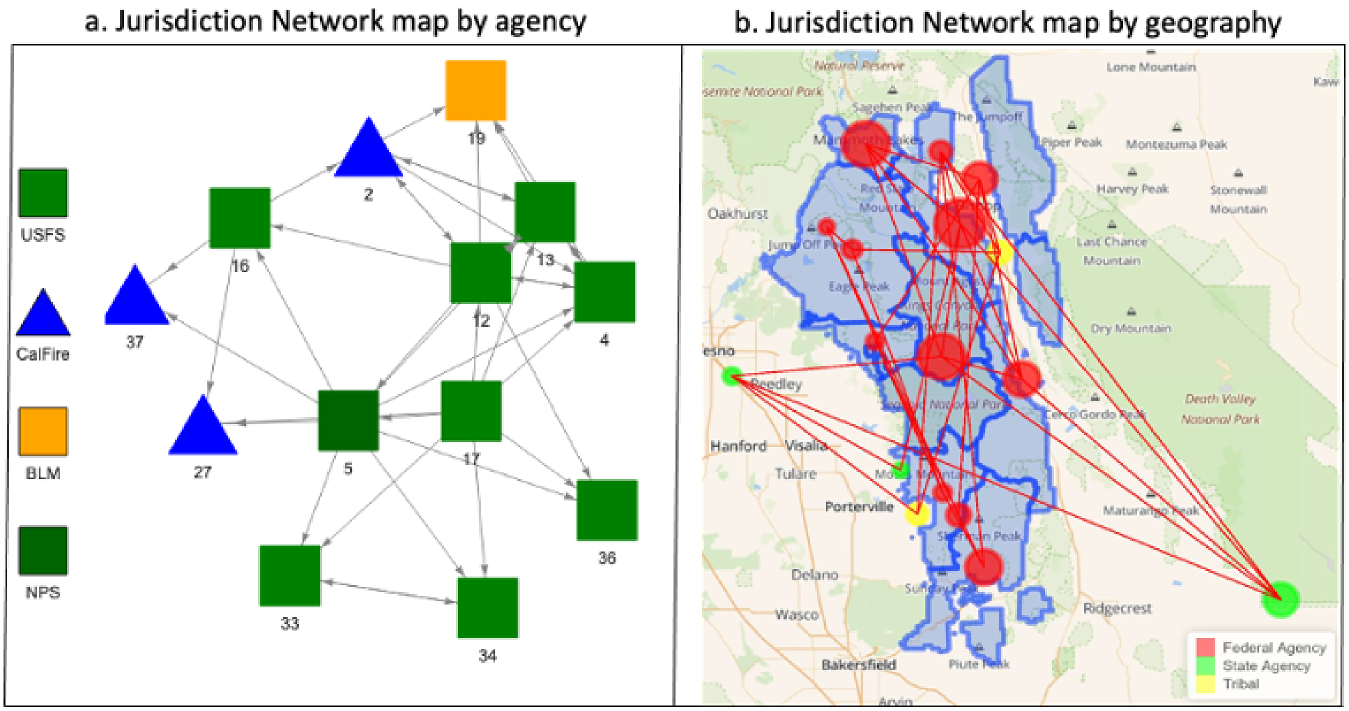
Furthermore, the jurisdiction and cross-sector networks have different whole network characteristics (Fig. 6). The jurisdiction network is denser and has more triadic clusters, whereas the cross-sector network is more centralized.

ERGM Results

We applied ERG models to this network dataset to infer whether a configuration occurs in a network more than would be expected by chance, given the other effects in the model (Table 1). We fitted two models. Model 1 is our jurisdiction network. The ERGM terms include categorical homophily effects for agency, ecotype, and shared border; node covariates and absolute difference effects for two continuous ecological terms (fire probability and perception of fire spreading); and node covariates and absolute difference effects for the two governance terms (confidence in operational capacity and useful information; Table 1). Figure 7 visualizes the ERGM coefficients for both models. Model 2 is our cross-sector network. The ERGM terms include homophily effects for organization type and node covariates and absolute difference effects for the two governance terms (confidence in operational capacity and useful information). Both models include the structural terms for edges, preferential attachment, and network closure.

