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QUANTITATIVE SOCIAL SCIENCE METHODS, SOCIAL NETWORKS, AND SCALAR MISMATCHES: ADVANCING SOCIAL-ECOLOGICAL SYSTEMS SCIENCE TOWARDS ADAPTATION AND TRANSFORMATION

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QUANTITATIVE SOCIAL SCIENCE METHODS, SOCIAL NETWORKS, AND SCALAR MISMATCHES: ADVANCING SOCIAL-ECOLOGICAL SYSTEMS SCIENCE TOWARDS ADAPTATION AND TRANSFORMATION

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Quantitative social science methods, social networks, and scalar mismatches: Advancing social-ecological systems science towards adaptation and transformation

Chairperson: Dr. Alexander L. Metcalf

Abstract

The adaptive capacity of social-ecological systems to maintain resilience or undergo transformation is increasingly important for navigating global change. Although social interactions and ecological disturbances are often cited as an essential element of social-ecological systems, social interactions are often undertheorized and simplistic, and the relative effects of both social and ecological processes are rarely considered in tandem. In this dissertation, I work towards advancing social-ecological systems research by highlighting opportunities for improved quantitative social science methods, using structurally explicit methods to evaluate the mechanisms underpinning social interactions, and characterizing scalar mismatches in a social-ecological system experiencing a regime shift. In Chapter 1, I provide an overview and introduction for my dissertation. In Chapter 2, I undertook a literature review of social-ecological system studies that quantified social interactions, concluding with a typology for improving conceptual clarity, a compendium of social interaction measures including mapped empirical relationships of each to focal concepts in social-ecological systems science to support theoretical development, and a discussion of opportunities for improved treatment of social interaction complexity in future studies. In Chapter 3, I assessed how social networks and disturbance influenced behaviors of agricultural producers navigating a wide-spread regime shift in the Great Plains biome of Nebraska, US. This social-ecological system is experiencing a regime shift, whereby eastern redcedar is encroaching upon grasslands causing persistent change. I found social network measures were not only more predictive of management behavior than disturbance, but also more predictive of transformative, rather than adaptive, behavior. These findings indicate social interactions, though often overlooked, are critical for influencing adaptive and transformative behavior in social-ecological systems. In Chapter 4, I characterized scalar mismatches between social and ecological components of the Great Plains biome in Nebraska. I found that individual producers respond to collective-level factors and regional-level disturbance as they attempt to manage this regime shift, often with limited success, indicating that the social level responsible for managing this transition is misaligned with the ecological level of the process. These findings highlight opportunities for higher social levels to support individual-level efforts to manage regime shifts in this social-ecological system in Nebraska with implications for detecting and characterizing scalar mismatches globally. In Chapter 5, I synthesize my findings and provide an arc of my contribution to social-ecological systems system.

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Lastly, I would like to acknowledge the privileged position I am in to be able to pursue my academic interests and a career that challenges and inspires me. I hope I can put it to good use as the world experiences increasingly severe social-ecological change.

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Chapter 1: Overview and introduction

The capacity of social-ecological systems to adapt to change or intentionally transform is increasingly important as the world faces fundamental shifts in society and our environment. A social-ecological system is one in which social and ecological components are linked through complex feedbacks that generate emergent properties (Colding and Barthel 2019) and adaptive capacity within that system helps it to maintain resilience or transform (Gunderson 2000, Carpenter et al. 2001, Walker et al. 2006, Cinner and Barnes 2019). Social interactions and ecological disturbances are often cited as essential for maintaining system resilience because they enable social learning, flexibility, and diversity. Yet while the ecological component of social-ecological systems is well-studied, some have argued that the social study of social-ecological systems is in its infancy (Folke 2006) and that social-ecological systems research offers few methodological tools to address social complexity (Béné et al. 2012). In this dissertation, I work towards advancing the social treatment of social-ecological systems through i) a review of studies that quantify social interactions in the context of social-ecological systems science (Chapter 2); ii) an application of social network theory to understand how adaptive capacity is mobilized in the face of wide-spread ecological change toward adaptive and transformative management (Chapter 3); and iii) an assessment of scalar mismatches between social and ecological components leading to wide-spread ecological change (Chapter 4).

In Chapter 2, I asked how social interactions have been quantified in social-ecological systems research to address issues of conceptual ambiguity, undertheorizing, and simplicity that continue to be described in the literature (Colding and Barthel 2019, Siders 2019, Vallury et al. 2022). I undertook a review of social-ecological systems studies that quantify social interactions to characterize the suite of measures that have been used in the literature and what empirical evidence there is for the relationship between social interaction constructs and adaptive capacity, resilience, cooperation, and behavior. I categorized measures based on the hypothesized underlying mechanisms and outcomes of these relationships, and the broad methodological approach used to characterize the interaction. I provided summary tables here and detailed appendices with measures, empirically established relationships, and citations and concluded with an overview of weaknesses and opportunities for further growth in the field. My intention for this review was to improve conceptual clarity and theoretical underpinnings, and enhance the complexity with which we study social interactions in social-ecological systems science.

In Chapter 3, I asked how social networks, as a dimension of adaptive capacity, and disturbance influence responses to system-wide regime shifts. Using the Great Plains in Nebraska, US as a study system, I sought to understand how agricultural producers' adaptive capacity, in combination with their experience of disturbance, influences their adaptive and transformative responses to cedar encroachment. This social-ecological system is undergoing a difficult to reverse regime shift, where the westward encroachment of eastern redcedar is transitioning the plains from grasslands to woodlands (Briggs et al. 2005, Van Oaken 2009). Limiting the extent and pace of this regime shift is essential for the maintenance of producers' livelihoods as well as the conservation of this grassland ecosystem (Merrill et al. 1999, Fuhlendorf et al. 2008, Lautenbach et al. 2017, Zou et al. 2018, Donovan et al. 2020). Focusing on producers' immediate communication networks, we administered an ego-network survey to producers in Nebraska. I built logistic regressions and worked with spatial ecologists to leverage remote sensing data to understand how individuals' social networks and exposure to disturbance influence their adaptive and transformative behavior. I found that social network variables were predictive of behaviors to manage cedar encroachment and that network variables were more important than disturbance variables for predicting transformative behavior. This research exemplifies a novel approach to understanding how social relational patterns influence producers' responses to widespread regime shifts. It provides an improved understanding of how producers navigate change through their social networks, with practical applications for this study system and for the broad study of regime shifts in social-ecological systems around the world.

In Chapter 4, I asked how scalar mismatches manifest to affect social-ecological system management. Scalar mismatches occur when the level of an ecological process and the level of society responsible for managing that process are misaligned such that social-ecological system processes and functions are severely affected (Berkes and Folke 1998, Gunderson and Holling 2002, Cumming et al. 2006). I used the Great Plains biome in Nebraska as a study system. While the ecosystem has been studied extensively in terms of how scalar interactions influence and propagate the shift from a grassland to a woodland regime (Briggs et al. 2005, Engle et al. 2008, Van Oaken 2009, Allred et al. 2012, Taylor et al. 2012, Twidwell et al. 2013, Uden et al. 2019), little is known about how cross-level ecological interactions and collective social factors influence the behavior of individual producers to manage regime shifts. Given that the state is predominantly private property (97.4%; Headwaters Economics 2019), understanding how producers respond to collective social factors and disturbance across different spatial levels is important for understanding how to better align social-ecological components of the system. I used data from the producer survey described briefly above, and rangeland landcover raster data to build logistic regressions predicting producer behavior. To characterize these mismatches, I assessed the relative effects of different spatial levels of disturbance, their interaction, and landowner involvement in rangeland management groups on the probability that a landowner engages in behaviors to manage cedar encroachment in Nebraska. I hypothesized that regional-level disturbance would have a larger effect on individual behavior than local-level disturbance, the effect of local-level disturbance on an individual's behavior would be dependent on the extent of regional-level disturbance, and collective efforts would significantly increase the likelihood of individual behavior to manage encroachment. We found support for these hypotheses, such that producers are responding to both social and ecological pressures beyond individual- and local-levels. These results highlight opportunities for higher-level social processes to engage in cedar encroachment for this particular system. Furthermore, this study provides a relatively straightforward example of studying scalar dynamics in social-ecological systems and highlights opportunities for aligning social and ecological components toward more sustainable management of social-ecological systems more broadly.

Authorship

I use the first person singular, “I,” here because this chapter represents my thinking across the entirety of my dissertation. I also use the first person singular, “I,” in Chapter 2 because I worked independently for that literature review, though with the hope of collaborating with committee members towards a publication in the future. In Chapters 3 and 4, I worked extensively with my committee members and other academics across multiple institutions to develop these ideas and prepare these chapters for publication. Thus, I use the first-person plural, “we,” throughout those chapters to indicate co-authorship with collaborators. This collaborative effort is part of a project funded by the National Science Foundation’s Established Program to Stimulate Competitive Research (Track 2), called “Resilience Informatics for the Convergence of Critical Capacities to Address Regional-scale Environmental Change,” involving academics at the University of Montana, the University of Nebraska-Lincoln, and Boise State.

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Chapter 2: Quantifying social interactions in social-ecological systems research

A review and synthesis of past studies towards improved clarity, theoretical grounding, and complexity

Abstract

In the study of social-ecological systems, social interactions are regularly highlighted as critical for understanding how to navigate global change sustainably. While there has been considerable progress in our ability to quantify social interactions and understand their relationship to adaptive capacity, resilience, cooperation, and behavior, the field continues to struggle with conceptual ambiguity, undertheorizing, and oversimplistic treatment of social relations. To address these issues, a thorough assessment of how social interactions have been quantified in the social-ecological systems literature is needed. Here, I undertook such a review, asking how social interactions have been defined and quantified in social-ecological systems science and what empirical evidence exists on the relationship between social interaction constructs and adaptive capacity, resilience, cooperation, and behavior. I categorized measures based on the underlying mechanism thought to affect these relationships and the outcome of these relationships (i.e., social capital, homogeneity, or contagion), as well as the methodological approach used to characterize the social interaction (i.e., descriptive, binary metaphorical, structurally explicit) to improve conceptual clarity. I provided summary tables here and detailed tables in the appendices for future researchers to better build off previous theory and advance the treatment of social interactions in social-ecological systems research. I conclude with an overview of current weaknesses and future opportunities for improving how we quantify the complexity of social interactions toward improved understanding and management of social-ecological systems.

Introduction

Since its inception, social-ecological systems research has highlighted the importance of social interactions to enable the capacity of a system to adapt to change. Early scholars discuss the importance of communication, trust, reciprocity, learning, leadership, and self-organization for adapting to global change through collaborative environmental governance and management (Berkes and Folke 1998, Adger 2000, Pretty and Ward 2001, Walker et al. 2002, Adger 2003, Dietz et al. 2003, Armitage 2005, Folke et al. 2005, Folke 2006, Ostrom 2009, Pahl-Wostl 2009, Armitage and Plummer 2010, Berkes and Ross 2013). At the same time, community based natural resource management, based on principles of communication, trust, and self-organization, has proliferated in almost every sector, touted for its ability to meet the interests of diverse stakeholders and achieve broad goals (Goldstein and Butler 2010, Schultz et al. 2012, Davis et al. 2017). Despite the popularity of these concepts both in the science and management of social-ecological systems, approaches for describing and measuring social interactions that enable adaptive capacity are broad, with little debate among academics that might improve theoretical clarity or management applicability (Siders 2019). Understanding how social interactions have been measured in the literature may reveal theoretical and methodological gaps in our approaches in an effort to inform such a debate. Given the ongoing and rapid pace of global change, engaging in this debate may be an essential yet missing piece of the puzzle for identifying growth opportunities in this field and improving our ability to manage social-ecological systems for adaptation and transformation.

The last few decades have seen a proliferation in the study of social processes that enable and hinder our ability to adapt to change through linkages between social and ecological components of a system. Scholars initially focused on the relationship between institutionalized local common property systems and ecosystem resilience (Berkes and Folke 1998), expanding the body of social-ecological systems research to include the role of social capital for integrating trust and networks into resilient institutions (Adger 2000). Scholars also described the role of dense networks characterized by frequent communication, reciprocity, and within and cross-level social connections for sustainable resource management (Pretty and Ward 2001). Other early influential works include studies on the importance of learning, flexibility, and experimentation for solutions to novel challenges (Walker et al. 2002), social capital, characterized by dense, trusting ties in a network for governing the commons (Dietz et al. 2003), social capital for collective action on climate change adaptation (Adger 2003), relationships for mediating conflict in community based natural resource management (Armitage 2005), and adaptive governance and social learning for navigating changes in social-ecological systems (Folke et al. 2005). In 2006, Folke highlighted the role of social scientists in contributing to the study of social-ecological system dynamics, suggesting that it was in an "explorative phase" of understanding social processes including learning, leadership, and social networks, and that critical challenges included understanding feedbacks within social-ecological systems towards a better understanding of adaptive capacity (Folke 2006). Since that review, scholars have continued to refine their understanding of self-organization for governing the commons (Ostrom 2009), multi-level learning processes and networks for resource governance regimes (Pahl-Wostl 2009), collaboration across diverse interests, flexible and nested institutions, trust and frequent interactions, continuous learning for operational environmental governance (Armitage and Plummer 2010), and social networks and leadership for community resilience (Berkes and Ross 2013).

Throughout this brief history, social capital and the mechanisms that it works through have been defined differently, not at all, or sometimes conflated. Most of the foundational pieces described above do not describe social concepts, particularly social capital, in any great detail or measure them through rigorous quantitative or qualitative means. Ishihara and Pascual (2009) argue that although social capital is regularly described as enabling collective action in environmental governance research, few studies examine how social capital facilitates collective processes. There is a strong sense of "hand waving" when researchers describe the importance of communication and trusting relationships with no clear articulation of what these concepts actually mean, how they were studied, and what specific mechanism was operating through them. This trend in social-ecological systems research may partly stem from the different early conceptions of social capital, including as occurring where social connections funnel resources (Bourdieu 1986), provide cohesion and support (i.e., bonding capital; Coleman 1988, Putnam 2000), or broker the flow of ideas and resources (i.e., bridging capital; Granovetter 1973, Burt 1992, Putnam 2000). These terms are ubiquitous in social-ecological systems foundations, but often lack theoretical or methodological precision. Bankston and Zhou (2002) argue that part of the issue stems from metaphorical confusion. While financial capital is a known quantity of assets and human capital is a known quantity of skills, social capital does not describe tangible quantities of resources. Instead, it describes social interactions across levels of analysis that lead to emergent properties. Thus, social capital is a process of embedded, social relations that result in social outcomes. Because these processes are inherently context dependent, highly variable, and conditional, social capital is a very complex concept. Surficial treatment of such a complex concept has likely contributed to broader issues in the field, particularly the occlusion of power dynamics (Leach 2008, Beymer-Farris et al. 2012, Cote and Nightingale 2012, Brown 2014, Fabinyi et al. 2014, Taylor 2015, Cutter 2016, Darnhofer et al. 2016, Blythe et al. 2018).

