Social–ecological network analysis of scale mismatches in estuary watershed restoration

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Resource management boundaries seldom align with environmental systems, which can lead to social and ecological problems. Mapping and analyzing how resource management organizations in different areas collaborate can provide vital information to help overcome such misalignment. Few quantitative approaches exist, however, to analyze social collaborations alongside environmental patterns, especially among local and regional organizations (i.e., in multilevel governance settings). This paper develops and applies such an approach using social–ecological network analysis (SENA), which considers relationships among and between social and ecological units. The framework and methods are shown using an estuary restoration case from Puget Sound, United States. Collaboration patterns and quality are analyzed among local and regional organizations working in hydrologically connected areas. These patterns are correlated with restoration practitioners' assessments of the productivity of their collaborations to inform network theories for natural resource governance. The SENA is also combined with existing ecological data to jointly consider social and ecological restoration concerns. Results show potentially problematic areas in nearshore environments, where collaboration networks measured by density (percentage of possible network connections) and productivity are weakest. Many areas also have high centralization (a few nodes hold the network together), making network cohesion dependent on key organizations. Although centralization and productivity are inversely related, no clear relationship between density and productivity is observed. This research can help practitioners to identify where governance capacity needs strengthening and jointly consider social and ecological concerns. It advances SENA by developing a multilevel approach to assess social–ecological (or social–environmental) misalignments, also known as scale mismatches.

social–ecological fit | environmental governance | multilevel governance | social–ecological networks | environmental restoration planning

More than a century ago, John Wesley Powell, second director of the US Geological Survey, advised politicians to align political borders with watersheds for successful resource management. His advice was ignored but continues to resonate (1). Spatial-scale mismatch, where the boundaries of governing organizations do not align with the environmental systems that they govern, often leads to failed or inefficient resource management (2–5).* For example, a small municipality cannot regulate upstream land use outside of its jurisdiction to protect water quality (7). Regional fisheries management may not respond to local stock variations or local fishermen's needs (2, 8).

Organizations, both public and private, can overcome scale mismatches through collaboration and coordination (9–13). This network approach to governing is not without challenges but is often preferable to rescaling existing sociopolitical and jurisdictional boundaries, which might undermine other government functions (14, 15). The strength and performance of the social network depends on the quality of collaborations and their configuration (16). Collaborations should also spatially align with the biophysical patterns underpinning the resource system referred to here by convention as the ecological network (12, 17, 18).† Examples include fisheries managers in different countries collaborating (social network) to manage migratory fish populations (ecological network) (19) or urban park managers coordinating with other land managers (social network) within pollination distance of the park (ecological network) (10). Such alignment can be analyzed using social–ecological network analysis (SENA) (17). SENA not only considers how social units interact—the purview of studies about natural resource governance using classical social network analysis (20–26)—but simultaneously considers interactions between and among social and ecological units (17, 18). These ecological units can represent specific plants or animals (27), habitat patches (10, 18), entire habitats or ecosystems (28), or water resource areas (29).

Significance

Spatial misalignments between governance and environmental systems, often called spatial scale mismatch, are a key sustainability challenge. Collaboration and coordination networks can help overcome scale mismatch problems and should align with the environmental system. Using an approach based on network science, this paper advances scale mismatch analysis by explicitly considering collaborations among local and regional organizations doing estuary watershed restoration (i.e., multilevel governance) and how these collaborations align with environmental patterns. Collaboration quality is considered to inform network-based theories for natural resource governance. Integrating network analysis results with ecological habitat data further provides a social–environmental restoration planning perspective. This research can help policymakers allocate resources and is a fundamental step toward addressing scale mismatch while considering multilevel governance.

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*This paper focuses on spatial-scale mismatch, while recognizing that it is not wholly independent from temporal and functional mismatches (6). Temporal mismatch occurs when governance arrangements are created at inopportune times or operate at different cycles (e.g., political elections) than relevant ecological processes. Functional mismatch occurs when governance arrangements lack capacity to respond to ecosystem dynamics (3, 5).

†This paper uses terms such as "ecological network" and "social–ecological system" as opposed to other terms often used in the wider sustainability sciences (e.g., "social–environmental" or "human–environment") to be consistent with the dominant literature using network sciences for natural resource management (11, 16) and avoid possible confusion with other network science papers. Ecology and environment are treated synonymously in this paper.

Analyzing scale mismatch with SENA is relatively new, and previous research largely focuses on single-governance levels (e.g., local municipalities) (10, 12, 28, 30, 31). Although a necessary first step to understand social–ecological systems as networks, single-level approaches fail to represent the reality of most natural resource governance, which unfolds at local, regional, and larger levels (32, 33). The multilevel SENA approach presented in this paper overcomes these limitations, offering a means to address multilevel social–ecological scale mismatch. The framework is shown by identifying scale mismatches in the context of estuary restoration for salmon recovery in the Whidbey Basin, northeast Puget Sound, Washington, United States. Different local and regional collaboration patterns are related to practitioners' assessments of collaboration productivity to inform network theories for natural resource governance. The SENA is also integrated with an ecological habitat assessment done by Washington State to provide a social–ecological approach to natural resource management planning. The framework and its application significantly advance a young literature that uses SENA (34, 35) and other network approaches (36–39) to study multilevel natural resource governance.

Estuary Restoration in the Whidbey Basin

The Whidbey Basin is a large semienclosed coastal basin (Fig. 1) fed by four large rivers that drain roughly 14,850 km^2 of land (40, 41). The basin spans four counties,[‡] the traditional lands of seven Native American tribes (six of which have reservation holdings), and roughly 30 cities and towns (41, 42). Many special purpose districts,[§] land trusts, nonprofits, and citizen groups are also involved with restoration (41, 42). The headwaters of the rivers are largely in federal and state holdings (42). The basin's scale mismatch challenges are layered and spatially variable (29) and must be overcome to restore a species, like salmon, with habitat use that spans multiple sociopolitical boundaries.