Our results suggest limited evidence that homophily (hypothesis 1), or similarity, drives partnerships. The ERGM parameters for same agency, same ecoregion, and shared boundary were all insignificant. This includes sharing a boundary (-0.257, $p > .10$), where we expected a geographical adjacency effect (Table 1). Although we did not find that connections between the same agencies were more likely in the jurisdiction network, we did find that the same types of organizations (federal–land manager, federal–science/policy/regulatory, state agency, NGO, tribal) were

Fig. 4. The jurisdiction network depicted with (a) attributes and (b) in its geographical context.



more likely to have connections to each other than to different organization types (0.662, p < .001). In the cross-sector network, common organization type increases probability of a tie by 66%.

The ecological parameter related to hypothesis 2, fire probability mean, indicates that having a higher fire probability does not itself drive more connections (1.267, p > .10), but that the difference between the mean fire probability in different jurisdictions is important. The negative parameter (-5.058, p < .05) means that organizations that are more similar in terms of their mean fire probability are more likely to have connections to each other. For each standard deviation (0.17) reduction in the absolute difference between any two jurisdictions mean conditional burn probability increases the likelihood they are connected by 10.17% (Table 1).

The governance-related parameters in hypotheses 3 and 4 are significant in our models for tie formation (Table 1). Organizations that were rated higher by their peers in terms of operational capacity to "prevent ignition or limit the spread of a large fire" have more network connections in both the jurisdiction (19.202, p < .001) and cross-sector (4.383, p < .001) networks. In both cases, a one-point increase in average rating of operational capacity (on a scale of 1–4) guarantees a tie to that organization (100% probability). A one standard deviation increase in this rating increases the likelihood of a tie by 6%. The difference in operational capacity was not significant in the jurisdiction model but was significant in the cross-sector model. In this case, the positive parameter (3.917, p < .001) indicates that a one standard deviation (0.06) reduction in the absolute difference between operational capacity ratings increases the likelihood of a tie by 5.8%.

Although "good information" did not have significant effects in the jurisdiction network, it did in the cross-sector network. Organizations that score higher in average rating of "good information provided by the organization" have more network connections (2.445, p < .0001) and those that are more similar in terms of their good information rating are more likely to be connected (-1.565, p < .001). For each unit closer in confidence in information increases tie probability by 17% (Table 1).

In both models, we saw significant effects for network closure, or when a new tie connects three nodes into a triad (jurisdictional network: -0.620, p < .001; cross-sector network: -0.233, p < .001) and for popularity, or preferential attachment, effects (jurisdictional network: 5.75, p < .001; cross-sector network: 1.194, p < .10; Table 1).

DISCUSSION

We found that certain measured variables were significantly predictive of tie formation for polycentric wildfire governance in the SEKI PACE. Although this study focuses on a single exemplary social-ecological system, this finding is indicative of leverage points that might motivate coordination among actors in multi-jurisdictional landscapes faced with wildfire and other cross-boundary management challenges.

Within the jurisdiction network, which contained land-managing entities, significant predictors of tie formation included both similarity in fire probability and the perception that partners have operational capacity to manage fire and fuels. That is, entities were more likely to be connected if fire was of similar importance to them and if their partner organization brought potential value in terms of supporting their fire management efforts. Similarity

Fig. 5. Cross-sector network. FED-manager refers to federal agencies that manage land, and FED-sci/pol/reg refers to federal agencies that do not manage land but instead focus on science/policy/regulatory activities.