Although social capital has been given a surface-level treatment, social relational theory does permeate much of the scholarship on social-ecological systems governance and management (Bodin et al. 2011). A significant challenge to the social study of social-ecological systems is how to consider both the patterns that characterize environmental governance and discourse as well as the nuance of processes at the individual level. Under a philosophically holistic approach, the focus is on how societal wide structures and discourse influence outcomes, including individual decision-making and agency, with less focus on how individuals may influence higher level processes. Under a philosophically individualistic approach, the focus is on how individuals influence outcomes, with less focus on how societal structures provide the context for their actions. Each approach is useful for answering different kinds of questions, but for social-ecological systems science, appreciating both social context and individual behavior is critical for understanding emergent properties and feedbacks that affect the entire system. An alternative to holistic and individualistic approaches is to understand actors as part of a system of social relations, where patterns emerge as a result of those relations. A social relational approach conceptualizes interactions between people as embedded in and co-creating the social context (Emirbayer 1997). Through these interactions, properties of social structure emerge. Social relational approaches are used to understand how patterns of human interaction enable or constrain the behavior of both individuals and the collective. In other words, how do the types and structures of interaction influence emergent properties or outcomes? Threads of social relational theory can be seen in research on collective action, which highlights how self-interested individuals can act for the benefit of the group under conditions characterized by reciprocity and trust formed through social processes and relationships (Ostrom, 1998). Even the concept of adaptive management exhibits elements of social relational theory (Holling 1973). How ecological knowledge is collected and transferred to inform decision making is inherently a social relational process, particularly when management involves collaborating across different groups and integrating different sources of knowledge (Armitage, 2005; Berkes, 2012).

Despite this building body of work and helpful criticism, the “social side” of social-ecological systems research struggles with persistent issues of conceptual ambiguity, undertheorizing, and simplicity. For example, a 2019 review of the history of social-ecological systems discourse found that there was no agreed upon definition nor cohesive framework for studying social-ecological systems, including the role that social interactions play in these systems (Colding and Barthel 2019). Another review in 2019 that examined 276 studies on adaptive capacity to climate change in social-ecological systems found over 64 indicator-based indices/frameworks and 37 proxy outcome measures, suggesting that adaptive capacity research has proliferated recently without much consensus or reference to past theory or findings (Siders 2019). A 2022 review of adaptive capacity found that studies regularly assess individual/household-level adaptive capacity and simply aggregate their findings to make inference at higher social levels. This approach potentially obscures the role of cross-level interactions for outcomes at higher social levels and results in mismatches between study design and policy implications (Vallury et al. 2022). Critics of social-ecological systems research suggest that this simplistic view of social systems is ironic, given that social-ecological systems research was born out of a need to understand the complexity of ecological systems and their management (Fabinyi et al. 2014). Failure to understand social complexity will likely limit the success of any practical applications of social-ecological systems research. While some critics have argued that the field provides no analytical tools to address this issue (Béné et al. 2012), a synthesis of previous studies may help clarify where there are strengths in current approaches and opportunities for further conceptual and methodological rigour in the treatment of social interactions.

Here, I reviewed how social interactions have been quantified in social-ecological systems research to address the issues of conceptual ambiguity, undertheorizing, and simplicity. Though a review of qualitative studies would be helpful, I focused on quantitative, rather than qualitative, studies because quantitative studies are more likely to undertheorize or oversimplify social interactions. Qualitative studies, rich with thick descriptions of social context, tend to enable a deep understanding of social complexity and are not usually the target of critiques on the study of social-ecological systems. Focusing on quantitative studies may also help facilitate integration of social and ecological data in quantitative models. Additionally, to limit the scope of the review, I focused on quantitative studies as it aligns with my own training and experience. To undertake this review, I first used typologies routed in social-relational theory (Bodin et al. 2011, Borgatti and Halgin 2011) to classify and synthesize my findings and reduce the conceptual ambiguity that is characteristic of much social capital research in the field. Second, I asked how social interactions have been quantified and what the empirical evidence is on the relationship between social interactions and social-ecological systems focal concepts, including adaptive capacity, resilience, cooperation, and adaptive behavior. I synthesized these measures to develop an understanding of what relationships are supported by the quantitative evidence. The intention behind describing and summarizing these empirical relationships is to provide a foundation of social measures (i.e., a table of citations with previously used items and their key findings) to support progress towards theoretically and empirically grounded research. Finally, I highlighted opportunities for the field to be more rigorous and less simplistic in its treatment of social interactions towards a better understanding of social-ecological systems overall.

Methods

Theoretical framing

I used a social-relational framing to organize this review and provide conceptual clarity. I relied heavily on scholarship from social network theory, which is routed in social relational theory, to categorize different studies based on how social interaction outcomes and mechanisms (Borgatti and Halgin 2011) as well as how social interactions are characterized (Bodin et al. 2011).

In social network theory, social interactions have been described as having two broad but different outcomes, success and choice, that occur through two different mechanisms (Borgatti and Halgin 2011). Social capital research broadly falls under the success outcome, whereby social interactions confer achievement or heightened performance, while social homogeneity research broadly falls under the choice outcome, whereby social interactions influence the choices an actor makes (usually towards social similarity). The mechanisms by which social interactions operate towards these outcomes include using social connections (or “ties” in network theory) as pipes of information or resource flows, or using social connections as bonds that facilitate coordination. While this typology has been used to explain social network theory, I’ve used it here to classify social-ecological systems research that quantifies social interactions (Table 1). Research that falls under the achievement category studies the flow of resources and information that enables improved resilience or adaptive capacity. Research that falls under the contagion category studies the flow of information that enables social learning and behavioral change (including implementing adaptation or innovation). Research that falls under the cooperation category studies how social connections enable coordination of actors in collective action or co-governance/management arrangements. Convergence studies are a fourth category, not relevant to this review, that includes studies on how similar social processes in different contexts result in convergent social outcomes.

Table 1: Proposed typology of studies quantifying social interaction in social-ecological systems research, based off of Borgatti and Halgin (2011).

	Social capital (success)	**Social homogeneity (similarity of choice)**
Flow (social connections as pipes)	Achievement (e.g., resilience, adaptive capacity)	Contagion (e.g., social learning, behavior change through diffusion and influence)
Coordination (social connections as bonds)	Cooperation (e.g., collective action, co-governance/management arrangements)	Convergence (not applicable in this review)

Another way to classify social interaction studies in social-ecological systems research is through the approaches used to characterize social relations, which include binary metaphorical, descriptive, and structurally explicit approaches (Bodin et al. 2011). In the binary metaphorical approach, research typically alludes to social relational ideas as an important component of governance, but does not explicitly measure the nature of social capital or networks (e.g., Olsson, Folke, & Berkes, 2004; Olsson, Folke, & Hahn, 2004). For example, Hahn et al. (2006) described a stewardship organization in Sweden that built a “loose social network” and acted as a bridge between different groups to foster relationship- and trust-building to perform complex tasks. Folke, Hahn, Olsson, & Norberg (2005) described social capital, such as trust, leadership, and polycentric social networks, as facilitating knowledge sharing, resource mobilization, and social memory, and thus being critical components of adaptive governance. Yet, the focus is more on the presence or absence of those relationships, rather than on the nature of those relationships. In the descriptive approach, scholars describe social relations with connections to foundational theory on social capital (e.g., Coleman, 1990; Pretty & Ward, 2001; Putnam, 1993).

Relationships are often described as having bonding and bridging qualities that build trust and connect diverse groups respectively (Tompkins and Adger 2004, Newman and Dale 2005, Jones et al. 2009), or has having horizontal and vertical structure (Sanginga et al. 2007). In the structurally explicit approach, network data are systematically collected and metrics are used to describe network patterns such that these patterns can be used to explain socially derived outcomes. For example, research suggests that network density improves collective action and knowledge generation, yet at high levels of density knowledge becomes homogenized and may decline (Bodin et al. 2006).

Article selection

I performed a literature review to determine how social interactions have been quantified in the context of social-ecological systems research. Because social-ecological systems research lacks a cohesive framework (Colding and Barthel 2019), I focused my review on adaptive capacity, resilience, cooperation, and adaptive/transformative behavior in social-ecological systems studies, but was inclusive of other related social concepts from empirical conservation and environmental science studies. A social-ecological system is one in which social and ecological components are linked through complex feedbacks and across scales that generate emergent properties (Colding and Barthel 2019). Adaptive capacity is a latent ability of a system to respond to or drive change (Gunderson 2000, Carpenter et al. 2001, Walker et al. 2006, Cinner and Barnes 2019). Resilience is a system property that enables it to absorb disturbance through change and reorganization while retaining the same function, structure, identity, and feedbacks (Walker et al. 2004). Cooperation includes both formal and informal social interactions toward a common goal (Leach 2010). Adaptive/transformative behaviors are actions individuals or collectives take to maintain system resilience or intentionally change systems and underlying power structures (Walker et al. 2004, Leach 2008, Beymer-Farris et al. 2012, Cote and Nightingale 2012, Taylor 2015, Chaffin et al. 2016*b*, Blythe et al. 2018, Scoones et al. 2018).

I used four steps to select articles for review (Figure 1). Given the wide array of disciplines covered by these criteria and the lack of consistency within the broad study of social-ecological systems (Colding and Barthel 2019), designing systematic search criteria that cast the net wide enough to be thorough, but narrow enough to be pragmatic was difficult. Thus, there was a need for a multi-step approach to building a set of papers for review. First, I defined my selection criteria such that social interactions had to be quantified, the article had to be empirical, at least one focal concept from social-ecological systems research had to be considered (e.g., coping/adaptive/transformative capacity, adaptive/innovative/transformative/collective action behavior, community/social resilience, vulnerability, adaptive/co- management, adaptive governance, adaptation/transformation, ecological outcomes of social interactions), and the article had to be in the context of conservation, environmental science, or resource management. Next, I identified 34 articles that met the above inclusion criteria based on my understanding of the literature with guidance from experts in the fields of social-ecological systems, social network analysis, and human dimensions of resource management. I bolstered my initial selection with additional articles taken from a systematic approach and building off of a previous literature review by Siders (2019). For the systematic search, I used Web of Science to search all databases for English articles and excluded a document if it was a review article, meeting, book, data study, data set, early access, unspecified, editorial material, or patent. I included topic search terms and topic exclusion terms shown in Figure 1. This approach resulted in 284 articles for review. I first read the titles of all articles and eliminated any articles that did not meet the inclusion criteria, resulting in 226 articles. I then read the abstracts of these 226 articles and eliminated any articles that did not meet the inclusion criteria, resulting in 62 articles. For these 62 articles, I read the full paper and did another round of elimination, resulting in 42 articles. Lastly, I examined the 276 articles reviewed by Siders (2019) in her article “Adaptive capacity to climate change: A synthesis of concepts, methods, and findings in a fragmented field.” In appendix 3 of the article, she provided a table of adaptive capacity determinants and where they exist in the literature. From there I selected 65 articles related to adaptive capacity determinants that may quantify social interaction. I read the titles and abstracts of these papers and eliminated any articles that did not meet the inclusion criteria, resulting in 11 additional articles. For these 11 articles, I read the entire paper and eliminated all but 6 articles, for a grand total of 82 articles reviewed.

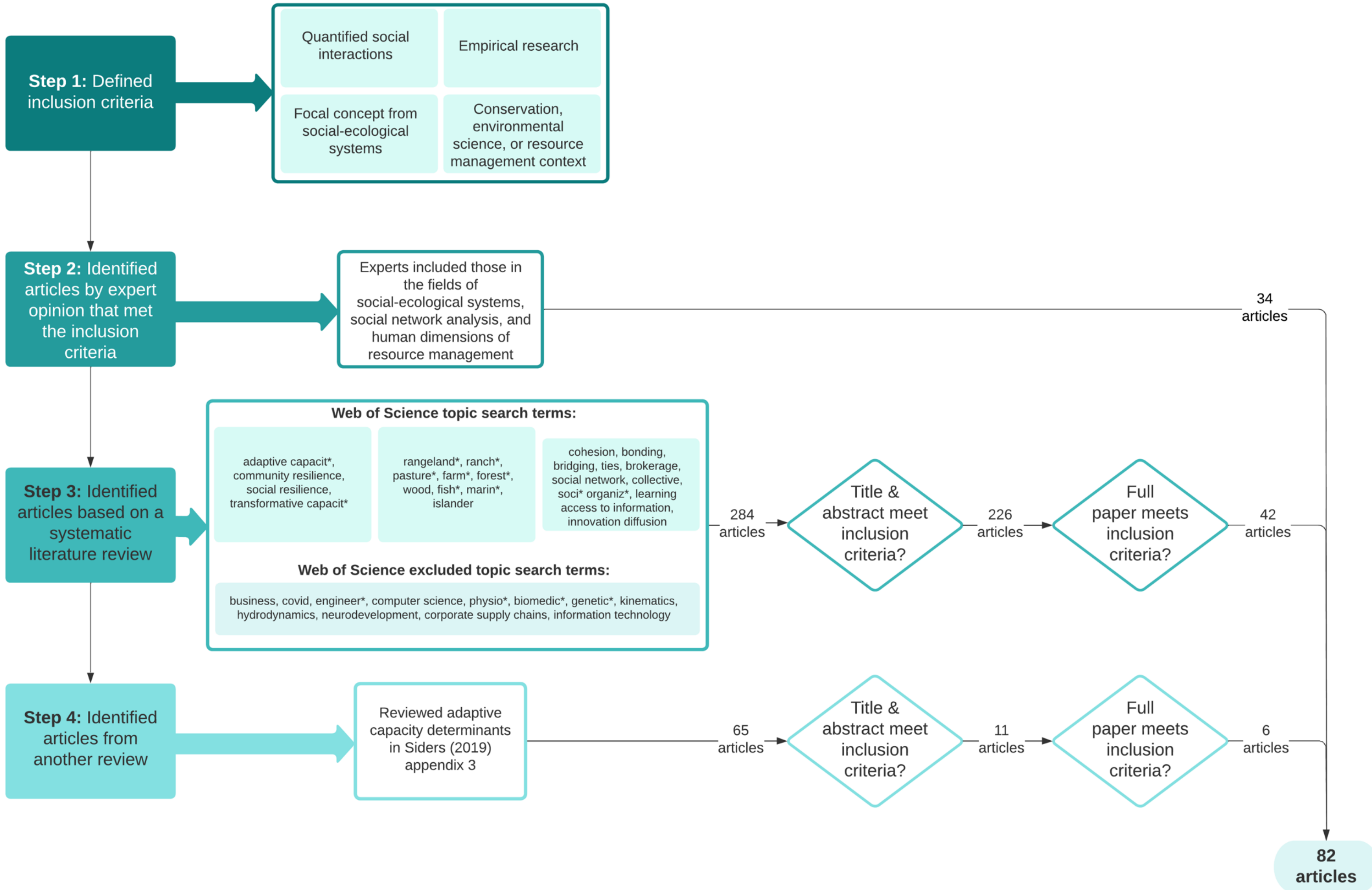

Figure 1: Article selection process. Web of Science search terms were in quotes between each comma. For the topic search terms, within each box there was "OR" where each comma is and between each box there was an "AND". For the excluded topic search terms, there was an "OR" where each comma is.