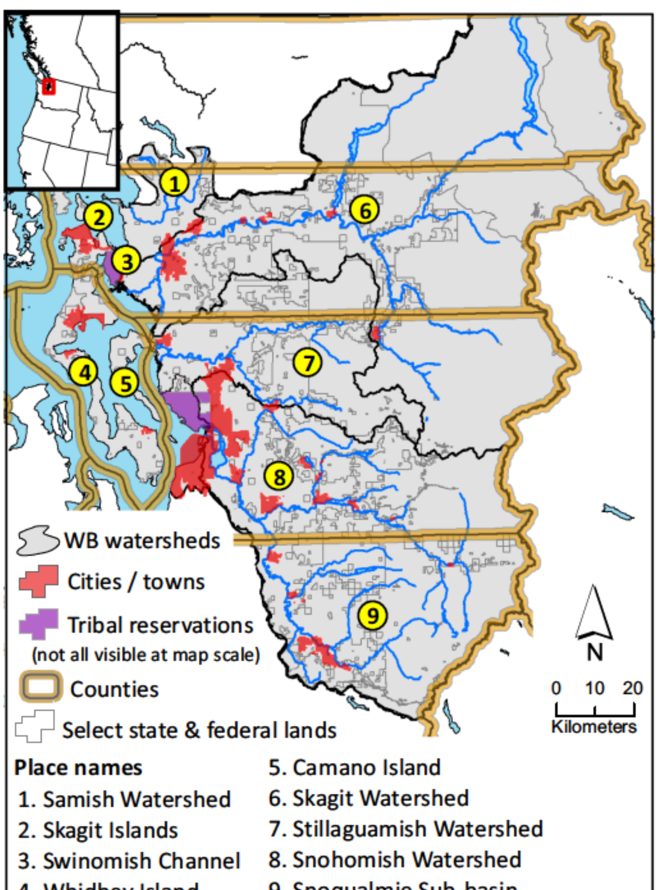

Fig. 1. The Whidbey Basin (WB) study area with place names used in the text. Major watersheds and several jurisdictional units are shown to illustrate scale mismatch. Only two of six tribal reservations are visible at this map scale. Depicted state and federal land holdings are not exhaustive but included for reference. Other jurisdictions and organizations are excluded for clarity.

The basin hosts several salmonid species listed as threatened under the US Endangered Species Act, which provides a federal mandate to restore salmon (42, 43). Degraded water quality, habitat losses (from farming and development), river obstructions (primarily caused by improperly sized culverts), and sedimentation from historic logging in the upper watersheds are among the many factors affecting salmon populations (41, 44, 45). Salmon spawn in specific rivers but use the entire nearshore environment during their juvenile life stage (41, 46). Development, conservation, or restoration actions in one area affect restoration successes in other areas (47). For example, the Skagit River salmon recovery plan outlines restoring key nursery areas along northern Whidbey and Camano Islands as an integral part of restoring salmon in the Skagit River (48). Cross-border coordination is necessary because these key nursery areas are in a different county than the river. Even along the river corridor itself, actions taken by each town, city, local flood control district, county department, tribe, state agency, land trust, private entity, or other sociopolitical organization will affect salmon restoration (positively or negatively) as fish migrate up- and downstream or clean or compromised water flows down into the basin (41, 45, 47). Although the state tried for several years to advance a basin-wide recovery planning and implementation effort, it was not supported by local organizations. Most restoration decisions continue to be made at smaller levels. Many are coordinated through watershed planning bodies for each river and often driven forward by funds from state and federal agencies (41).

Network Framework

Approaching the Whidbey Basin as a Social-Ecological Network. To analyze salmon restoration in the Whidbey Basin using SENA, social and ecological units are represented as nodes, and their relationships are represented as edges. Because salmonids are an aquatic resource, the region's hydrology is used to define the ecological components of the network. Small watershed units called hydrologic unit code 10s (HUC 10s) are represented as ecological nodes ($n = 38$). HUC 10s are part of a national water resource database and commonly used for restoration planning; they range from 160 to 1,010 km^2 (datagateway.nrcs.usda.gov; ref. 49). The river network connecting HUC 10s is represented as edges to account for water quantity and quality flows from up- to downstream (50) and fish moving upstream to spawn and downstream to complete other life stages (43). Edges among adjacent coastal HUC 10s are also included to represent salmonid movement in the nearshore environment. No distinction is made between up- or downstream movement when defining these edges. Analysts wishing to consider directionality will find necessary details in *SI Appendix*. Organizations working on salmon restoration are represented as social nodes ($n = 210$) (a detailed listing is in *Materials and Methods*) and were identified using a survey and interviews. Edges among social nodes

[‡] A fifth county overlaps in northern headwaters, but because the land is in federal holding, the county is almost never involved with Whidbey Basin restoration.

[§] Special purpose districts are autonomous quasigovernment entities with taxation authority that manage specific issues, such as but not limited to flood control or port management (www.mrsc.org/subjects/governance/spd/spd-definition.aspx).

represent interorganizational collaborations and their productivity for meeting restoration objectives as assessed by survey participants. Edges between social and ecological units represent where organizations work as recorded in interviews or from publicly available documents.

The simplest social–ecological network consists of two social and two ecological nodes (18). In the Whidbey Basin case, these nodes would be two governing organizations and two HUC 10s. Expanding this idea to a multilevel governance framework, the simplest network consists of eight nodes (Fig. 2*A*): two HUC 10s (ecological nodes) each containing two "local" organizations (totaling four local social nodes) and two "regional" organizations (or regional social nodes) with spatial extent that spans the two HUC 10s. The difference between local and regional social nodes is their ability to influence a single (local) or multiple (regional) ecological nodes (i.e., HUC 10s in this case).[¶]

Analysis of these aforementioned relationships is done through a social–ecological network matrix (*SI Appendix*, Fig. S1). Local and regional organizations are defined by edges depicting where organizations work and biophysical connections among HUC 10s. Then, the number, configuration, and quality of edges among local and regional organizations are analyzed between biophysically connected HUC 10s to understand scale mismatch. Only collaborations that span HUC 10s are analyzed to illustrate if and how scale mismatches are overcome. For example, local organizations may be collaborating across HUC 10s as might regional organizations but with little local to regional collaboration. Although scale mismatch is being addressed separately by local and regional organizations, disconnect between local and regional organizations might undermine natural resource governance. Collaborations within a single HUC 10, such as among several small towns and special districts, are excluded from analysis because they do not affect scale mismatches as defined here. Computational details are provided in *Materials and Methods* and *SI Appendix*. For clarity, this paper is restricted to the most straightforward example of potential scale mismatch: the relationship patterns among organizations (social nodes) working in two connected HUC 10s (ecological nodes). However, the methodology can be expanded to include *N* ecological nodes (additional discussion and methods are in *SI Appendix*).