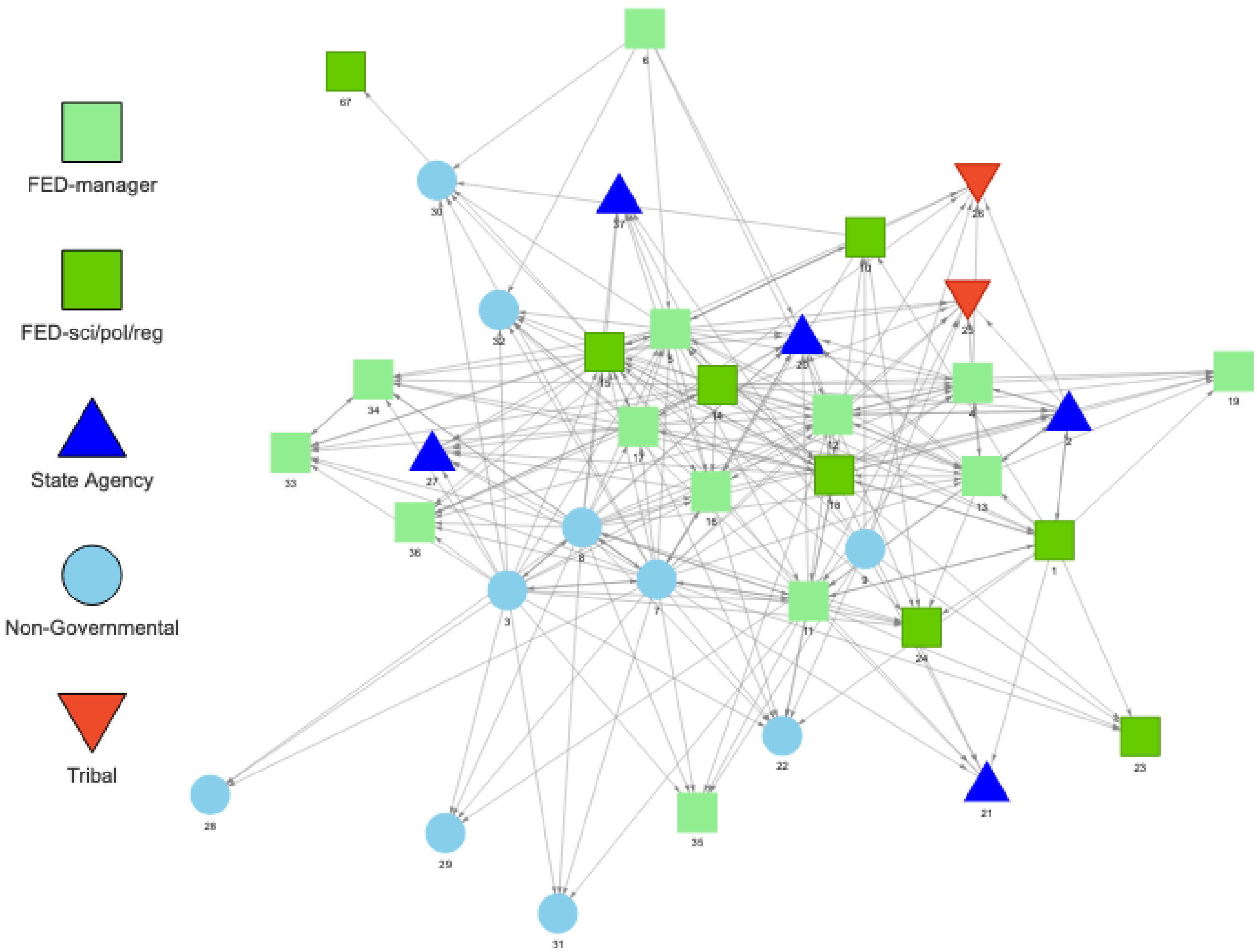


Fig. 6. Descriptive statistics for the jurisdictional (network 1) network and cross-sector (network 2) network.

	Network 1 (Jurisdictions)	Network 2 (Cross-sector)
Nodes	14	38
Connections	50	254
Density	.275	.181
Centralization	.218	.294
Transitivity	.619	.476
Strength of ties	Communication: 26% Coordination: 2% Collaboration: 72%	Communication: 34% Coordination: 11% Collaboration: 55%

Fig. 7. Exponential random graph (ERG) coefficients and confidence intervals for jurisdictional and cross-sector terms.

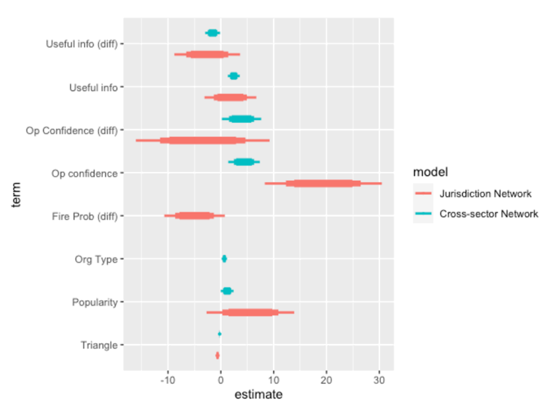


Table 1. ERGM results examining whether tested variables affect network ties and structure. Model 1 is the jurisdiction network and model 2 is the cross-sector network.