Analysis

I read each article and built a table (Appendi) that described the following aspects of the paper. I then used this table to synthesize my results, identify research gaps, and make recommendations for future research.

- Overarching research framework
- Research question
- Sector
- Type of disturbance studied, if any
- Social level of analysis
- Spatial level of analysis
- Location
- Whether the study describes social interactions through a binary metaphorical, descriptive, or structurally explicit approach
- Whether the study was cross-scalar or enabled cross-scalar inference
- Data collection methods or sources
- Quantitative analytical approaches
- Focal concept from SES research discussed and any subdimensions of that concept
- Independent/explanatory/X variables
- Dependent/response/Y variables, latent variables, or classes
- Social interaction concept that was quantified, a description of the concept or items used to quantify it, and its quantified relationship to an SES focal concept
- Implications of findings

Results

General description of articles

I reviewed 82 articles (Appendi). The articles used a wide array of research frameworks (Figure 2), the most common of which were social-ecological systems (41 studies), social network analysis (32 studies), and vulnerability (16 articles). The numbers throughout do not always add up to 82 because articles were classified into multiple categories where appropriate. The research questions asked in these articles covered a wide range of topics (see Figure 3 for illustrative research questions).

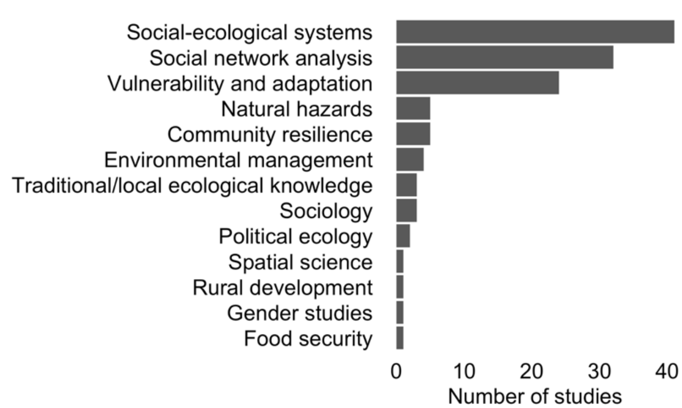

Figure 2: Frameworks used to study social interactions in social-ecological systems research of the studies reviewed.

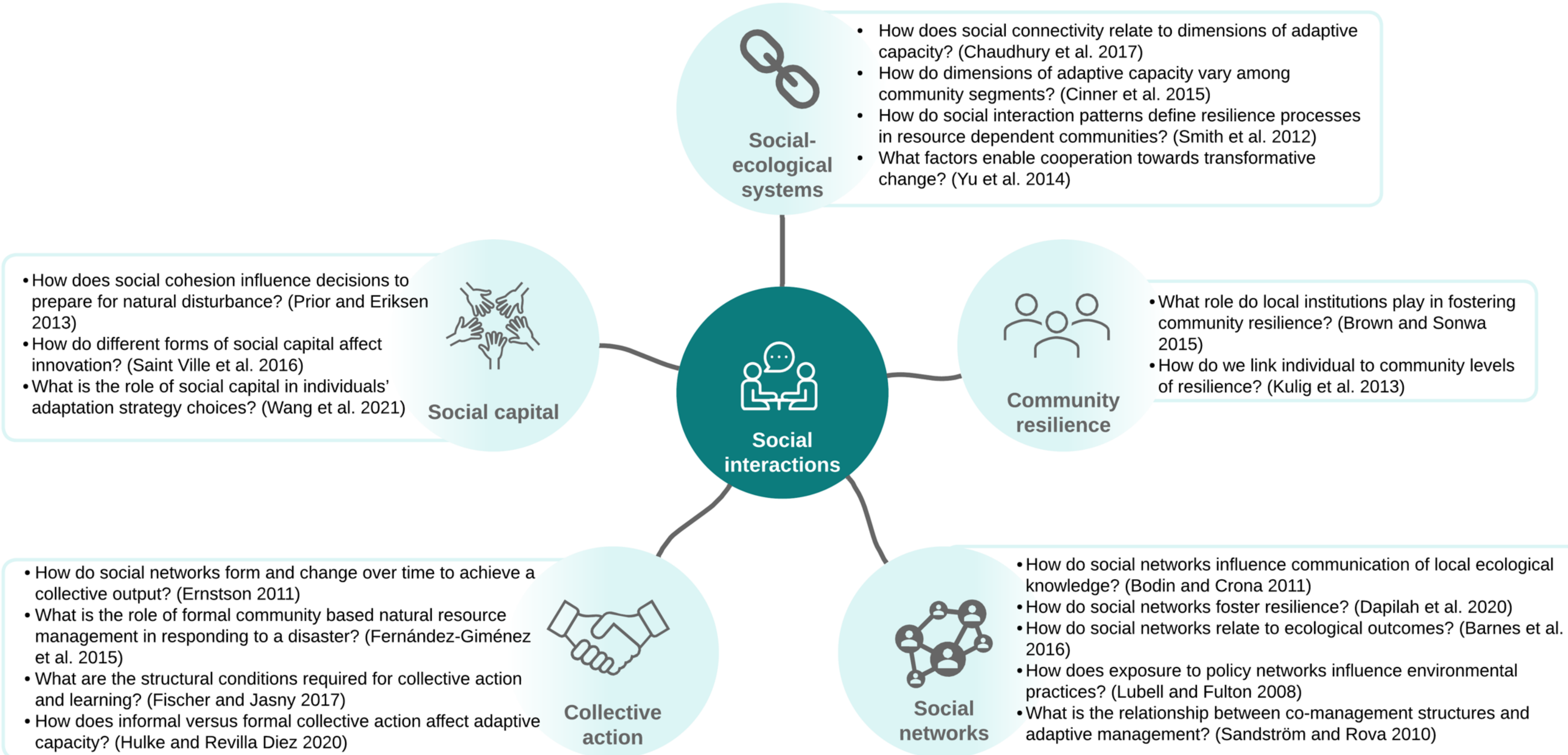

Figure 3: Illustrative research questions relating to social interaction concepts that were asked in the articles reviewed.

The articles were also focused on several different disturbances, locations, sectors, social levels, and spatial levels (Figure 4). The most common disturbance type was climate change (35 articles) and locations were geographically distributed across the globe. The most common sector was agriculture (28 articles). Most articles focused on both collective and individual levels (34 articles) or the perceptions of social interaction at the individual level (32 articles). Spatial levels varied but most studies were across multiple local areas (31 articles) or within one local area (22 articles).

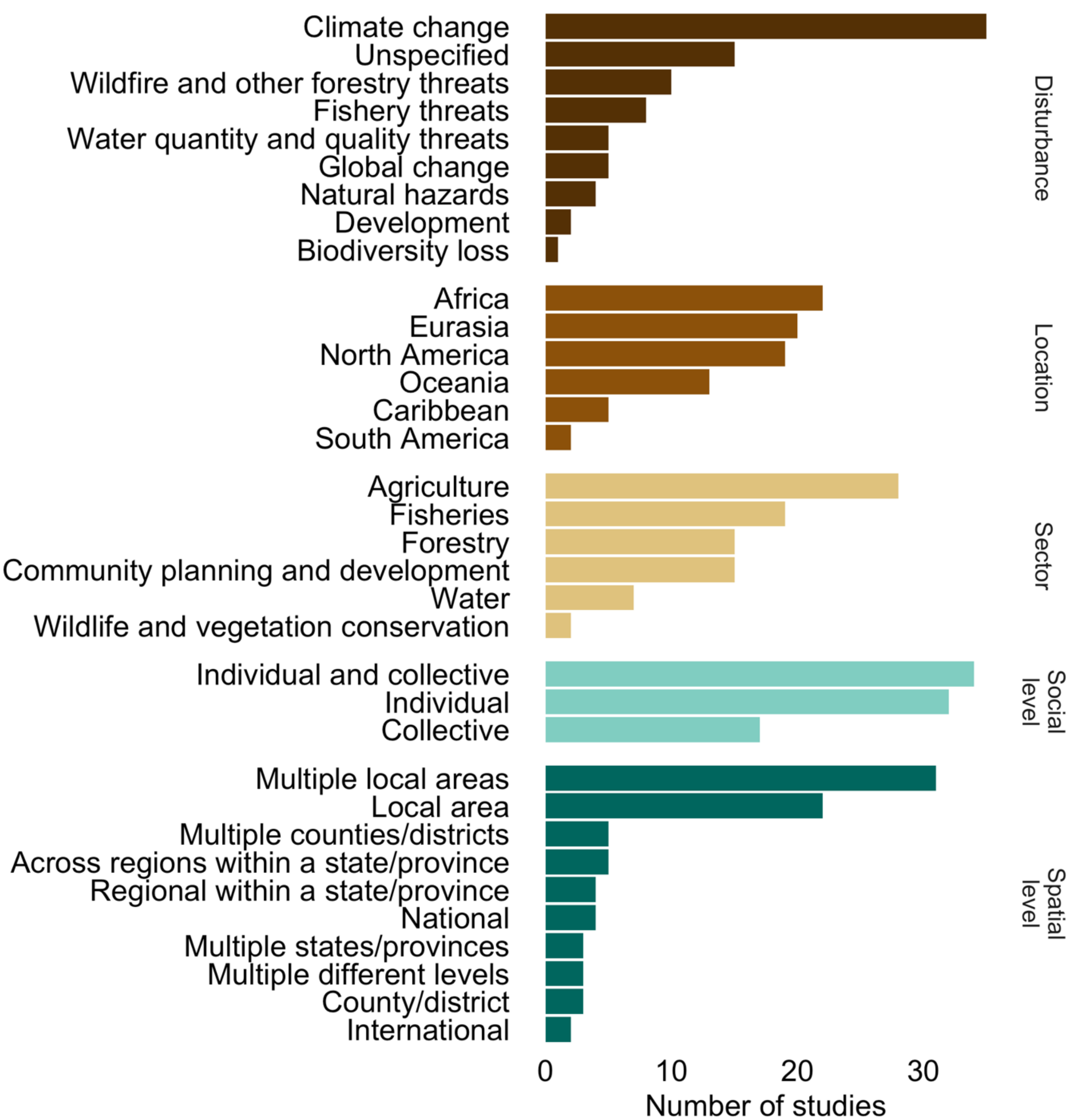

Figure 4: Disturbances, locations, sectors, social levels, and spatial levels of focus for the studies reviewed.

Summary of methodological approaches

A wide variety of data collection methods and quantitative analytical approaches were used by studies in this review (Figure 5). There were 36 articles that used a binary metaphorical approach to quantifying social interactions and 35 that used a structurally explicit approach to quantifying social capital (Table 2). Several articles also used descriptive, qualitative approaches in addition to other approaches (7 that combined binary metaphorical and descriptive, 4 that combined structurally explicit and descriptive).