Measuring Network Structures and Function for Scale Mismatch. Large networks, such as the Whidbey Basin's network with 210 organizations, are too big to analyze by visual inspection alone. Summary statistics are required to understand patterns (Fig. 2*B*). This paper uses two well-known measures of network structure (density and centralization) and one measure of edge quality to analyze scale mismatch.

Network density (D) measures the number of edges present between organizations working in biophysically connected HUC 10s relative to the total number of edges possible (ranging from 0 = no edges to 1 = all possible edges). Density has direct implications for overcoming scale mismatches. A sparse network may not facilitate adequate collaboration or information sharing among social nodes working in different HUC 10s. However, hyperconnectivity can be time consuming and inefficient and result in redundant information sharing (16, 51–53). Optimum

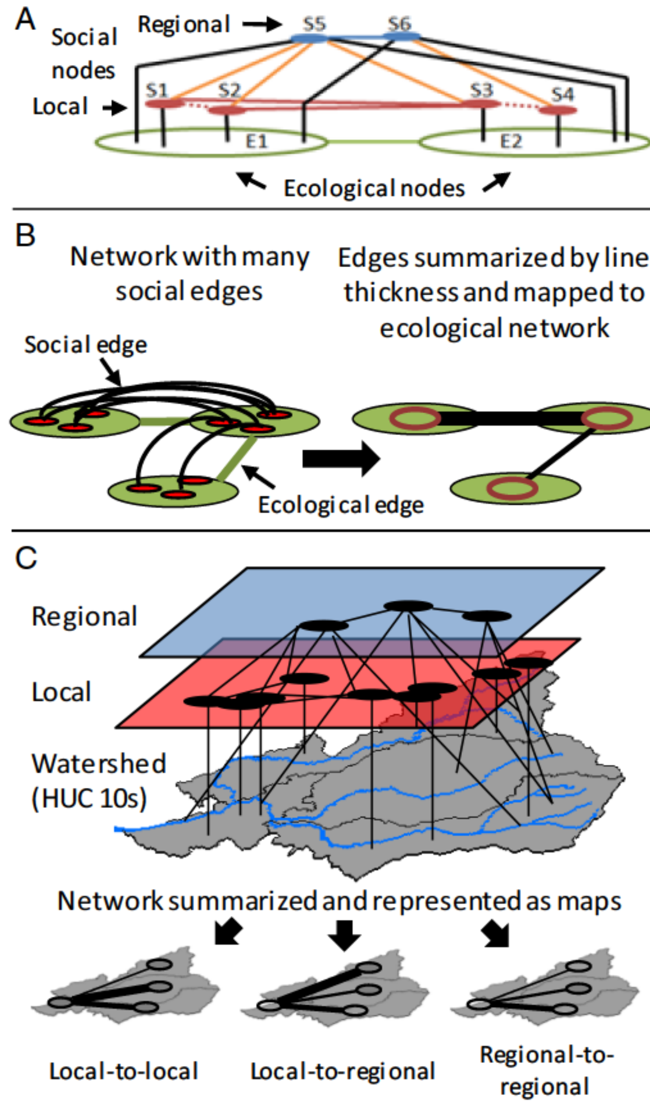

Fig. 2. Conceptual diagram of multilevel network relationships for overcoming scale mismatches. Social and ecological units are called nodes and connected by edges. Social edges should align with ecological edges to overcome scale mismatch. (*A*) There are two types of social nodes, each defined by the spatial expanse in which they work. Local nodes (S1–S4) work within a single ecological area (i.e., have an edge to only one ecological node). Regional nodes (S5 and S6) work in more than one ecological area (i.e., have edges to multiple ecological nodes). Three types of social relationships or edges may exist: (*i*) local to local (solid red), (*ii*) local to regional (orange), and (*iii*) regional to regional (blue). These relationships can be combined for an overall summary, referred to as "all combined" in the text. Edges between social nodes in the same ecological node [S1–S2 and S3–S4 (dashed red)] do not overcome scale mismatch as defined here and are not included in analysis. (*B*) For analysis, social edges patterns are summarized using measures of network structure and function and depicted graphically using line thickness and color (only thickness is shown here). Summarized edge patterns are then graphically mapped onto the ecological network. *C* depicts how the approach is applied using HUC 10s as ecological nodes. For cartographic clarity, the rivers (i.e., ecological edges) are depicted as straight lines, and social collaborations (i.e., social edges) are summarized and mapped onto the rivers.

[¶]This paper uses the term "regional node" to avoid confusion with other work that has focused on "scale-crossing broker nodes" (10) and "bridging organization nodes" (31). The regional node is defined by spatial expanse because it spatially overlaps two ecological nodes. Cross-scale brokers, however, are defined based on jurisdictional hierarchy and link organizations across the hierarchy that manages ecosystem processes at different scales (10). The framework presented here is not based on a jurisdictional hierarchy but rather, the spatial location and expanse in which organizations work. This area is defined by HUC 10s in the Whidbey Basin case. Alternatively, bridging nodes link together disconnected social nodes in general and do not need to be defined based on hierarchal levels of the social–ecological system (31). Although some regional nodes may play or have the potential to play scale-crossing broker or bridging roles, they may also exist as isolated nodes in the network and contribute to scale mismatch.

density is always somewhat context-specific but theoretically, resides at intermediate levels (16, 52, 54).

Network centralization (C_D) measures the evenness of edge distribution among organizations working in biophysically connected HUC 10s (ranging from 0 = even to 1 = uneven). In a highly centralized network ($C_D = 1$), a single node holds everyone together. From a structural perspective, centralized networks are vulnerable to targeted node removal (53, 54). The loss of a central actor could end collaborations meant to overcome scale mismatch. High centralization, however, may be necessary for efficient coordination and is likely durable in governance settings characterized by high trust and where priorities are agreed on (16, 26). This outlook is common in the policy implementation literature (6) and forms the basis of the risk hypothesis that high centralization is efficient and favorable in high-trust settings (26, 36). However, situations exist where high centralization leads to or stems from asymmetric power relations, which can erode legitimacy and trust (16, 55). Therefore, much of the commons literature favors decentralized governance (6, 56). Although there is likely no optimum centralization (57), these different theories speak to the strengths and challenges of centralization under different contexts, which of course, might change over time (16, 26, 36, 53).