	SEKI Model 1	SEKI Model 2
Edges	-115.681***	-41.372***
	(30.708)	(8.075)
Triangle	-0.620***	-0.233***
	(0.148)	(0.019)
Popularity	5.758+	1.195*
	(3.257)	(0.472)
Agency	-0.807	
	(0.685)	
Organizational type		0.662***
		(0.197)
Shared boundary	-0.257	
	(0.696)	
Ecoregion	0.481	
	(0.603)	
Fire probability	1.267	
	(1.891)	
Fire probability (diff)	-5.059*	
	(2.136)	
Operational confidence	19.202***	4.383***
	(4.396)	(1.163)
Operational Confidence (diff)	-3.244	3.917**
	(4.717)	(1.446)
Useful information	1.774	2.445***
	(1.838)	(0.438)
Useful information (diff)	-2.374	-1.566**
	(2.320)	(0.550)
AIC	146.1	1137.9
BIC	188.8	1179.9
Log.Lik.	-59.047	-560.973

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

in fire probability can explain network ties because those two entities face similar challenges, and such challenges in turn make it likely that the entities will find themselves requiring, investing in, and using the same resources; attending similar trainings, workshops, and information sessions; following similar information sources; and sharing other network ties with collaborators, contractors, employees, etc. Each of these factors boosts the chances that two entities will be in contact with one another and that they will cooperate to share resources or ideas. Meanwhile, the perception of one actor that another actor has high operational capacity is likely to lend itself to trust and credibility within the interaction, where there is respect that the partner entity will be able to assist as challenges evolve and emerge.

These factors reduce the cost of collaboration for participating actors. The costs of establishing and maintaining polycentric governance connections in a wildfire-prone multi-jurisdictional landscape may include the investment of time required to interact meaningfully with partners, keep them updated on planning and conditions, and come to group decisions (Margerum 2007, Gallemore et al. 2015, Kark et al. 2015, Bodin et al. 2016, Prager et al. 2018, Davis et al. 2021); the investment of human and technical resources in shared management activities (Tschirhart 2009, Davis et al. 2014); investment of funds in fire and fuels control measures undertaken for the sake of the collaboration between partners and with communities (Tavoni et al. 2011, Davis et al. 2014, Moseley and Charnley 2014, Nielsen-Pincus et al. 2018); and opportunity costs incurred because of the need to coordinate with others as activities are undertaken (Waldhardt et al. 2010, Mazor et al. 2013). In some cases, the collaboration must begin with trust development, a process that may require particularly large time investment (Pretty 2003, Stern and Baird 2015, Stern and Coleman 2015, Bodin et al. 2019b).

If there is uneven starting-point access to resources within a collaboration, costs may be borne disproportionately. For example, one partner may have more resources to offer to the collaboration than the other partner, with the result that working alone is a more efficient and less costly approach for the first partner. In such cases, the benefits of collaboration must be sufficient to outweigh costs. Such benefits may include increased success of fire control efforts directly (Fleming et al. 2015) or more indirect benefits such as long-term reduction in risks (Bihari and Ryan 2012), increased capacity to leverage collaborations to bolster decision making in other arenas, improved stakeholder relations outside the collaboration, and others.

Unlike the factors discussed above, confidence in the information received from a partner was a significant predictor of ties in the cross-sector network. Information flow goes beyond direct management of resources, so actors may find it valuable to be linked to knowledgeable partners even if they differ in entity type or manage no land. Furthermore, differing entities may obtain information via different routes, suggesting that ties to a diversity of partners could enhance the total amount of information flowing through a network. For example, some actors may obtain information from industry groups or the internet whereas other actors have access to workshops, trainings, and extension agents (Aslan et al. 2009). If an actor has proved trustworthy and offers information from a unique set of sources, regular communication with them may be perceived as enough of a benefit to overcome the time and effort costs of such communication.

Homophily was similarly important in the cross-sector network but not the jurisdictional network. The cross-sector network included the full set of potential players in the system and the widest possible variation in entity type. As such, this network held the most power to detect the effect of homophily, which emerged as a significant tie predictor because variance in actor characteristics within linkages was smaller than that variance between linkages. As with perceived operational capacity and similarity in fire probability, high homophily reduces the cost of collaboration and brings entities into proximity through various mechanisms. Entities that are more alike are more likely to find themselves participating in the same events and information sessions and trainings and utilizing the same resources, all opportunities for connection and trust formation (McPherson et al. 2001). Entities that are more alike are also likely to share needs; for example, they may need to use the same machinery in fuels management or face high fire risk during similar seasons (Sapat et al. 2019). Such shared needs can facilitate sharing of resources such as a seasonal fire crew. High homophily also suggests that entities may share similar mandates and philosophies (e.g., a commitment to conservation, resource protection, or recreation) or shared governance (e.g., federal, state, and tribal entities differ in regulations and responsibilities). In any landscape, connections between actors that share characteristics are likely to form sooner and more easily than those between actors that lack shared characteristics.