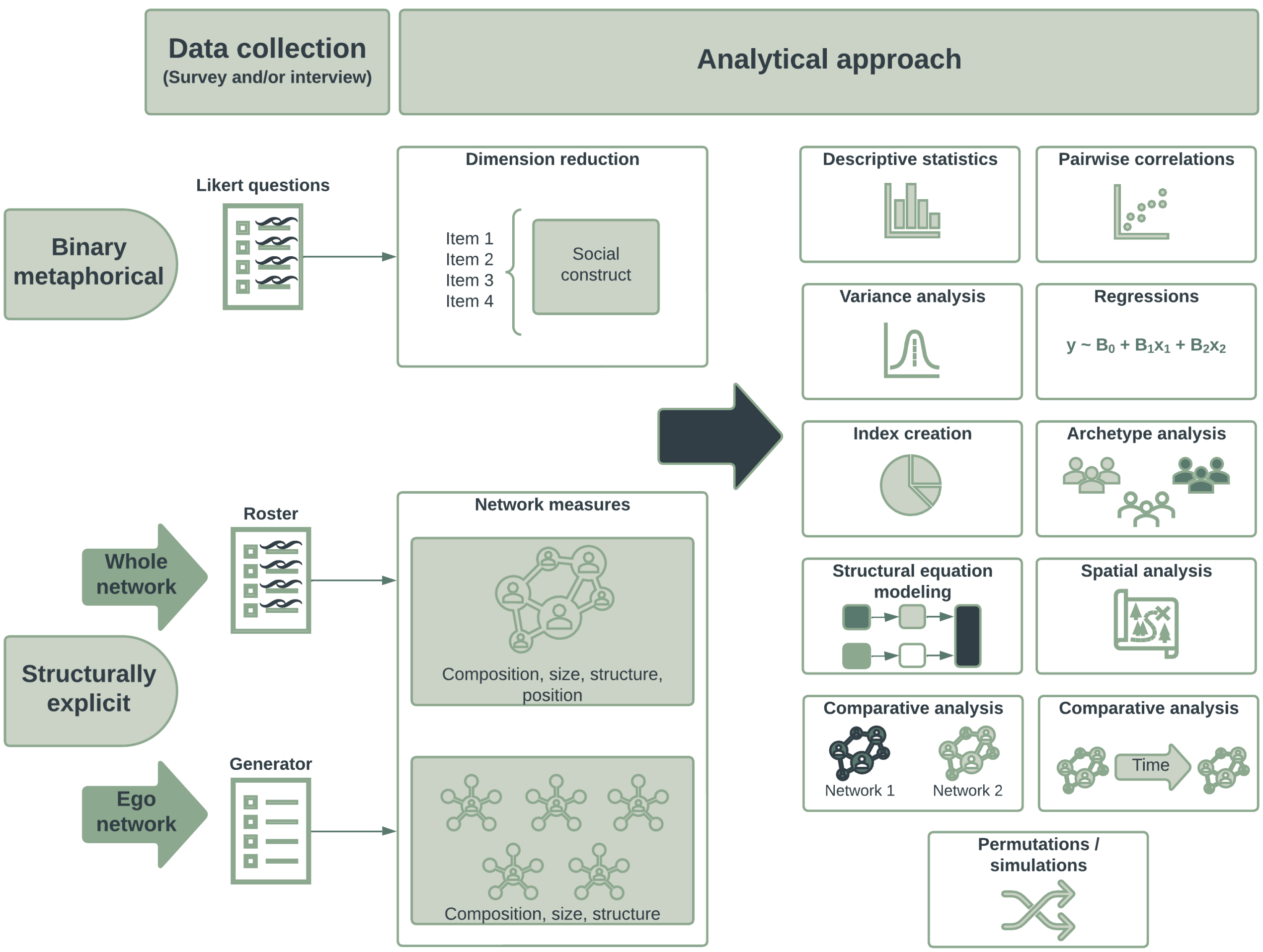

Figure 5: A summary of commonly used approaches for quantifying social interactions and their relationship to focal concepts in social-ecological systems science. Other data collection methods not shown here include using a census, document review, focus groups, informal conversations, key informant interviews, observations, participatory mapping, use of publicly available data, and workshops.

Table 2: Data collection methods/sources for each type of approach to characterizing social capital.

Type of approach	Example data collection method or source	Example quantitative analytical approach
Binary metaphorical (36 articles)	Document review, focus groups, informal conversations, interviews, observations, publicly available data, surveys	Archetype analysis, comparative analysis, correlations, descriptive statistics, dimension reduction, index creation or assessment, , regression, spatial analysis, structural equation modeling, variance analysis
Descriptive (11 articles)	Document review, focus groups, informal conversations, interviews, observations, surveys	Comparative analysis, correlations, descriptive statistics, dimension reduction, regression, social network analysis
Structurally explicit (35 articles)	Census, document review, informal conversations, interviews, focus groups, key informant interviews, observations, participatory mapping, surveys, workshops	Archetype analysis, comparative analysis, descriptive statistics, dimension reduction, permutations/simulations, regression, social network analysis, spatial analysis, structural equation modeling, variance analysis

Each of these approaches uses different data collection methods or sources (Table 3, Figure 6). The most common method for binary metaphorical and structurally explicit approaches to quantifying social interaction was with surveys. In the binary metaphorical approach, researchers typically asked binary or Likert style survey questions to a random sample to measure, for example, whether the respondent participates in different community/social groups, whereas in the structurally explicit approach using whole network design, researchers typically asked respondents to report on their ties to each actor from a pre-developed roster, providing structural and position data about the network. Rosters were developed by the researcher (sometimes in consultation with others) through a random or snowball sample, or a census. In an ego network study, researchers do not build a roster, rather the respondent lists their contacts through a name, position, or resource generator approach, which provides structural or resource access information. Other common approaches to data collection included interviews, focus groups, and document analysis. Less common approaches included informal conversations, key informant interviews, observations, participatory mapping, publicly available datasets, and workshops.

Table 3: Descriptions for each type of data collection method or source. Articles that use each method are provided.

Data collection method or source	Description	Citations
Census	Provides a complete understanding of the population; difficult to do except in small populations; can provide information about an entire social network	Barnes et al. 2020
Document review (e.g., reports, meeting minutes,	Can serve several different functions including informing holistic descriptions,	Alexander et al. 2015, Brown et al. 2010, Chaffin et al. 2016, Chaudury et al. 2017, Larson et al. 2013, Smith et al. 2013, Yu et al. 2014

Data collection method or source	Description	Citations
plans, legal material, historical/archival documents)	providing context, or providing social relational data on participants, group membership, frequency and types of interactions, etc.	
Focus groups	Can serve several different functions including informing holistic descriptions and qualitative analysis, providing context, or providing social relational data on participants, group membership, frequency and types of interactions, etc.	Alexander et al. 2015, Dapilah et al. 2020, Frazier et al. 2013, Fernández-Giménez et al. 2015, Ho et al. 2022,Lowitt et al. 2015, Nagel 2020, Rahman et al. 2018, Saint Ville et al. 2016, Salpeteur et al. 2016, Thong Anh Tran et al. 2020, Wang et al. 2021, Witinok-Huber &Radil 2021, Wongbusarakum et al. 2021
Informal conversations	Can serve several different functions including informing holistic descriptions and qualitative analysis, providing context, setting direction for relevant research questions, providing sampling information for surveys, providing feedback on findings, etc.	Barnes-Mauthe et al. 2013, Dapilah et al. 2020, Nagel 2020, Ramirez-Sanchez & Pinkerton 2009
Interviews	Can serve several different functions including collecting data on social interactions, informing holistic descriptions and qualitative analysis, providing context, setting direction for relevant research questions, providing sampling information for surveys, providing feedback on findings, etc.	Alexander et al. 2015, Barnes-Mauthe et al. 2013, Barnes et al. 2020, Bennett et al. 2014, Berardo et al. 2014, Brown et al. 2010, Brown et al. 2015, Carien De Villier et al. 2014, Chaudhury et al. 2017, Cinner et al. 2015, Crona and Bodin 2006, Crona and Bodin 2010, Dapilah et al. 2020, Dow et al. 2013, Eakin et al. 2016, Fischer and Jasny 2017, Frazier et al. 2013, Hulke and Diez 2020, Isaac and Dawoe 2014, Isaac et al. 2007, Kulig et al. 2013, Larson et al. 2013, Lowitt et al. 2015, Lubell et al. 2017, Mandryk et al. 2015, Nagel 2020, Noblw 2019, Osbahr et al. 2010, Paveglio et al. 2017, Prior and Eriksen 2013, Rahman et al. 2018, Robinson and Berkes 2011, Rockenbauch et al. 2019, Rubio et al. 2021, Saint Ville et al. 2016, Salpeteur et al. 2016, Schramski et al. 2018, Smith et al. 2012, Thiault et al. 2019, Thong Anh Tran et al. 2020, Tuda et al. 2019, Wang et al. 2021, Wongbusarakum et al. 2021, Yu et al. 2014
Key informant interviews	Can serve several different functions including informing holistic descriptions and qualitative analysis, providing context, setting direction for relevant research questions, providing sampling information for surveys, providing feedback on survey design, etc.	Barnes et al. 2020
Observations	Can serve several different functions including informing holistic descriptions and qualitative analysis, providing context, setting direction for relevant research questions, providing sampling information for surveys, providing context for different social interactions to aid in interpretation, etc.	Alexander et al. 2015, Dapilah et al. 2020, Ernstson 2011, Robinson & Berkes 2011
Participatory mapping	Can be used with participants to identify important areas on a map, provides spatially explicit data	Noble et al. 2019
Publicly available datasets	Typically used to inform large scale analyses	Cutter et al. 2014, Vincent 2007
Surveys	Used to quantify social constructs and interactions, typically from the perspective of the individual though can be done at higher social levels (e.g., organizations, agencies) with representatives	Afkhami et al. 2021, Akamani et al. 2015, Amadu et al. 2021, André et al. 2017, Barnes-Mauthe et al. 2013, Barnes-Mauthe et al. 2014, Barnes et al. 2016, Bennet at al. 2014, Bodin & Crona 2011, Brown et al. 2015, Brown et al. 2018, Chaffin et al. 2019, Chaudhury et al. 2017, Dapilah et al. 2020, Dow et al. 2013, Eakin et al. 2016, Ernstson 2011, Garcia de Jalon et al. 2018, Ho et al. 2022, Hulke et al. 2020, Jacobs & Cramer 2017, Jaja et al. 2017, Kulig et al. 2013, Legegui et al. 2022, Lockwood et al. 2015, Lowitt et al. 2015, Lubell et al. 2013, Lubell & Fulton 2008, Lubell et al. 2017, Malherbe et al. 2020, Marshall et al. 2016, Marshall & Smajgl 2013, Mukherjee & Siddique 2020, Nagel 2020, Orchard et al. 2015, Osbahr et al. 2010, Prior & Eriksen 2013, Rahman et al. 2018, Ramirez-Sanchez & Pinkerton 2009, Rockenbauch et al. 2019, Saint Ville et al. 2016, Salpeteur et al. 2016, Sandström & Rova 2010, Satumanatpan & Pollnac 2020,

Data collection method or source	Description	Citations
		Schramski et al. 2019, Schwarz et al. 2011, Shah & Dulal 2015, Sherrieb et al. 2012, Thennakoon et al. 2020, Thiault et al. 2019, Thong Anh Tran et al. 2020, Tindall et al. 2011, Tindall & Robinson 2017, Tuda & Machumu 2019, Vincent 2007, Wang et al. 2021, Wickes et al. 2015, Witinok-Huber & Radil 2021, Wongbusarakum et al. 2021, Yu et al. 2014
Workshops	Can serve several different functions including informing holistic descriptions and qualitative analysis, providing context, setting direction for relevant research questions, providing sampling information for surveys, providing feedback on findings, etc.	Chaudhury et al. 2017

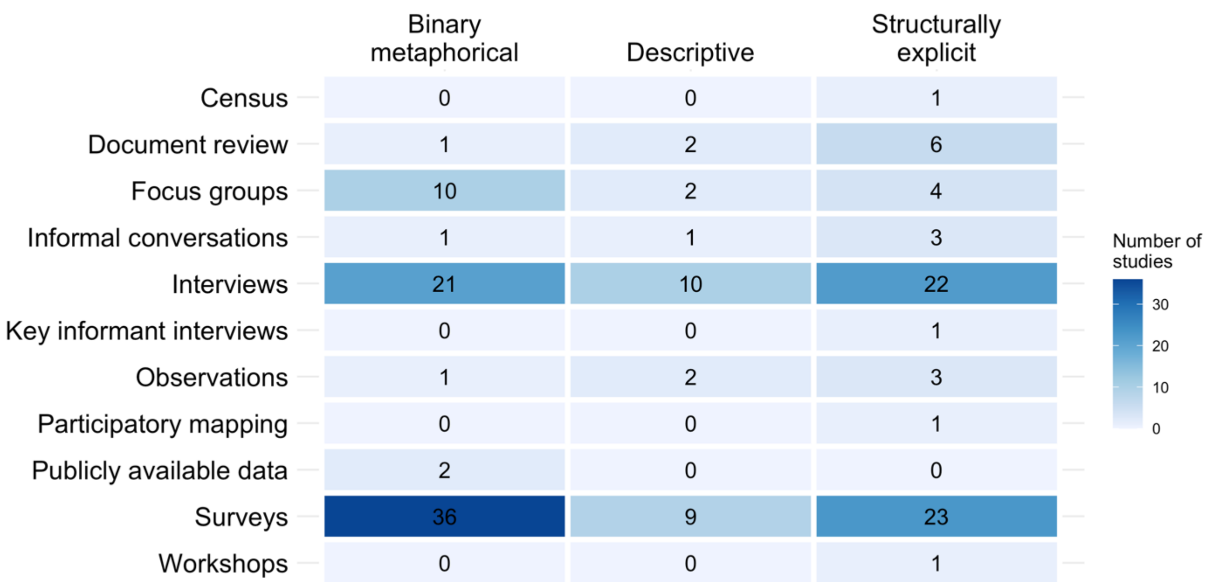

Figure 6: Number of binary metaphorical, descriptive, and structurally explicit studies that used each type of data collection method or source.

Studies also used a variety of approaches to quantitatively analyze social interactions and their relationship with social-ecological focal concepts (Table 4, Figure 7). With binary metaphorical approaches, after using a survey, interview, or other method to measure a latent social interaction, researchers typically used dimension reduction techniques to create composite variables. These composite variables were made up of different items that measured different components of the latent construct. For example, researchers in one article quantified bonding social capital using four items in a survey that asked about household trust, leadership, working together, and supporting one another (Akamani and Hall 2015). Using dimension reduction techniques, they converted these four items into one composite variable. After dimension reduction, some researchers used descriptive statistics and correlations (Eakin et al. 2016) or analysis of variance techniques (Fernández-Giménez et al. 2015) to understand patterns and relationships with other variables. Other researchers used regression techniques (Sherrieb et al. 2012, Akamani and Hall 2015, Wickes et al. 2015, Tran et al. 2020, Wongbusarakum et al. 2021) or structural equation modeling (Prior and Eriksen 2013) to understand more complex relationships. Dimension reduction techniques were also used to create indices that measured different components of resilience or adaptive capacity, which were combined to generate an overall index (Cutter 2016). In all the studies reviewed, at least one of these dimensions included a measure of social interaction. Researchers also sought to classify respondents into different groups or archetypes based partly on different social interactions (Marshall and Smajgl 2013, Paveglio et al. 2017, Rubio et al. 2021, Lecegui et al. 2022). Two articles also used spatially explicit methods to quantify binary metaphorical social relations (Frazier et al. 2013, Cutter et al. 2014).