Relationship context and quality are also important for understanding a network's potential to overcome scale mismatches (7). Quality is considered here by assessing the percentage of time that network members consider a given collaboration to be productive for meeting their organization's restoration objectives (details are in *Materials and Methods*). Productivity is relevant for understanding scale mismatch because organizations may work together, perhaps out of obligation, but it may not help them do restoration. In such cases, stakeholders need to think about how the working relationship can be improved, for example, by galvanizing around common goals or interests (58). Changing collaboration patterns might also be warranted if, for example, centralization creates power asymmetries, resulting in one organization not trusting the other to convey their interests to a third organization or worrying that their voice is not heard (16, 26, 36, 55). Productivity is assessed by comparing the ratio of productive and unproductive edges among organizations working between biophysically connected HUC 10s. Productivity ranges from −1, where 100% of edges among social nodes are reported as unproductive, to 1, where 100% are reported as productive. Zero indicates a 50/50% split.

Results

Assessing Collaborations in Hydrologically Connected Regions. The analysis of the Whidbey Basin salmon restoration network shows that edge density is generally much lower among local organizations than among regional or between local and regional ones (Fig. 3*A*).[#] There are 12 instances of complete social–ecological scale mismatch at the local level, where no local nodes collaborate across connected ecological nodes (i.e., $D = 0$) (Fig. 3*A*). This pattern is confirmed when comparing observed density with random simulations that control for the number of social nodes in different areas (Fig. 3*B*) and is necessary because density is affected by network size. In most areas, including where $D = 0$, edges among local organizations are lower than expected. When density is higher than expected, P values are high (i.e., $P < 0.25$ and $P < 0.50$), implying that the finding may not be robust. From a structural perspective, scale mismatch is not being overcome through network collaborations at the local level. Alternatively, regional nodes seem to play a major role in overcoming scale mismatches. Regional densities (between local and regional nodes and among regional nodes) tend to be higher than expected (Fig. 3*B*).

Many local to local and local to regional collaborations are highly centralized (Fig. 3*C*), meaning a few nodes play major roles. A combination of low density and high centralization in some areas, especially at the local level, further suggests that many organizations work in isolation or collaborate with very few organizations. Regional nodes, however, are less centralized.

Although clear structural network patterns exist, not all collaborations are created equal. The lowest and highest productivity scores exist among local organizations (Fig. 3*D*). In total, however, local to regional productivity scores are slightly higher than local and regional ones. Interestingly, opposite north to south productivity gradients exist at different governance levels. Productivity is highest at the local level in the lower Skagit and surrounding nearshore, whereas at the regional level, these areas have lower relative productivity than other locations.

Relating Network Collaboration Patterns to Productivity. Permutation-based multiple linear regressions were used to understand relationships between density, centralization, and productivity. Permutation-based tests are necessary because network data do not adhere to many classical statistical assumptions (59). Five statistical models were considered that include a nonlinear relationship with density (i.e., D^2) and interactions between density and centralization (Table 1). A positive D and negative D^2 coefficient would support literature claiming that intermediate levels of density are preferable in social networks (16, 52). A negative C_D coefficient would support the rich literature on decentralized governance (56), whereas a positive coefficient would support the risk hypothesis that high centralization is efficient and favorable in high-trust settings (26, 36).

Regression results show that centralization has a negative effect on productivity, whereas the effect of density varies. No significant relationships exist at the local level (models 1.1–1.5) (Table 1). Without controlling for nonlinearity (i.e., D^2), density has a negative effect on productivity, indicating that hyperconnectivity is perceived to be less productive than sparse connectivity. Surprisingly, D^2 has a positive and significant effect among the local to regional edges (models 2.2, 2.4, and 2.5), which would indicate that intermediate density is detrimental to collaboration productivity. Among regional collaborations, the highest productivity is found at intermediate density levels (i.e., positive D with negative D^2 in models 3.2, 3.3, and 3.5); however, D^2 is not significant in the regional data but is significant when considering all edges combined (model 4.2).

The interaction between density and centralization is significant in several cases. Among local to regional edges (model 2.3), density and productivity are inversely related when centralization is low; however, when centralization is high, increasing density increases productivity. These findings are contrary to what would be expected if high centralization plays an effective coordinating role, where high centralization can substitute for density. Alternatively, the opposite effect is observed among regional edges (model 3.3). Increasing density increases productivity when centralization is low and decreases it when centralization is high. This interaction is expected if centralization plays an effective coordinating or broker role in the network. The interaction between D and C_D may not be straightforward, however, as indicated by the significant interaction term in model 3.5. When centralization is low, increasing density increases productivity up to a given point, after which further increasing density decreases productivity (i.e., the relationship resembles a ∩). At high levels of centralization, increasing density initially decreases productivity up to a given point, after which further increasing density increases productivity (i.e., the relationship resembles a ∪).

[#] In Fig. 3*A*, $D = 1$ because there is only one local social node in each HUC 10. The observation is not an extreme case of collaboration.