Interestingly, however, the homophily effect was not significant in the jurisdiction network in that two United States Forest Service (USFS) ranger districts did not show a propensity to work together more than a USFS-BLM pair. Being from the same agency would make it easier for the entities to work together to address challenges as they evolve and emerge because they have the same funding mechanisms (few barriers to resource sharing), regulatory structures, etc., and there may be an expectation that they cooperate given the hierarchical nature of the bureaucracy, rather than the social selection preference in polycentric systems. Entities find it useful to cooperate when they are not in the same agency, presumably because maintaining ties carries other benefits, such as information or resources that are not distributed through the agency.

Our results also highlight the significant role of network closure, or the propensity for a new tie to make a triangle. Because our research interests were focused on social and ecological drivers, we had no specific hypothesis associated with this parameter, yet it is interesting for it continues to confirm the role of bonding social capital and the risk hypothesis that suggests network closure occurs in collaborations that involve higher levels of risk (Berardo and Lubell 2016). The benefit of bonding capital is that dense and overlapping relationships create trust, which helps sustain cooperation over time. Bonding social capital can decrease transactions costs and be instrumental in solving collective action (Bodin 2017). This is the tendency of a "friend of a friend is my friend" and although it can be associated with positive characteristics of social capital in these cases, it can also limit new or different information, including innovations, from making it into tightly knit clusters.

Limitations and future work

Our study extends the scholarship related to the mechanisms of polycentric governance but is limited to looking at two networks in one landscape. Future network-based and quantitative studies on polycentric governance can add to this effort by drawing on empirical network data from multiple geographic domains and different hazards. Our study is also limited by the cross-sectional nature of the network data collected that failed to capture longitudinal change. For example, in September 2021 two large wildfires burned 6109 acres of giant sequoia groves in the study area. It is likely that new network connections would be reported if we repeated the survey. This research was also limited in being a survey-based, quantitative study. Supplementing our ERGM findings with qualitative research would provide a more in-depth understanding of how actors conceive the role of operational capacity and useful information in working across jurisdictions. Qualitative work should also inquire if organizations are aware of how these factors shape their decisions to collaborate or not and distill some principles around building trust between agencies and organizations, which likely shapes the perception of operational capacity and useful information. Our findings have raised many new and important questions for future inquiry.

CONCLUSION

Together, the patterns detected in this study suggest that actors in a multi-jurisdictional, social-ecological system are likely to coordinate when they see value to such coordination and are brought into proximity, thus facilitating the interaction and reducing its cost. Given how resource-limited and overburdened most actors are in such systems, these patterns make sense. No matter how well meaning or amiable an individual may be in a network, they simply will not have time or resources to spare for coordination if it is too difficult to achieve or unlikely to assist them in achieving their overall management objectives (Kark et al. 2015). Our findings contribute to a literature suggesting that methods of reducing costs of collaboration may be important to increasing its frequency in a landscape. For example, boundary-spanning entities that link previously disconnected actors can reduce the costs of collaboration (Jensen-Ryan and German 2019, Davis et al. 2021, Hamilton et al. 2021). Given the increasing challenges posed by environmental change at large landscape scales, efforts that pave the way for cooperation among actors have the potential to expand the toolkit of hard-pressed managers by increasing their access to resources and information. The past four decades have seen a four-fold growth in wildfire extent and management costs in the American West, an indicator of the escalating price of global change worldwide (Kizer 2020, Burke et al. 2021). Recognition of the value of cross-jurisdictional coordination is an important evolution in landscape ecology and management and may prove critical as novel conditions and challenges continue to emerge.

These results are similarly applicable to ecosystems and challenges beyond forests and wildfires. Coordination across boundaries is likely to be of increasing relevance as environmental change continues and drives conservation challenges, including land use change, climate change, and biological invasions in ecosystems from grasslands to coral reefs to deserts (Henwood 2010, Abatzoglou and Kolden 2011, Marazzi et al. 2015, Keyser et al. 2019, Madin et al. 2019). To maintain gene flow and connectivity, it may be necessary for managers across such diverse systems to coordinate their efforts across boundaries, and our results suggest that such coordination will be facilitated by a perception that both managers face similar challenges and by the judgment that a prospective coordination partner brings necessary resources to the table. Regardless of the location, factors that reduce the costs of collaboration are likely to promote cross-boundary efforts and to thus support landscape-scale responses to conservation challenges.

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Data Availability:

The anonymized data and R code supporting this study's findings are available at https://github.com/rpbixler/SEKI. Ethical approval for this research study was granted by The University of Texas at Austin, Protocol Number 2020-05-0003.

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