Table 4: Quantitative analytical approaches to analyzing social interactions and their relationship with social-ecological systems focal concepts. Articles that used each approach are provided.

Quantitative analytical approach	Description	Citations
Descriptive statistics	Used to summarize data, often used in conjunction with other analytical approaches to highlight differences among cases/groups or over time	Barnes-Mauthe et al. 2013, Bennett et al. 2014, Brown et al. 2015, Brown et al. 2018, Chaudhury et al. 2017, Cinner et al. 2015, Crona & Bodin 2006, Crona & Bodin 2010, Dapilah et al. 2020, Dow et al. 2013, Lowitt et al. 2015, Mandryk et al. 2015, Marshall et al. 2016, Osbahr et al. 2010, Sandström & Rova 2010, Thiault et al. 2019
Correlations	Typically used to relate different latent dimensions of a social construct with that of another	Eakin et al. 2016, Thiault et al. 2019
Variance analysis (e.g., ANOVAs, ANCOVAs, PERMANOVAs)	Used to determine statistical differences among groups	Barnes-Mauthe et al. 2013, Fernández-Giménez et al. 2015, Salpeteur et al. 2016, Witinok-Huber & Radil 2021
Dimension reduction (e.g., factor analysis, principal component analysis)	Used to create composite variables based on items typically in a survey or interview, typically used to measure latent social constructs, sometimes used to create indices	Afkhami et al. 2021, Akamani & Hall 2015, Amadu et al. 2021, Cutter et al. 2014, Eakin et al. 2016, Fernández-Giménez et al. 2015, Garcia de Jalon et al. 2018, Kulig et al. 2013, Lecegui et al. 2022, Lockwood et al. 2015, Nagel 2020, Paveglio et al. 2017, Prior & Eriksen 2013, Schramski et al. 2018, Sherrieb et al. 2012, Thong Anh Tran et all. 2020, Wickes et al. 2015, Witinok-Huber & Radil 2021, Wongbusarakum et al. 2021
Archetype analysis (e.g., cluster analysis, latent class analysis)	Used to group data into categories, often used to categorize respondents based on items in a survey or interview	Lecegui et al. 2022, Marshall & Smajgl 2013, Paveglio et al. 2017, Rubio et al. 2021
Structural equation modeling	Used to measure the relationships between variates and a latent construct, often variates are correlated	Afkhami et al. 2021, Amadu et al. 2021, Lockwood et al. 2015, Prior & Erkisen 2013
Index creation or assessment	Used to assess resilience or vulnerability of populations, often over space (e.g., Baseline Resilience Indicators for Communities, Livelihood Vulnerability Index, Sustainable Livelihoods Index, National and Household Adaptive Capacity Indices,	Cutter et al. 2014, Ho et al. 2022, Malherbe et al. 2020, Mukherjee & Siddique 2020, Vincent 2007, Witinok-Huber & Radil 2021

Quantitative analytical approach	Description	Citations
	Local Agricultural Potential Index), typically generated with dimension reduction techniques	
Comparative analysis - cases, longitudinal	Used to compare similar cases or one case over time, supports causality for small sample sizes (as in social network analysis studies)	Alexander et al. 2015, Chaffin et al. 2016, Ernstson 2011, Isaac et al. 2007, Jaja et al. 2017, Orchard et al. 2015, Rahman et al. 2018, Sandström & Rova 2010, Tuda et al. 2019
Regression (e.g., linear, logistic, autologistic actor attribute, ordinary least squares)	Used to understand the effects of variables on an outcome	Akamani & Hall 2015, Barnes et al. 2016, Barnes et al. 2020, Chaffin et al. 2019, Garcia de Jalon 2018, Ho et al. 2022, Hulke & Diez 2020, Isaac & Dawoe 2011, Jacobs & Cramer 2017, Lubell et al. 2013, Lubell & Fulton 2008, Paveglio et al. 2017, Satumanatpan & Pollnac 2020, Schramski et al. 2018, Schwarz et al. 2011, Shah & Dulal 2015, Sherrieb et al. 2012, Smith et al. 2012, Thennakoon et al. 2020, Thong et al 2020, Tindall et al. 2011, Tindall & Robinson 2017, Wang et al. 2021, Wickes et al. 2015, Wongbusarakum et al. 2021, Yu et al. 2014
Permutations, simulations	Used with small sample sizes to test for statistical significance; a special kind of permutation technique for whole network analysis is called exponential random graph modeling, which is used to predict the probability of ties among nodes in whole networks, necessary because whole network data violate independence assumptions of standard statistic procedures	Berardo 2014, Crona & Bodin 2006, Fischer & Jasny 2017, Nagel 2020, Rubio et al. 2021
Social network analysis - whole	Used to understand how social relations affect outcomes (e.g., social choice research on influence and diffusion, social success research on cooperation and resource/knowledge acquisition) typically for a defined group, or to understand how a condition or stimulus affects social relations, requires a high level of participation in the study for reliable results	Afkhami et al. 2021, Alexander et al. 2015, Barnes-Mauthe et al. 2013, Barnes-Mauthe et al. 2014, Barnes et al. 2016, Berardo 2014, Bodin & Crona 2011, Brown et al. 2010, Carien de Villiers et al. 2014, Chaffin et al. 2016, Chaffin et al. 2019, Chaffin et al. 2016, Chaudhury et al. 2017, Crona & Bodin 2006, Crona & Bodin 2010, Ernstson 2011, Fischer & Jasny 2017, Isaac et al. 2007, Isaac and Dawoe 2011, Jacobs & Cramer et al. 2017, Jaja & Jackie 2017, Larson et al. 2013, Lubell et al. 2017, Nagel 2020, Noble et al. 2019, Ramirez-Sanchez & Pinkerton 2009, Rockenbauch et al. 2019, Rubio et al. 2021, Saint Ville et al. 2016, Schramski et al. 2018
Social network analysis - ego	Used to understand how the immediate social relations of an individual affect outcomes, collected through random sampling methods typically and can be used with standard statistical procedures, sometimes ego centric approaches are used in conjunction with whole network approaches	André et al. 2017, Barnes et al. 2020, Isaac & Dawoe 2011, Orchard et al. 2015, Tindall et al. 2011, Tindall & Robinson 2017
Spatial analysis	Used to understand spatial variation in social concepts, including social relations	Cutter et al. 2014, Frazier et al. 2013, Noble et al. 2019

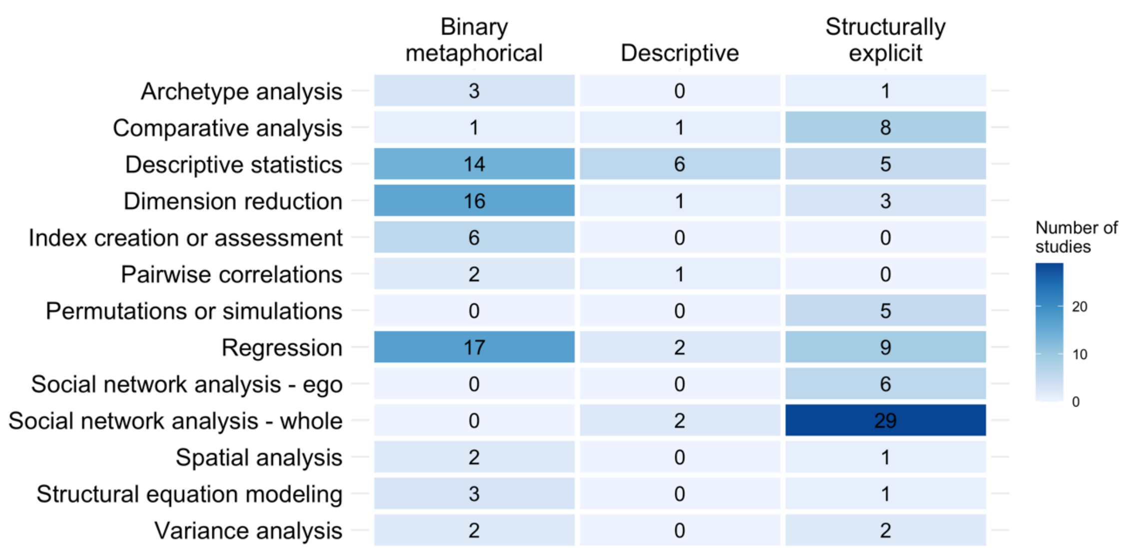

Figure 7: Number of binary metaphorical, descriptive, and structurally explicit studies for quantitative analytical approaches to analyzing social interactions and their relationship with social-ecological systems focal concepts

In structurally explicit approaches, researchers used either a whole or ego network design (Figure 8). Whole network research designs were more common and study the ties among nodes in a set of nodes. The relationship between every pair of nodes is quantified as a dyadic variable. For instance, in a study on communication between people in a community watershed group, there would be a value for every pair of people where 0 might mean no communication between the pair and 1 might mean that they communicate with one another. In contrast, ego network designs (also called personal, ego centered, or egocentric network designs) study the interpersonal relationships of an ego, that is the person of focus. The nodes that ego is tied to are called alters. With ego network design, the researcher is interested in a person's immediate contacts, in other words, ego's surrounding social environment. Ego networks typically look at ego-alter and alter-alter ties, although sometimes alter-alter ties are not examined (or data are not available). Researchers may sample a set of egos from a population, and each ego's alters need not be an ego in the study. Ego networks can also be examined within whole networks.

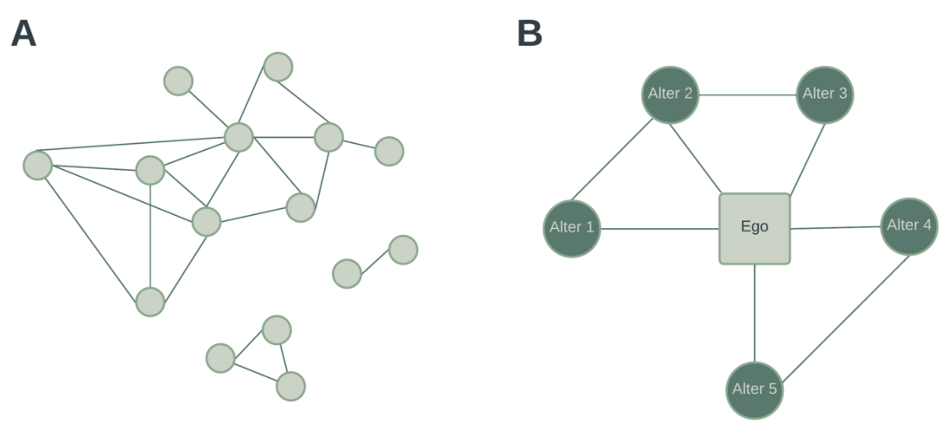

Figure 8: A whole network (A) and an ego network (B) visualized.

Whole network data were analyzed in several different ways. First, specific network measures were quantified for a network and often descriptive statistics were used to summarize these measures (Crona and Bodin 2010, Barnes-Mauthe et al. 2013, Chaudhury et al. 2017). Using network measures as an explanatory variable, researchers assessed relationships with other variables using structural equation modeling (Afkhami et al. 2021) or regression techniques (Barnes et al. 2016, Jacobs and

Cramer 2017, Schramski et al. 2018, Chaffin et al. 2019). In some instances, causality was established with longitudinal studies, which examined networks at different temporal snapshots (Ernstson 2011, Chaffin et al. 2016*a*), or by comparing different networks in similar contexts through case studies (Sandström and Rova 2010). Because whole network designs are cumbersome and resource intensive, they are often limited by small sample sizes. While the network may have a large number of nodes, if a researcher only studied one network, the sample size would be one (depending on the inferences made). In these cases, a few studies used permutation and simulation techniques to generate larger sample sizes and improve inferential power (Crona and Bodin 2006, Nagel 2020). To use network connections themselves as the response variable, specialized techniques are required because whole network research typically does not come from a random sample and by definition violates the assumption of case-wise independence. A few articles reviewed used exponential random graph models to predict the probability of ties (Berardo 2014, Fischer and Jasny 2017, Rubio et al. 2021). A few studies in this review examined how a condition or stimulus affects social relations (Ernstson 2011, Barnes-Mauthe et al. 2013, Berardo 2014, Orchard et al. 2015, Chaffin et al. 2016*a*). Only one structurally explicit study used spatial approaches to quantify social interactions (Noble et al. 2019). Ego network studies typically used descriptive statistics and regression techniques (Evans 2011, André et al. 2017, Tindall and Robinson 2017).

Summary of social interaction measures

I organized social interaction measures based on the type of social outcome studied and the mechanism (i.e., ties as pipes or bonds) driving the social outcome (Table 5; Borgatti and Halgin 2011). Social outcomes include success that is brought about by social interactions (i.e., social capital) or similarity of choice based on social interactions (i.e., social homogeneity). In the context of social-ecological systems studies, success via piping social interactions includes studies examining improved resilience or adaptive capacity, whereas success via bonding social interactions includes studies of cooperative arrangements or collective action toward resource management. Similarity of choice via piping social interactions includes studies examining social learning process, knowledge sharing, and innovation diffusion that alter adaptive strategies or behaviors. Different social interaction concepts based on the social outcome of concern and the mechanism driving that outcome are shown in Table 5. Studies did not always differentiate between ties as bonds that achieve cooperation versus ties as pipes that achieve resilience/adaptive capacity, in part because social processes are linked to one another and highly contextual. Although I show measures and studies falling into different categories, often the social outcomes and mechanisms were difficult to categorize because multiple outcomes and mechanisms can exist at once.

Table 5: Typology of social interaction measures, based partly on Borgatti and Halgin (2011).

Social outcome (success vs similarity of choice)	**Mechanism (ties as pipes vs bonds)**	**Concept**
Social capital (success)	Pipes -Achievement (e.g., improved resilience, adaptive capacity)	Information and/or resource exchange
		Social power and equity through resource access
	Bonds – Cooperation	Collective action (co-management, community based natural resource management, environmental activism, etc.)
		Cohesion, network shape, and ties
		Social power and equity through structural position
		Leadership
		Group membership
		Reciprocity
		Strength of ties
		Conflict
		Constraint
Social homogeneity (similarity of choice)	Pipes - Contagion (e.g., diffusion of information or behavior)	Communication of information and social learning
		Diversity and exposure vs redundancy and specialization
		Innovation engagement

Example measures of social interaction using binary metaphorical approaches are classified based on this typology in Table 6 for social capital and in Table 7 for social homogeneity. Example measures of social interaction using structurally explicit approaches are classified based on this typology in Table 8 for social capital and in Table 9 for social homogeneity. I selected illustrative examples for this these tables – for a complete list of measures and an overview of social network measures, see Appendi.