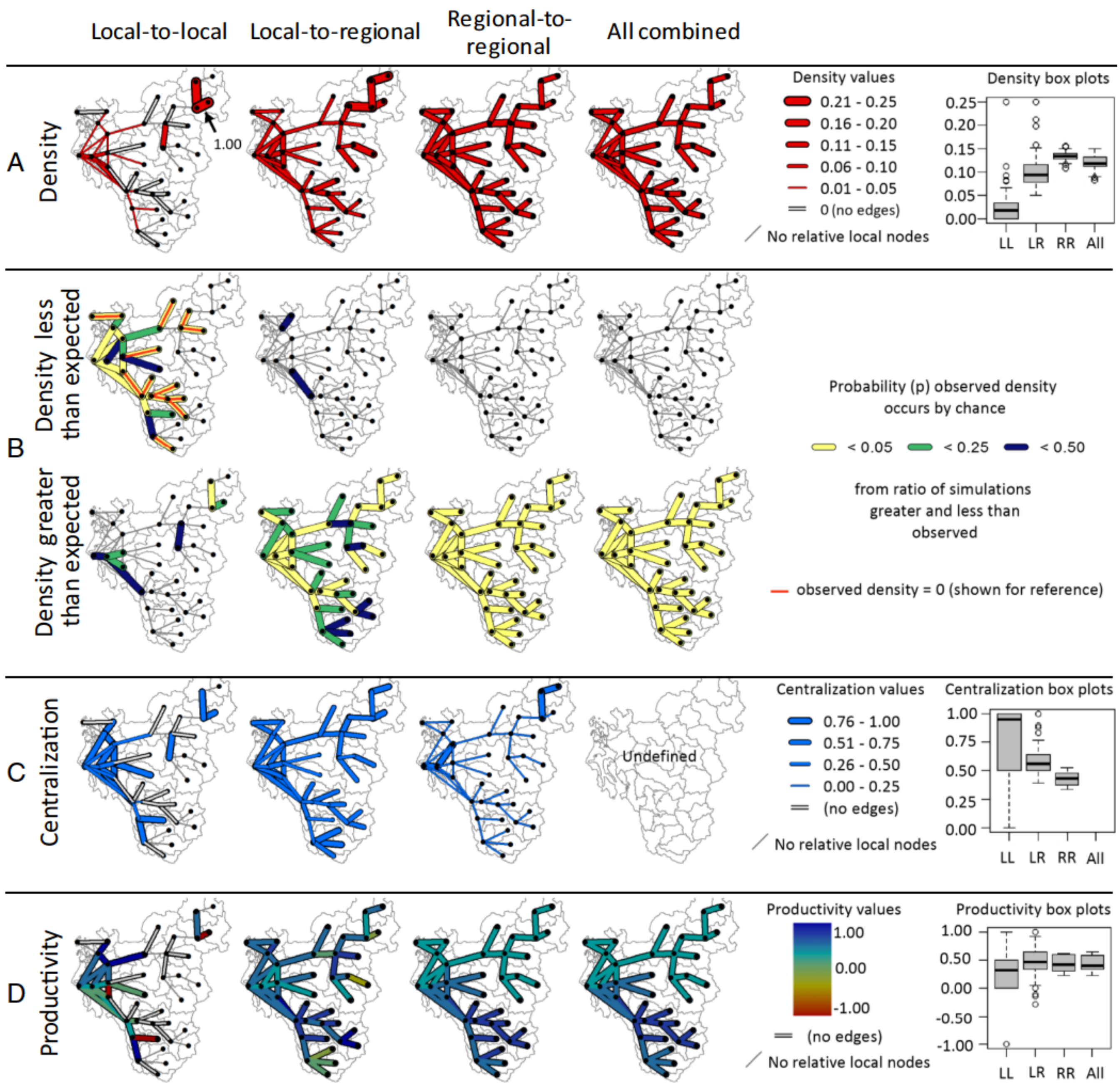

Fig. 3. Measures of network structure and quality among social nodes ($n = 210$) working in hydrologically connected ecological nodes ($n = 38$). Collaborations among and between different governance levels are depicted in map tiles from left to right. Line thickness and color are used to summarize social network patterns, which are mapped onto the ecological network. (*A*) Density (*D*) quantifies the ratio of collaborations present (ranging from 0 = none to 1 = all) to help overcome scale mismatch between two HUC 10s. (*B*) Assessing if observed density is greater or less than expected (based on 1,000 random simulations) (*Materials and Methods*) illustrates, from a structural perspective, if scale mismatches are being overcome. Comparing observed and expected values controls for the confounding effect of network size on density, which prohibits directly comparing different areas. If observed density is less than expected, more edges should be present by chance, and scale mismatch is not being overcome. If greater than expected, scale mismatch is being overcome. Probability values (*p*) are grouped at 0.05, 0.25, and 0.50 thresholds (i.e., there is less than a 5, 25, or 50% chance, respectively, that the observation occurs randomly). (*C*) Centralization (C_D) quantifies the distribution of edges between two HUC 10s and indicates if a single node holds the network together ($C_D = 1$) or if all nodes are connected equally ($C_D = 0$). Centralized networks are vulnerable to targeted node removal and sometimes associated with power asymmetries but can increase efficiency under certain conditions. C_D is mathematically undefined at the aggregate level (*Materials and Methods*). (*D*) Productivity depicts the ratio of productive and unproductive edges (−1 = 100% unproductive and 1 = 100% productive) as assessed by study participants and identifies where there may be collaboration and coordination problems. The abbreviations LL, LR, and RR refer to local to local, local to regional, and regional to regional, respectively.

Discussion

Networks and Scale Mismatch in the Whidbey Basin. The density and centralization maps (Fig. 3) reveal several areas where collaborations to overcome scale mismatch are nonexistent, weak, or easily fragmented. Low productivity in several locations also illustrates that edges may be present but functioning poorly. Linking network patterns and collaboration quality to key landscape restoration needs can help identify critical

Table 1. Permutation-based regression results showing the effects of density (D) and centralization (C_D) on productivity

Collaboration type	Model	D	D^2	C_D	$D{:}C_D$	$D^2{:}C_D$	Adjusted R^2
Local to local	1.1	0.047		−0.024			−0.109
	1.2	−0.017	0.068	−0.026			−0.177
	1.3	0.078		−0.040	−0.045		−0.176
	1.4	−0.090	0.258	−0.086	−0.159		−0.243
	1.5	1.994	−5.095	0.796	−2.536	6.282	−0.198
Local to regional	2.1	−0.045		-0.073^{+}			0.101*
	2.2	−0.432**	0.405*	−0.095*			0.188**
	2.3	−0.010*		−0.084*	0.058*		0.184*
	2.4	−0.313	0.249	−0.092*	0.033		0.184*
	2.5	−0.300	0.233	−0.096*	−0.011	0.040	0.165*
Regional to regional	3.1	−0.031*		−0.106***			0.757***
	3.2	0.316	−0.351	−0.102***			0.766***
	3.3	−0.284*		−0.104***	−0.035*		0.774***
	3.4	0.032	−0.061	−0.104***	−0.031		0.769***
	3.5	0.205	−0.272	−0.074***	−0.823*	0.803*	0.790***
All combined	4.1	−0.048*					0.116*
	4.2	0.625***	−0.676***				0.300***