Binary metaphorical achievement – social capital via pipes

A few binary metaphorical studies quantified achievement through pipes that convey social capital (i.e., resources, access to important information; Table 6). Methods included surveys or interviews to have individuals state the extent to which they agree/disagree (Likert scale) with certain statements about how social interactions influence their success. Further analyses were then used to understand the relationship between the success brought about by social interactions and their adaptive capacity or personal resilience (Lockwood et al. 2015). A less common approach was to ask individuals who helped them during a crisis, and then classify those individuals as providing bridging linkages to external resources/information if they were representatives from government or other organizations, or as providing bonding linkages to others in the community for some type of material support (Fernández-Giménez et al. 2015). Several studies highlighted that local bonding capital is often strong, but its effect on resilience/adaptive capacity can be limited by a lack of bridging capital to external resources/information (Bennett et al. 2014, Fernández-Giménez et al. 2015). Some studies examined how community group membership influenced resource access and decision-making input, and thus resilience/adaptive capacity (Cutter et al. 2014, Cinner et al. 2015, Fernández-Giménez et al. 2015, Dapilah et al. 2020, Satumanatpan and Pollnac 2020). Four studies specifically examined how differential access to resources and information can lead to social stratification of resilience/adaptive capacity. To do so, one study specifically asked about equal access and vulnerability (Malherbe et al. 2020), another study asked about bargaining power in market exchanges of natural resources (Thiault et al. 2019), while the other two studies compared access among social groups (Cinner et al. 2015, Witinok-Huber and Radil 2021).

Binary metaphorical cooperation – social capital via bonds

Several articles in this review used binary metaphorical approaches to study achievement through bonds that convey social capital for cooperation (Table 6). Studies typically examined how social capital (broadly described as conveying cohesion, reciprocity, leadership, and trust) enabled some form of cooperation towards conservation or natural resource management (e.g., community based natural resource management (CBNRM), co-management, collection action in the form of activism, etc.). Studies asked questions about the extent to which people participate in collective action arrangements (Akamani and Hall 2015, Fernández-Giménez et al. 2015, Jacobs and Cramer 2017) and related social capital measures to participation. For example, bonding social capital, whereby household members trust and support one another, work together, and have good leadership, had a significant, positive effect on collaborative resource management participation (Akamani and Hall 2015), while sense of community had a positive effect on collective problem solving on wildfire preparedness (Prior & Eriksen 2013). However, results were not always consistent across studies and contexts. For example, another study on community wildfire preparedness examined how social cohesion influenced different types of community level planning, finding that cohesion had a significant, positive effect for some types of community activities and no effect for others (Paveglio et al. 2017). Similarly, there are mixed results on how trust and frequency of interaction, indicators of the strength of the relationship, influenced collaborative outcomes. For example, there is a positive relationship between trust/frequency of interaction and livelihood resilience in fishers (Amadu et al. 2021) and between trust in peers/government/researchers and some dimensions of transformative capacity in agricultural producers (Marshall et al. 2016), yet no effect on perceptions of resilience in agricultural producers in another study (Lockwood et al. 2015), on post flood recovery (Wickes et al. 2015), and on adaptive/transformative behavior in an island community (Barnes et al. 2020). While cooperation is mostly described in a positive light, a few studies examined how binding ties forced cooperation in a constraining manner. For example, while formal networks influenced choice of adaptation strategies in agricultural producers, informal networks negatively affected behavior suggesting that close ties with family/friends may constrain choices (Wang et al. 2021). In a slightly related vein, heterogeneity of actors in a cooperative setting paralyzed decision making and constrained collaborative abilities in the Netherlands (Mandryk et al. 2015).

Binary metaphorical contagion – social homogeneity via pipes

There is strong binary metaphorical quantitative evidence that information exchange through social interactions has a positive effect on innovation diffusion and adaptive behavior in social-ecological systems research. There were several binary metaphorical social homogeneity studies that quantified social interactions as conduits (i.e., pipes) of information toward innovation diffusion or behavior changes like adaptation (Table 7). Borgatti and Halgin (2011) refer to this concept as contagion – how something spreads through social interaction. Most studies examined contagion in the context of knowledge exchange, access to information, and external or social learning. These concepts were quantified by asking a respondent with which groups they were in contact regarding conservation information (Lubell et al. 2013) or the extent to which (on a Likert scale) they engaged in communication with their peers and other organizations (Eakin et al. 2016, Marshall et al. 2016, Tran et al. 2020). Studies then related these interaction measures to behavioral change. For example, social learning (quantified in various ways) had a positive relationship with adaptive behavior (Marshall et al. 2016) and adaptive management (Eakin et al. 2016) in agricultural producers. Bridging linkages between households and government leadership, presumably as information conduits, had a positive effect on a household's adaptive behavior (Thennakoon et al. 2020) and influenced choice of adaptation strategies (Wang et al. 2021) in agricultural producers, while bonding linkages had a significant, positive effect on climate change concerns, highlighting how close, trusting relationships may be among the most influential when preparing for wildfire (Jacobs & Cramer 2017).

Table 6: Binary metaphorical example measures and quantified relationships for social capital studies. Please note that the relationships listed in the final column are specific to the studies mentioned and may be highly contextual in some instances.

Mechanism	Concept	Example measures	Quantified relationships with a social-ecological systems concept
Pipes - Achievement (e.g., improved resilience, adaptive capacity)	Information and/or resource exchange	**Local networks (LN)** As a result of building connections with local groups… LN1 - I am better able to achieve my nature conservation goals LN2 - I better understand how my conservation management contributes to communities LN3 - I better understand the social, economic, and environmental factors affecting my property (Lockwood et al. 2015) **Structural social capital (bonding vs bridging)** Who helped you during a time of need in the last 5 years (bonding - actor listed has a similar social position; bridging - actor listed is an expert, government, bank, NGO) (Fernández-Giménez et al. 2015) **Group membership** Total groups - Number of community groups to which the respondent belonged (Cinner et al. 2015, Cutter et al. 2014, Dapilah et al. 2020, Fernández-Giménez et al. 2015, Satumanatpan & Pollnac 2020)	Local networks and social capital have been shown to have positive, significant effects on adaptive capacity and personal resilience (Fernández-Giménez et al. 2015, Lockwood et al. 2015), a positive, but insignificant effect on food security (Shah & Dulal 2015), and a negative effect on vulnerability (Malherbe et al. 2020). Bonding capital may improve adaptive capacity to a point, though may limit actors when it is too strong (Fernández-Giménez et al. 2015). Although local bonding capital mitigates the effects of high-level constraints, higher level social processes act as barriers, particularly for cross-boundary issues, and may require more bridging capital to alleviate (Fernández-Giménez et al. 2015, Bennet et al. 2014). Group membership may be related to increased adaptive capacity (Fernández-Giménez et al. 2015) and resilience (Satumanatpan & Pollnac 2020) through livelihood diversification and resource access (Dapilah et al. 2020) and decision-making input (Cinner et al. 2015); however, it is also related to exclusion (Dapilah et al. 2020). Group membership also has a positive effect on income in one study (Smith et al. 2012).
	Social power and equity through resource access	**Equal access to services and resources** EA1 - Would you say that everyone in this community is equally vulnerable or are some people more vulnerable than others? EA2 - How equal is access to resources in your community? (Malherbe et al. 2020) **Bargaining power** Level of trust in middlemen (Thiault et al. 2019)	While women have less resource access and leadership opportunities than men in one study (Witinok-Huber & Radil 2021), equal access and gender equity has been shown to decrease vulnerability (Malherbe et al. 2020). Individuals with the least decision-making input also have the lowest social capital, indicating social stratification and a need for targeted interventions (Cinner et al. 2015). Generic adaptive capacity is significantly, positively correlated with specific adaptive capacity (including bargaining power) (Thiault et al. 2019).
Bonds - Cooperation	Collective action (co-management, community based natural resource management (CBNRM), environmental activism, etc.)	**Participation in collective action** Level of participation in CBNRM (Akamani & Hall 2015, Fernández-Giménez et al. 2015), etc. **Collective action oriented around emergency preparedness (CA; only social items in scale shown)** CA1 - Most people in…would attend public education and emergency preparedness presentations CA2 - If there is a community event to assist people with becoming prepared for X, most people will participate in some way CA4 - Most people in…participate in community activities CA5 - If there was an emergency, people would come together to solve the problems CA7 - People in…work together with government to benefit the community (Jacobs & Cramer 2017)	Sense of community has a positive effect on collective problem solving (Prior & Eriksen 2013). Bonding social capital has a significant, positive effect on collaborative resource management participation (Akamani & Hall 2015) and climate change concerns (Jacobs & Cramer 2017). Community-based natural resource management participants exhibit more knowledge exchange, information access, linking social capital, and proactive behavior, and thus higher adaptive capacity (Fernández-Giménez et al. 2015).
	Cohesion, network shape, and ties	**Social cohesion (SC)** SC1 - Residents share a sense of values and culture SC2 - Residents have a strong sense of community SC3 - Residents are vested in the future and well-being of each other (Paveglio et al. 2017) **Community engagement (CE)** CE1 - There is a sense of pride among people in my community CE2 - People who live in my community have similar values or ideas CE3 - The people in my community are open to new ideas CE4 - People in my community help out one another CE5 - Residents of my community participate in community events (Kulig et al. 2013) **Bonding social capital (BO)** BO1 - My household members trust one another BO2 - My household has effective and visionary leadership BO3 - My household members work closely with one another to address household needs BO4 - My household members are supportive of one another (Akamani & Hall 2015) **Bridging social capital (BR)** BR1 - My household members work closely with other households to address household needs BR2 - My household members and other households trust one another	Cohesion has mixed effects on local collective adaptation depending on the context (Paveglio et al. 2017). Bonding social capital has a significant, positive effect on collaborative resource management participation (Akamani & Hall 2015). Bridging social capital has a positive relationship with collective climate change adaptation because it helps overcome limited political supporting one study (Dow et al. 2013), while in another bridging social capital does not have an effect on collaborative resource management participation (Akamani & Hall 2015). A lack of bridging ties may hinder local efforts to adapt (Bennett et al. 2014, Fernández-Giménez et al. 2015).

Mechanism	Concept	Example measures	Quantified relationships with a social-ecological systems concept
		BR3 - My household members and other households support one another (Akamani & Hall 2015) **Organization membership** Level of representation from different organizations across sectors (Dow et al. 2013)	
	Leadership	**Opinion leadership** OL1 - I share information with people who would not otherwise communicate with each other OL2 - I think most people consider me to be an opinion leader in the industry (Lubell et al. 2013) **Leadership and empowerment (LE)** LE1 - My community has strong community leadership LE2 - Leaders in my community listen to the residents LE3 - The changes in my community are positive LE4 - When a problem occurs, community members are able to deal with it (Kulig et al. 2013)	Households with strong leadership may cope better with past shocks and be better prepared for future issues, while community collaboration and cohesion around leaders improve perceived adaptive capacity (Schwarz et al. 2011). Opinion leaders with access to conservation information were more likely to participate in conservation programs (Lubell et al. 2013). Leadership has mixed effects on local adaptation depending on the context in one study (Paveglio et al. 2017) and limited effects on adaptive capacity in another (Fernández-Giménez et al. 2015).
	Reciprocity	**Reciprocity (R)** R1 - I feel a responsibility to make a contribution to the community I live in R2 - If there was a serious problem in this community, people would get together and solve it R3 - People around here are generally supportive of each other (Lockwood et al. 2015) **Cognitive social capital (CSC)** CSC1 - People in my community always try to help each other CSC2 - People in my community help each other in times of need CSC3 - Most people in my community are trustworthy CSC4 - People in my community mainly look out for themselves (reverse coded) CSC5 - If given the chance, people in my community will take advantage of others (reverse coded) CSC6 - I am concerned that our community is getting less friendly, people are less connected to each other and not looking out for each other (reverse coded) (Fernández-Giménez et al. 2015)	There is a positive, significant relationship between some adaptive capacity dimensions and community commitment (Eakin et al. 2016) and between personal resilience and reciprocity (Lockwood et al. 2015). Cognitive social capital has a moderate effect on adaptive capacity in one study (Fernández-Giménez et al. 2015). Community competence may contribute to community resilience (Sherrieb et al. 2012).
	Strength of ties	**Interpersonal trust (IT)** IT1: How many trustworthy relatives and friends does your family have in X? IT2: What extent do you trust in outsiders? IT3: Trust in central government, news media, village cadres (Wang et al. 2021) **Frequency of neighboring (FN)** FN1 - How often do you and people in your community do favors for each other? FN2 - How often do you and people in your community visit in each other's homes or on the street? FN3 - How often do you and people in your community ask each other for advice about personal things such as child rearing or job openings? (Wickes et al. 2015)	There is a positive relationship between self-organization capacity (which included elements of trust and frequency of interaction) and livelihood resilience (Amadu et al. 2021), and between trust in peers/government/researchers and some dimensions of transformative capacity (Marshall et al. 2016). Interpersonal and institutional trust influence the choice of different adaptation strategies (Wang et al. 2021). In some instances, tie strength does not have an effect, such as with interaction frequency in one study examining the differences between areas affected and not affected by a hazard (Wickes et al. 2015) and with trust in studies examining perceived adaptive capacity (Lockwood et al. 2015) and adaptive/transformative behavior (Barnes et al. 2020).
	Constraint	**Informal networks (IN)** IN1: Number of relatives and friends visiting during the Spring Festival IN2: Relationships with relatives and friends IN3: Number of relatives and friends who provide help during busy farming season (Wang et al. 2021) **Heterogeneity of actors' interests within a network** Number of related actors, number of farmers, number of private companies, number of nature protection organizations (Mandryk et al. 2015)	Formal networks influence choice of adaptation strategies, yet informal networks negatively affect behavior suggesting that family/friends may constrain choices (Wang et al. 2021). Bonding social capital improves adaptive capacity to a point, but results in limited flexibility when it is too strong (Bennett et al. 2014). Heterogeneity of actors' interests indicates an inability to agree on common goals and priorities, paralyzing decision making and inhibiting adaptive management (Mandryk et al. 2015). Adaptive capacity at local social levels can be constrained by higher governance levels (Fernández-Giménez et al. 2015).