Local to local adjusted R^2 values can be interpreted as $R^2 = 0$; they are negative because of compensating for multiple variables in models with low explanatory power. All coefficients are standardized to help interpret interaction terms (*Materials and Methods*). The local level outlier $D = 1$ was removed from analyses (details are in ¶). C_D is excluded when analyzing combined edges because it is undefined at the aggregate level (*Materials and Methods*). Therefore, models 4.1 and 4.2 only consider D and D^2; models 4.3–4.5 are ignored because interactions are not possible. Colons represent interactions between variables. Significance values are $^{+}<0.1$, $^{*}<0.05$, $^{**}<0.01$, $^{***}<0.001$.

scale mismatches. For example, several instances of weak collaboration were found in important ecological habitat connections for salmon, including the Swinomish Channel, areas between the islands (Whidbey and Camano) and three major rivers (Skagit, Stillaguamish, and Snohomish), as well as the lower Skagit River (46, 60).

The observed inverse productivity gradient, north to south, between the local and regional data is somewhat puzzling. In the past, there has been contention between county and tribal groups in the Skagit (61–63), perhaps reflected in the lower regional productivity scores. Variations in how several new regional coordinating organizations were being formed at the time of study (41) may also affect regional productivity patterns and would speak to one of the underlying challenges of certain governance systems characterized by overlapping task-specific governing bodies, often with flexible or permeable membership definitions [i.e., type II governance (64)]. These new arrangements can be fraught with trust and legitimacy issues (15), which take time to overcome (65, 66). Additional research is needed to fully explain these scale mismatch patterns. The framework and approach taken in this paper, however, provide a way to analyze the diverse forms that multilevel governance can take.

The framework can also be used to understand other key aspects of multilevel governance involving local and regional actor dynamics, such as participation in decision-making (15, 67). Local actors are often thought to have more detailed knowledge of resource management issues, whereas regional actors often bring greater professional capacities for resource management (15). There is certainly evidence of this in the Whidbey Basin; as one local Whidbey Island participant said, “we don’t have any large restoration outfits [here, so] its really vital for us to bring [them] here to help do [activities like biological assessments or analysis using geographic information systems]” (29, p. 96). Tensions can exist, however, between local and regional actors’ priorities (15). The Whidbey Basin is not immune to this given documented tensions between local farmers and regional environmental groups in the Skagit watershed (62, 63). The relatively higher local to regional productivity scores observed in Fig. 3 suggest that the benefits of cross-level collaborations, either because of outcomes, or the legitimizing effects of participatory governance (15, 69), outweigh the costs.

In terms of considering specific governance network configurations, the regression models provide some evidence that intermediate density correlates with productive collaborations, but in general, hyperconnectivity was associated with lower productivity. This result does not necessarily mean that organizations should interact with fewer groups across the board (i.e., lower the density). The important role of collaborations to overcome scale mismatch is well-established (10, 11, 14). One explanation for these findings may be that some collaborations are imposed, which based on previous research in the Whidbey Basin, correlates with lower productivity when compared with collaborations based on shared interests (58). Additionally, as stated by several research participants, many organizations are stretched thin. One participant said, “We are all so busy ... One thing takes us in one direction; we are going in that direction and forgetting about this other stuff that we are working on because it is sort of being handled” (29, p. 91). Another said, “[we] missed ... a whole summer of cooperating and collaborating with [colleagues at other organizations] because we don’t have the manpower” (29, p. 91). Such comments indicate that enhancing the capacity to collaborate could raise productivity. Although the empirical results on density and productivity are somewhat inconclusive, low centralization was always associated with higher productivity. Low centralization, where organizations working at different levels have multiple and direct contacts with each other, is often considered a key component of successful multilevel governance (15, 68, 69). Results from the Whidbey Basin reaffirm the importance of low centralization for overcoming scale mismatch as defined and presented in this study.

Significant interaction effects were found between density and centralization in several instances. In the local to regional data, hyperconnectivity (high density) was more desirable when centralization was high, which may imply that density is acting as a countermeasure to potential power asymmetries that previous research has related to high centralization (16, 55). Alternatively, at the regional level, hyperconnectivity (high density) was less desirable when centralization was high. Rather than illustrating power asymmetries, centralization in regional relationships may indicate a higher level of coordination and efficiency that is made possible by high levels of preexisting trust between organizations (16, 26). Although this study provides insight into the complex interactions between density and centralization, the more complex models that included interaction terms did not really fit the data better than the simpler models (R^2 values were often similar or lower) (Table 1). Following Occam's razor, the simpler models may be preferable. However, interactions between density and centralization certainly warrant additional study.

Management Implications. Landscape restoration, whether for estuaries or other large ecosystems, requires understanding both the biophysical and the sociopolitical landscape (70). Restoration, conservation, and development actions in one location affect those elsewhere (47, 71). Restoration planning (as well as broader conservation sciences) often starts with coarse-grained systematic analyses of biophysical conditions, which are used to inform additional site-specific analysis for restoration actions (43, 50, 72, 73). Comparable analyses of sociopolitical conditions, including scale mismatch patterns, are rarely conducted. Such endeavors are fundamental, however, if restoration and other natural resource management goals are to be met. The framework and analysis in this paper are a starting point. In the same way that ecological health might be characterized to identify restoration needs, scale mismatch analysis can identify where governance capacity is strong and where it may need enhancement.

As a first step, the network mapping and regression analysis presented here could enable conversations in the Whidbey Basin to address scale mismatch. Restoration authorities might sponsor focus groups to discuss the results. Similar efforts have proven useful elsewhere. In Oregon, United States, for example, discussing social network findings helped establish collaborations among terrestrial and freshwater management groups (74).

The scale mismatch analysis might also be used to jointly consider sociopolitical and ecological concerns. Fig. 4 integrates the SENA results with an existing habitat integrity index developed by Washington for salmon conservation (43). Each data point represents a small hydrologic unit used for habitat integrity mapping. Units with low habitat integrity values (*y* axis) are degraded and would be restoration priorities from a strictly ecological perspective. Network productivity is used in this example (*x* axis) to indicate strong and weak governance capacity. Density or centralization could also be integrated with the ecological data to show how mismatches (i.e., less than expected density) or easily fragmented areas (e.g., high centralization) align with ecological conditions. Combining these ecological and social indicators highlights the range of challenges facing natural resource managers.