Table 7: Binary metaphorical example measures and quantified relationships for social homogeneity studies. Please note that the relationships listed in the final column are specific to the studies mentioned and may be highly contextual in some instances.

Mechanism	Concept	Example measures	Quantified relationships with a social-ecological systems concept
Pipes - Contagion (e.g., diffusion of information, behavior)	Communication of information and social learning	**Knowledge exchange** I know people I can talk with about disaster preparedness and risk management (Fernández-Giménez et al. 2015) **Conservation information sources** Level of contact respondent had with conservation/environmental groups, conservation districts, agencies, extension, college/university researchers (Lubell et al. 2013) **External learning performance (ELP)** ELP1 - When necessary, I can call on extension officials for help ELP2 - When attending seminars, I usually take part in discussions with other participants ELP3 - I am assisted by extension officials enthusiastically ELP4 - The learning interactions between locals and extension officials take place during seminars ELP5 - I usually visit successful management areas to learn and follow ELP6 - Shared learning and discussions provide me with compelling initiatives ELP7 - I usually discuss conservation/management activities when having coffee or parties with friends (Thong Anh Tran et al. 2020) **Learning and knowledge seeking (LKS; only social items in scale shown)** LKS6 - I like to discuss challenges facing my industry with researchers LKS7 - I seek the advice of other people in my industry in the region (Eakin et al. 2016)	Social learning and knowledge exchange has a significant, positive relationship with adaptive capacity (Thong Anh Tran et al. 2020, Lockwood et al. 2015, Fernández-Giménez et al. 2015). Strategic skills (including communicating about management) and adaptive behavior have a positive relationship (Marshall et al. 2016), as do learning/knowledge seeking and adaptive management (Eakin et al. 2016). Self-organization (including information access) as a dimension of adaptive capacity is significantly, positively related to different adaptation strategies (Lecegui et al. 2022). Bridging linkages between households and government leadership have a positive effect on a household's adaptive behavior (Thennakoon et al. 2020) and influences choice of adaptation strategies (Wang et al. 2021).
	Diversity and exposure	**Policy network contacts** Number of agencies contacted by respondent from a list (Lubell & Fulton 2008) **Formal networks** FN1: Does the family member have any person holding a village cadre or administrative position? FN2: Does the family member participate in mutual aid associations or organizations? (Wang et al. 2021)	Network exposure has positive, significant effects on some innovative behaviors (Lubell & Fulton 2008), while exposure to formal networks influences choice of adaptation strategies (Wang et al. 2021).
	Innovation engagement	**Access to markets** Access to formal and informal markets (Lowitt et al. 2015)	Access to markets enables innovation (Lowitt et al. 2015).

Structurally explicit achievement – social capital via pipes

Studies that examined social capital and homogeneity through structurally explicit measures used social network analysis to quantify interactions. For social capital studies focused on the "ties as pipes" mechanism (Table 8), studies were typically designed to focus on networks where information/resources were exchanged for tangible outputs like funding and project implementation or less tangible outputs like expertise (Fischer and Jasny 2017). Studies then examined how different tie characteristics or positions within the network influenced an individual's success, such as being a leader (Chaffin et al. 2019), or a collective's success, such as improved collective adaptive capacity (Ramirez-Sanchez 2007, Robinson and Berkes 2011, Jaja et al. 2017). A few studies also examined how network cohesion influenced adaptive capacity, finding a positive relationship between network cohesion and collective adaptive capacity (Carien De Villiers et al. 2014, Orchard et al. 2015). In one study, trust influenced the extent to which individuals shared information with one another such that the exchange of trustworthy information helped to mitigate the effect of resource scarcity in fishery dependent communities (Ramirez-Sanchez and Pinkerton 2009).

While there is movement away from describing ties based on the characteristics of the nodes they connect in social network analysis literature in other fields, it appears to be common practice in the social ecological systems literature. For example, studies examined how vertical linkages (ties between different jurisdictional levels) and horizontal linkages (ties at the same jurisdictional level) influenced adaptive capacity, finding that vertical linkages between communities and government were important for funneling resources/information (Robinson and Berkes 2011), and that consistency in those interactions was essential for adaptive capacity (Jaja et al. 2017). One study also examined how linking ties, that is, connections among communities, mitigated the effects of resource scarcity among fishing communities (Ramirez-Sanchez 2007). Finally, studies also examined bonding and bridging ties. Sometimes this description referred to tie characteristics, where bonding ties are between similar nodes and bridging ties are between dissimilar nodes, and other times it referred to structural elements, where dense ties are considered bonding and ties across holes are considered bridging. Often both tie characteristic and structural descriptions apply simultaneously, such as with homophilous ethnic subgroups in a Hawaiian fishery (Barnes et al. 2016). In one of the few studies to examine the relationship between social networks and ecological outcomes, Barnes et al. (2016) demonstrated that though these ethnic subgroups have few bridging ties among them, where they do, these ties significantly reduce bycatch (the accidental catch of non-target fish species).

Network position of individual actors was also studied in relation to adaptive capacity. One study found that the type of centrality measure used was important for predicting adaptive capacity – for example, high degree centrality, but not betweenness centrality, was associated with higher adaptive capacity (Schramski et al. 2018). A few studies examined how network position can result in differential access to resources and information by comparing network positions among different groups (Barnes-Mauthe et al. 2013, 2014, Barnes et al. 2016, Chaudhury et al. 2017).

Structurally explicit cooperation – social capital via bonds

For structurally explicit social capital studies focused on the "ties as bonds" mechanism (Table 8), studies were typically designed to focus on different kinds of collaborative networks such as cooperative vs non-cooperative governance (Yu et al. 2014) and co-management arrangements (Sandström and Rova 2010, Alexander et al. 2015) for natural resource management. These studies found that network size (Yu et al. 2014) had a negative effect on cooperative/co-management arrangements, while bridging ties (Sandström and Rova 2010, Yu et al. 2014, Alexander et al. 2015) and horizontal/bonding ties had a positive effect (Sandström and Rova 2010, Alexander et al. 2015). "Closed networks" characterized by high cohesion or by specific network shapes that enable a coordinating actor to funnel information and resources exhibited more elements of adaptive management (Sandström and Rova 2010) and had access to diverse/novel information (Tuda and Machumu 2019). Centralized networks with core and periphery actors may be more effective at cooperating (Lubell et al. 2017), transforming environmental protections (Ernstson 2011), or transitioning to co-management (Alexander et al. 2015) in some instances, while in others, a dense, star-shaped network with high heterogeneity exhibits more elements of adaptive management (Sandström and Rova 2010). Only a few studies examined how collaborative governance arrangements change over time, finding that structures evolve to serve different purposes over the course of a project (Ernstson 2011, Chaffin et al. 2016*a*).

While the above examples illustrated connections between whole network metrics and collaboration, other metrics focused on specific individuals within the network based on their position or attributes. For example, position in the network may be related to an individual actor's ability to access information and resources, communicate with others, or lead/hinder collective action. Central actors were shown to have an outsized influence on collaboration – sometimes positive in the case of leadership in stormwater governance initiatives (Chaffin et al. 2019) and other times negative in the case of blocking collective arrangements for adaptation in fisheries management (Crona and Bodin 2006, 2010). High density in an actor's immediate ego network may also constrain their behavior.

Other studies examined the composition of a network by asking respondents to describe their level of participation in a collective action. They then related networks measures to collective action participation. Studies found that individual participation in collective action increased with increasing exposure to environmental organizations (i.e., number of ties to different organizations, Tindall and Robinson 2017) and whether individuals were part of a subgroup that stood to gain from that action (Crona and Bodin 2006). These studies can also be thought of in the context of innovation diffusion leading to innovative behavior (i.e., social contagion), whereby information through network exposure leads to more collective action (one could argue an innovative behavior).

Trust is another important component of bonding social interactions that can be measured through structurally explicit methods. Trust can be quantified by designing the network study to ask questions about who participants trust. Trust can be measured through the strength of the tie between nodes based on the extent to which someone is trustworthy. For example, one study asked Likert style questions to understand the extent to which a relationship was based on cognitive trust ("I can rely on this person to complete tasks they agreed to do for me") and affective trust ("I feel comfortable going to this person to share problems and difficulties that I am facing"; Chaffin et al. 2019). Another way to measure tie strength is through interaction frequency (Brown et al. 2010, Chaffin et al. 2019) or relationship type (Tindall et al. 2011), which can be related to collective action engagement. For example, individuals with strong ties (i.e., friends, family) to people in provincial environmental non-government organizations (ENGOs) were more likely to be dissatisfied with provincial forestry, and thus more likely to engage in collective environmental activism, whereas weak ties to provincial ENGOs had less of an effect, suggesting the mechanism for engaging in provincial collective action was through strong, bonding ties (Tindall et al. 2011). Similar to above, these studies can also be described in terms of social contagion, where network measures relate to innovative, collective behavior.

The vast majority of studies discussed here focused on collaboration networks, yet one study examined spatially explicit conflict networks. They used a combination of participatory mapping and social network analysis to identify actors and areas of high conflict in a marine protected area (Noble et al. 2019).

Structurally explicit contagion – social homogeneity via pipes

For structurally explicit social homogeneity studies focused on the "ties as pipes" mechanism (Table 9), studies were typically designed to focus on social interactions characterized by communication of information, which were quantified by asking respondents with whom they interact for advice, information, or social engagement (Isaac et al. 2007, Ramirez-Sanchez and Pinkerton 2009, Bodin and Crona 2011, Berardo 2014, André et al. 2017, Chaudhury et al. 2017). Studies then examined how exposure to diverse sources of information influenced behavior, or how redundancy in social interactions influenced specialization and tacit knowledge transfer.

Most structurally explicit contagion research focused on how network composition influenced diversity and exposure. For example, several studies found a positive relationship between heterogeneity and innovation (Rockenbauch et al. 2019, Tuda and Machumu 2019) and heterogeneity and climate change perceptions (André et al. 2017). Homophily, the tendency for ties to exist between similar nodes for a given attribute, had mixed effects across studies. Homophily inhibited access to new information, innovative behavior, and adaptive capacity in several studies (Barnes-Mauthe et al. 2013, 2014, Fischer and Jasny 2017), but had a positive effect on adaptive/transformative behavior in another suggesting the normative influence that similar individuals have over one another (Barnes et al. 2020). Network range, which is the number of ties to other nodes who are different from the focal node for a given attribute, is another way to study network composition. In a study on environmental activism, individuals with high exposure to local environmental organizations (i.e., range) were more likely to be dissatisfied with local forestry practices and engage in local activism (Tindall and Robinson 2017). Because the effect on dissatisfaction was greater for weak ties than strong ties at the local level, researchers suggested an information diffusion mechanism, whereby actors have access to more information through their weak ties, rather than a social influence mechanism, whereby actors are influenced by their close ties.

Network centrality and size have a positive effect on innovation and adaptive behavior in social-ecological systems research, which also supports information diffusion mechanisms due to access to more diverse sources of information, while high levels of density may have a negative effect. Specifically, researchers have found that network centrality influenced innovation (Bodin and Crona 2011, Berardo 2014), information seeking behavior and experimentation (Isaac et al. 2007), information dissemination behavior (Chaudhury et al. 2017), and climate adapted behavior (Nagel 2020). In a study on agricultural producers, researchers found that those with larger ego networks were more likely to have recently innovated (Saint Ville et al. 2016). On the other hand, another study found a negative relationship between ego network density and on-farm biodiversity, indicating that dense networks constrain innovative behavior (Isaac and Dawoe 2011).

A limited number of studies reviewed here examined the relationship between information redundancy and knowledge specialization. One study suggested that dense communication networks have more redundant information, which may contribute to higher ability to self-organize and thus higher resilience (Orchard et al. 2015). Another study examined the relationship between specialization in traditional ecological knowledge domains and network cohesion. They found that cohesive subgroups specialized in different domains, highlighting the importance of overlapping ties for the transfer of non-codified or tacit information (Salpeteur et al. 2016).

Table 8: Structurally explicit example measures and quantified relationships for social capital studies. Please note that the relationships listed in the final column are specific to the studies mentioned and may be highly contextual in some instances.