The largest management challenges are in areas that are ecologically degraded and have low collaboration productivity (Fig. 4*B*, *Lower Left*). These areas might be considered "social–ecological restoration hotspots," because improving ecological conditions will also require building social capital for restoration. Both social and ecological subsystems require resource investments. Alternatively, areas where restoration is needed and the governance capacity to do it is strong (Fig. 4*B*, *Lower Right*) might be considered "restoration low-hanging fruit"; it will be easier to do restoration in those areas. There is no objective cutoff for these categories. The cutoff should be guided by local context and local experts. This mapping can also highlight areas of potential concern, where habitat is healthy, but collaboration is unproductive (or nonexistent if looking at presence–absence of collaborations). If habitat conditions worsen, the social infrastructure to do restoration would not be in place. Conversely, areas with healthy ecology and productive collaborations could rapidly respond to problems. In a world where resource management organizations are stretched thin, often operating on insufficient budgets, such social–ecological characterization provides critical information about the spectrum of problems and where resources are needed.

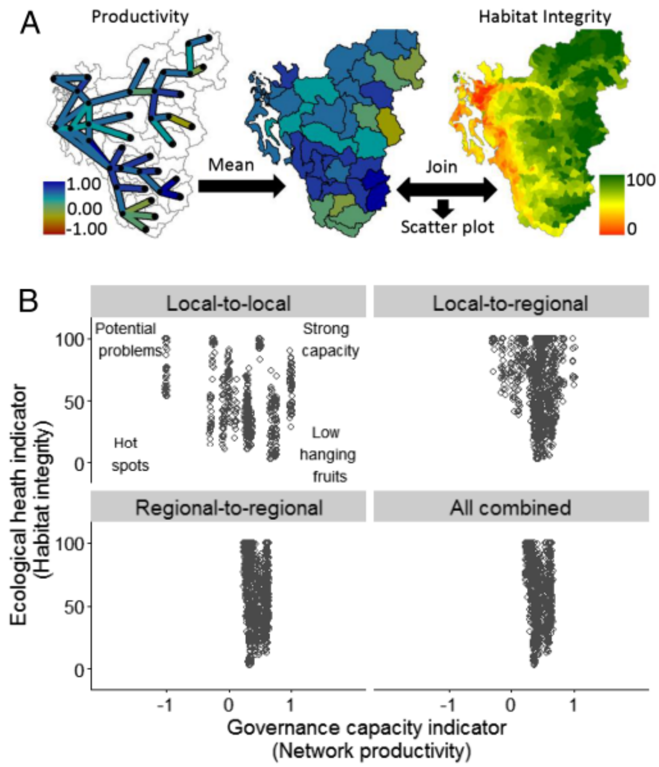

Fig. 4. Habitat integrity index plotted against productivity. (*A*) Average productivity edge values were calculated for each ecological node (HUC 10s). Local to regional is shown as an example. HUC 10s and smaller habitat integrity units were spatially joined to combine social and ecological attributes. (*B*) Habitat integrity is plotted against productivity to simultaneously consider ecological and social opportunities and challenges for restoration (*Discussion*).

Although providing a social–ecological planning perspective, integrating these data is not without challenge. The base unit of the network approach is the edge, the connections among and between ecological and social nodes. Although the ends of edges (i.e., the nodes) are defined spatially, the edge itself does not have a true spatial manifestation. Rather, it is the relationship between spatial entities. The habitat index, however, does have a spatial manifestation, the entire terrestrial surface, because it is based on land use and terrestrial hydrology (43). For this reason, average edge productivity was calculated for each HUC 10 (ecological node), so that the spatial structure of the network data "fit" the habitat data (Fig. 4*A* and details in *SI Appendix*). Future work might create a dataset where habitat quality indicators are represented as different ecological edge values in an ecological network as done in some theoretical modeling studies (30, 75). Additional advances should also incorporate multiple social and multiple ecological network relationships (58, 76–79) into the analysis of scale mismatch. At the time of this study, however, habitat data for Whidbey Basin did not exist in network format, and the aim was to use Washington's existing habitat analysis to make the research relevant to local stakeholders by aligning it with their ongoing work.

Conclusion

Spatial-scale mismatch is an enduring sustainability problem that can be overcome through collaboration and coordination. The SENA framework developed in this paper and its application to estuary restoration advance how scale mismatches in multilevel governance settings are diagnosed and analyzed. Applying the framework in the Whidbey Basin identified several concerning areas where scale mismatches may not be effectively overcome: collaboration networks were structurally weak, had low productivity, or both. Furthermore, centralization correlated with lower network productivity, providing insight about what network shapes effectively help overcoming scale mismatches. Although relationships between density and productivity were inconclusive, several complex interactions between density and centralization were observed that warrant additional study. An important advancement in analyzing scale mismatch, the framework can further be applied to other key multilevel governance issues involving local and regional actor dynamics.

Beyond core questions of multilevel governance, this research shows the benefits of approaching natural resource governance as a social–ecological system (or synonymously, social–environmental system) using tools, such as SENA. Landscapes and the benefits that societies derive from them are never governed in isolation. They are governed by networks of people and organizations that may or may not map onto the underlying ecological system. Environmental problems cannot be divorced from their social contexts. Integrating information about ecological health and social collaboration is essential. The results will help identify where to invest resources to improve environmental conditions as well as improve the social infrastructure to do so.

Materials and Methods

Network Construction. Edges among social nodes (SS edges) were recorded using an open-ended recall survey that was administered online. This survey design used a list of known network groups to elicit an initial response and solicited unknown groups via write-in responses. Participants reported who they worked with to do restoration, defined as directly or indirectly helping degraded ecosystems recover to support human wellbeing and local economies. Edges used weak symmetrization, meaning that they were recorded if both parties said they work together or if one organization said they work with another but the other did not reciprocate or participate in the survey. Participants also report perceived partnership productivity for achieving restoration goals using a five-point ordinal scale (details are in *SI Appendix*). To account for groups reporting different interaction productivity with one another, the network was symmetrized based on maximum and minimum values to examine the data's range. Maximum symmetrization depressed the data's range, whereas minimum symmetrization expanded it with no noticeable effects on spatial patterns or regression results. Minimum symmetrization is reported in the text because it preserves weaker edges, allowing for deeper inquiry into possible network problems and interventions. Maximum symmetrization is reported in *SI Appendix*.

Edges among ecological nodes (EE edges) were defined by linking each HUC 10 to the one up- and downstream of it following surface hydrology (datagateway.nrcs.usda.gov) or its adjacent coastal neighbors (details are in *SI Appendix*). Within the HUC 10 data, Whidbey and Camano Islands are one unit. They were split to better represent local geography.

Edges between social and ecological nodes (SE edges) were established by asking groups where they worked; people provided this information during survey recruitment and semistructured interviews for a subset of participants (details are in *SI Appendix*). Gray literature provided information for nonparticipating groups (e.g., a land trust webpage describing where the trust works). The data were combined in a spatial database (details are in *SI Appendix*) and spatially joined to the HUC 10 data using a negative 0.5-km buffer to remove small overlaps. Interview results guided integration of the surveys and spatial data.

Recruitment and Participation. In total, 206 survey participants were recruited at 186 organizations using snowball sampling. The survey had a 68% response rate (n = 140). Multiple participants were pursued at several organizations to account for subprograms or staff that split geographic regions. Responses were merged to form single organizational responses (details are in *SI Appendix*).

In total, 210 organizations were documented in the salmon restoration network (41 nonprofit organizations, 37 city or town departments, 24 special districts, 20 coordination or watershed groups, 14 tribal organizations/departments, 13 state departments, 13 county departments, 12 citizen groups, 12 federal departments/agencies, 11 for-profit businesses, 5 educational institutions, 4 public utilities, and 4 organizations that did not fit this classification). The SE edges for 17 organizations could not be identified. These groups were kept in the social–ecological network but effectively removed from analysis, which requires an SE edge. Their prevalence in the network is low, and therefore, their omission should not alter the results. Survey participants account for 56.67% of the total social nodes in the network.

Analysis. Network analysis was done in the R language environment with the packages network and sna (80, 81). SE and EE edges were used to define local and regional membership roles based on the social–ecological network matrix (details are in *SI Appendix* and *SI Appendix*, Fig. S1). The social component of the network for each ecological node pair was then block modeled. Block modeling is a specific network analysis technique that groups nodes into roles based on a membership criterion, which can be defined a priori or structurally (e.g., core-periphery modeling). The block modeled data were then used to calculate density, centralization, and productivity (details are in *SI Appendix*). In the block model, local to local and local to regional SS edges produce a bipartite network structure, meaning two sets of nodes only have interset edges and the total edges possible are the product of the number of nodes in each set. Regional to regional edges are not bipartite, and the total possible edges among N regional nodes are $N(N-1)$ because nodes cannot have self-edges. Density was calculated as follows:

$$D_{local-to-local} = \frac{E_p}{2(n_{l1} \times n_{l2})}, \quad [1]$$

$$D_{local-to-regional} = \frac{E_p}{2(n_r(n_{l1} \times n_{l2}))}, \quad [2]$$

$$D_{regional-to-regional} = \frac{E_p}{n_r(n_r - 1)}, \quad [3]$$

$$D_{\text{all combined}} = \frac{E_p}{2((n_{l1} \times n_{l2} + n_r(n_{l1} \times n_{l2})) + n_r(n_r - 1)}, \quad [4]$$

where E_p = edges present for the relevant node sets, and n_{l1}, n_{l2}, and n_r = numbers of nodes per block model membership among local nodes in ecological node 1, local nodes in ecological node 2, and regional nodes, respectively. Equations are given for digraphs.

To control for network size effects on density, observed density measures were compared with those of 1,000 random permutations of the social to social node component of the social–ecological network (*SI Appendix*, Fig. S1). The entire social to social component was randomized by simultaneously permuting its rows and column, whereas the rest of the social–ecological network was unaltered. This process preserves spatial location (SE edge), while changing the probability of having a specific collaboration (SS edge) (details are in *SI Appendix*).

For degree centralization (C_D), Freeman's (82) formula was used for regional to regional edges, and the modified bipartite C_D by Everett and Borgatti (83) was used for local to local and local to regional edges. Following the work by Everett and Borgatti (83), isolates (nodes with no SS edges) were ignored for all C_D measures, and nodal centrality was normalized by the number of nodes in the opposite node set for bipartite measures. Centralization is defined as

$$C_D = \frac{\sum_{i=1}^{n}[C_D(P^*) - C_D(P^i)]}{n^2 - 3n + 2}, \quad [5]$$

$$C_{D\ \text{bipartite}} = \frac{\sum_{i=1}^{n}[C_D(P^*) - C_D(P^i)]}{\frac{(n_0 \times n_i - n_i - n_0 + 1)(n_i + n_0)}{n_i \times n_0}}, \quad [6]$$

where $C_D(P^*)$ = maximum degree, $C_D(P^i =$ degree of node i, n = number of nodes, n_0 = nodes in the bipartite set with the node of highest degree, and n_i = the other bipartite node set. Centralization for the summation of all edges was not calculated because this summation is essentially a hybrid between a normal and bipartite network structure, and no formal equation exists to define centralization in this hybrid case.

Lastly, productivity is defined as

$$Productivity = \frac{E_{pr}}{E_p} - \frac{E_{npr}}{E_p} \text{ if } E_p > 0; \text{not defined if } E_p = 0, \qquad [7]$$

where E_{pr} and E_{npr} = numbers of edges perceived productive $\geq 75\%$ of the time and $\leq 50\%$ of the time, respectively, as recorded on the five-point ordinal scale.

Relationships between productivity, density, and centralization were assessed using permutation-based multiple linear regression using the R package lmPerm (84, 85). To facilitate interpretation of interaction effects, all independent variables were standardized (i.e., mean = 0, and SD = 1). To compare network patterns with existing ecological restoration planning work, the SENA was spatially joined to the Washington State Department of Fish and Wildlife's salmon habitat integrity index (43) in Arc GIS (details are in *SI Appendix*).

Ethics Statement. This research was approved by Arizona State University's Institutional Review Board (1203007596). Informed consent was obtained from all participants.

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