Mechanism	Concept	Example measures	Quantified relationships with a social-ecological systems concept
Pipes - Achievement (e.g., improved resilience, adaptive capacity)	Information and/or resource exchange	**Network type** Social interactions are quantified by asking respondents questions like, "What organizations do you interact with for the purposes of planning, funding, or implementing work, or for obtaining information or expertise?" (Fischer & Jasny 2017) **Tie characteristics** Vertical vs horizontal linkages - Connections between different jurisdictional levels vs the same jurisdictional level Linking ties - Connections between communities Bonding vs bridging ties - Connections between similar nodes vs connections between dissimilar nodes Tie strength – The magnitude of the interaction between two nodes, which can be based on the level of trust in the relationship **Position** Centrality - The extent to which individual actors are in central network positions with potentially high access to information and resources Structural holes - Connections across open areas in the network; i.e., between subgroups characterized by dense connections within groups relative to among groups; individual actors who sit at structural holes have open networks **Structure** Cohesion – The extent to which the network "hangs together," can be measured by how dense the connections among nodes are	A lack of bonding and bridging ties may be associated with lower adaptive capacity (Fischer & Jasny 2017). Individuals with central positions and open networks are more likely to be nominated as leaders in environmental governance arrangements (Chaffin et al. 2019). Specific organizations provide vertical linkages between communities and higher level government which may be essential for building adaptive capacity (Robinson & Berkes 2011), while consistent vertical linkages over the lifespan of a project may improve adaptive capacity (Jaja et al. 2017). To mitigate their vulnerability, communities experiencing resource scarcity develop linking ties with less vulnerable communities, but information/resource exchange within and among communities is heavily influenced by trust (Ramirez-Sanchez & Pinkerton 2009). Homophilous ethnic subgroups tend to have few bridging ties among them, but where they do, these ties reduce specific negative ecological consequences of fishing (Barnes et al. 2016). Actors with high degree centrality (many connections) were associated with higher adaptive capacity, while actors with high betweenness centrality (lying on the path between other actors) were not associated with higher adaptive capacity (Schramski et al. 2018). Network cohesion is associated with higher adaptive capacity in holistic environmental managers (Carien De Villiers et al. 2014). Transitions to a globalized economy are associated with lower network cohesion, ecosystem dependency, and livelihood diversity, reducing self-organization elements of adaptive capacity (Orchard et al. 2015).
	Social power and equity through resource access	**Position** Centrality or structural hole variation - The extent to which positions vary among actors/subgroups in the network	Households (Chaudhury et al. 2017) and ethnic subgroups (Barnes-Mauthe et al. 2013, Barnes-Mauthe et al. 2014, Barnes et al. 2016) exhibit variation in their network position, indicating social stratification in information and resource access and thus adaptive capacity.
Bonds – Cooperation	Collective action (co-management, community based natural resource management, environmental activism, etc.)	**Network type** The researcher may choose to study particular collaborative groups as a naturally bound network **Composition** Level of participation in collective action can be thought of as an attribute of the actors in the network	There are a few studies that relate structurally explicit network measures to cooperative vs non-cooperative governance (e.g., Yu et al. 2014) and co-management arrangements (e.g., Alexander et al. 2015, Sandström & Rova 2010). The likelihood of individuals to participate in collective action is influenced by their exposure to environmental organizations (Tindall & Robinson 2017) and subgroup membership (Crona & Bodin 2006).
	Cohesion, network shape, and ties	**Structure** Cohesion - Network closure can be thought of as how directly well-connected the network is, where higher density indicates more closure Shape - The extent to which networks can be characterized by certain shapes; network closure can also be thought of as how indirectly connected the network is through a coordinating actor, thus centralized "star-like" shapes are considered to be more closed than other shapes **Tie characteristics** Vertical vs horizontal linkages - Connections between different jurisdictional levels vs the same jurisdictional level Bonding vs bridging ties - Connections between similar nodes vs connections between dissimilar nodes	Network closure is associated with more elements of adaptive management (Sandström & Rova 2010) and access to diverse and novel information (Tuda & Machumu 2019). Centralized networks with core and periphery actors may be more effective at cooperating (Lubell et al. 2017), transforming environmental protections (Ernstson 2011), or transitioning to co-management (Alexander et al. 2015) in some instances, while in others, a dense, star-shaped network with high heterogeneity exhibits more elements of adaptive management (Sandström & Rova 2010). Network structure can evolve over the course of a project (Chaffin et al 2016, Ernstson 2011). Cross-institutional links/bridging ties have a positive effect on collaborative processes (Yu et al. 2014, Alexander et al. 2015, Sandström & Rova 2010). Horizontal/bonding ties also have a positive effect on co-management arrangements, while low cohesion has a negative effect (Alexander et al. 2015, Sandström & Rova 2010).

Mechanism	Concept	Example measures	Quantified relationships with a social-ecological systems concept
	Social power and equity through structural position	**Position** Centrality or structural hole variation - The extent to which positions vary among actors/subgroups in the network	Individuals who are most central and thus most influential in the network are least likely to engage in collective action because they are in a subgroup who stands to gain the least from change (Crona & Bodin 2006). Opinion leaders in central positions can enable or hinder adaptation the most among individuals in the network (Crona & Bodin 2010).
	Leadership	**Composition** Leadership can be thought of as an attribute of the actors in the network; individuals can be nominated by others as a community leader or by asking "Which people are most critical for achieving X outcome?" (Chaffin et al. 2019) **Position** Centrality - The extent to which individual actors are in central, and potentially influential, network positions	Higher adaptive capacity, driven partly by more leadership nominations, is related to higher network cohesion in holistic environmental managers (Carien De Villiers et al. 2014). Individuals are more likely to be nominated as an informal leader if they occupy central, open positions and are a woman (Chaffin et al. 2019). Opinion leaders in central positions can enable or hinder collective adaptation the most among individuals in the network (Crona & Bodin 2006, Crona & Bodin 2010).
	Group membership	**Size** Degree - Number of nodes in the network **Composition** Group membership can be thought of as an attribute of the actors in the network who self-identify as members; membership can be used to describe how diverse the composition of the network is or to define subgroups with natural boundaries.	Network size has a negative effect on cooperation due to higher transaction costs in one study (Yu et al. 2014), while size of an individual's immediate network (i.e., ego network size) has a positive effect on environmental governance leadership nominations in another study (Chaffin et al. 2019).
	Reciprocity	**Tie characteristics** Social interactions can be quantified based on a direction; an interaction is reciprocal when both actors in a dyadic pair identify one another, such as both giving and receiving advice	No studies in this review explicitly examined reciprocal ties in the context of cooperation.
	Strength of ties	**Network type** Social interactions characterized by trust can be quantified by asking questions like, "Who do you consult to obtain trustworthy information regarding...?" (Ramirez-Sanchez & Pinkerton 2009) **Tie characteristics** Tie strength - The magnitude of the interaction between two nodes, which can be based on the type of relationship, the level of trust in the relationship, the frequency of interaction, etc.	Trust influences the extent to which individuals share information with one another such that information is shared through friendship, kinship, and then acquaintances and exchange of trustworthy information helped to mitigate the effect of resource scarcity in resource dependent communities (Ramirez-Sanchez & Pinkerton 2009). Individuals with large trust networks who frequently contact others are more likely to be identified as an informal leader in an environmental governance arrangement (Chaffin et al. 2019). Individuals with strong ties (i.e., friends, family) to people in provincial environmental non-government organizations were more likely to be dissatisfied with provincial resource management, suggesting a social influence mechanism through strong ties (Tindall et al. 2011).
	Conflict	**Network type** Social interactions characterized by conflict can be quantified by asking respondents to nominate actors with whom they have had conflict	Conflict nominations are spatially patterned (Noble et al. 2019).
	Constraint	**Position** Structural holes - An actor who is well-connected to well-connected actors (i.e., occupies the opposite of structural holes) may be constrained in their behavior	Households in a community with high ecosystem dependency and low effects from the globalized economy had higher network density and overlapping ties, potentially constraining their behavior but providing resiliency through redundancy (Orchard et al. 2015).

Table 9: Structurally explicit example measures and quantified relationships for social homogeneity studies. Please note that the relationships listed in the final column are specific to the studies mentioned and may be highly contextual in some instances.

Mechanism	Concept	Example measures	Quantified relationships with a social-ecological systems concept
Pipes - Contagion (e.g., diffusion of information, behavior)	Communication of information and social learning	**Network type** Social interactions characterized by communication of knowledge, information, or advice can be quantified by asking respondents with whom they interact	Several studies examine communication networks in the context of social-ecological systems (Bodin & Crona 2011, Isaac et al. 2007, Orchard et al. 2015, Ramirez-Sanchez & Pinkerton 2009, André et al. 2017, Chaudhury et al. 2017, Berardo 2014).
	Diversity and exposure vs redundancy and specialization	**Composition** Heterogeneity - How diverse the network is based on node attributes Homophily - Tendency for ties to exist between similar nodes for a given attribute Range or diversity (node-level measure) - Number of ties to other nodes who are different from the focal node for a given attribute	Heterogenous networks may have access to more diverse, non-redundant information, thus positively influencing innovation (Tuda & Machumu 2019). Actors with larger, more heterogeneous ego networks were more likely to perceive climate change and potentially appreciate the need for climate change adaptation (André et al. 2017). Though advice comes from higher level extension sources, innovation is high among those who migrate and build translocal networks despite having limited access to extension information (Rockenbauch et al. 2019). Homophily can inhibit access to new information, innovative behavior, and adaptive capacity (Fischer & Jasny 2017), but can be mitigated when ties exist between homophilous groups (Barnes et al. 2016). Homophily can have social equity effects, whereby some homophilous subgroups have more external connections than others and thus more access to information, resources, and innovation potential (Barnes-Mauthe et al. 2013, Barnes-Mauthe et al. 2014). Homophily may have positive effects: exposure to households exhibiting adaptive/transformative behavior positively affects adaptive/transformative behavior uptake in others (Barnes et al. 2020). Exposure to environmental organizations (i.e., range) increases environmental activism because individuals with weak ties (i.e., acquaintances) to people in local environmental non-government organizations were more likely to be dissatisfied with local resource management, suggesting an information diffusion mechanism through weak ties (Tindall & Robinson 2017).
		Position and size Centrality - The extent to which individual actors are in central positions, potentially with high information access Degree – The size of an individual's network may increase information access	Actors in central positions are more likely to be social innovators (Bodin & Crona 2011), more likely to seek information from external sources and experiment (Isaac et al. 2007), more likely to have diverse livelihood strategies, higher adaptive capacity, disseminate information (Chaudhury et al. 2017), and access novel information that fosters innovation (Berardo 2014). Centrality has a positive effect on innovation engagement and climate adapted behavior (Nagel 2020). Individuals with large ego networks are more likely to have recently innovated (Saint Ville et al. 2016).
		Structure Cohesion – Density may help confer redundant or tacit information, yet dense networks may be highly constraining	Dense communication networks may have more redundant information, which may contribute to higher ability to self-organize and thus higher resilience (Orchard et al. 2015). Network cohesion among subgroups is associated with specific traditional ecological knowledge domains (Salpeteur et al. 2016). A negative relationship between ego network density and property biodiversity may indicate that dense networks constrain innovative behavior (Isaac & Dawoe 2011).
	Innovation engagement	**Composition** The degree to which an actor innovates can be thought of as a node attribute	Several studies examine the composition of the network to determine which nodes have engaged in innovation (Saint Ville et al. 2016) or climate adapted behavior (Nagel 2020).

Discussion

The quantitative study of social interactions in social-ecological systems research is an exciting, relatively new arena. This synthesis provides an overview of how social interactions have been quantified in social-ecological systems research toward three goals. Described in the results, the first was to apply typologies borrowed from social network analysis to improve conceptual clarity on the underlying mechanism of social interaction constructs, while the second was to provide a summary of social interaction measures, empirical relationships, and their citations to provide a resource for future researchers hoping to build off of previous work in the field. The third goal, described in more detail below, was to provide a synthesis of weaknesses and opportunities towards a more rigorous treatment of social interactions in social-ecological systems research. This review demonstrates that a wide array of measures is used to quantify social interactions in social-ecological systems literature. Some measures seem to be coalescing, providing quantitative evidence for how social interactions influence adaptive capacity, resilience, cooperation in natural resource management, and adaptive/transformative behavior, while other measures are ill-defined and inconsistently used. Given how multi/inter/trans-disciplinary and new the field is, perhaps it comes as no surprise that there continue to be growing pains. Nonetheless, as the world continues to undergo rapid change, it is increasingly important to understand how we can collectively, through our social interactions, navigate that change towards adaptation and transformation.

Contagion studies

There is growing and consistent evidence that social interactions influence behavior in social-ecological systems research, likely through ties that act as conduits for novel information, though the mechanism is not always clear. This contagion category is perhaps the strongest of those reviewed, in part because information exchange and behavior change are among the most tangible concepts social scientists attempt to measure. It is simply easier (i.e., more accurate/reliable and precise/valid) to measure how much people interact with one another and with whom they interact than it is to measure social cohesion, leadership, reciprocity, and community (Babbie 2016). Similarly, it is easier to measure whether someone engages in a behavior or an action than it is to measure adaptive capacity, resilience, or cooperation. Although there was minor variation in how concepts were defined and measures used both from a binary metaphorical and structurally explicit viewpoint, findings were generally consistent. On the binary metaphorical side, survey items or interview questions were always about the extent to which an individual communicates with others (e.g., peers, government officials, non-profits, etc.) about the environmental/resource management issue in question. These variables were then related to a specific behavior, such as knowledge seeking, innovation, adaptation, or adaptive management (Lubell et al. 2013, Eakin et al. 2016, Marshall et al. 2016, Thennakoon et al. 2020, Tran et al. 2020, Wang et al. 2021). In one case, they were related to attitudes toward climate change adaptation (Jacobs & Cramer 2017). In all instances, the relationship was positive: social interactions are positively related to the behavior or attitude. Though the relationship is consistent, the underlying mechanism with these approaches is often obscure.

Structurally explicit methods provide a slightly more complex story and one that starts to grapple with the underlying mechanisms of social contagion. Studies defined their measures consistently, though sometimes used different names for a term. Most studies found that actors with access to diverse networks, in central positions, or with large networks were more likely to exhibit environmentally adaptive or innovative behavior or environmental activism, supporting the hypothesis that diversity provides a mechanism for information diffusion (Bodin and Crona 2011, Isaac and Dawoe 2011, Berardo 2014, Saint Ville et al. 2016, André et al. 2017, Chaudhury et al. 2017, Tindall and Robinson 2017, Rockenbauch et al. 2019, Tuda and Machumu 2019, Nagel 2020). Other studies examining homophily found mixed results – two found that homophily inhibited innovative behavior (Barnes-Mauthe et al. 2013, 2014, Fischer and Jasny 2017) while one found a positive relationship between homophily and adaptive/transformative behavior (Barnes et al. 2020). In homophily studies, it is often difficult to understand the underlying mechanism driving the outcome. Is it social selection – whereby individuals choose to interact with those who are similar to them and thus exhibit the same behavior – or is it social influence – whereby individuals are more influenced by those who are close to them? Under a social selection mechanism, you might expect that innovative behavior is inhibited because new behaviors are unlikely to infiltrate a network that is reinforcing social norms, unless new ties are developed. Under a social influence mechanism, you might expect that innovative behavior is inhibited within a network holding consistent attitudes, unless attitudes within the network begin to change. In the one study that found a positive relationship between homophily and behavior, they found that ties remained relatively consistent over time, suggesting that attitudes within the network were changing and thus behavior change was perhaps the result of a social influence mechanism, though likely both are acting simultaneously to some degree (Barnes et al. 2020). Both diversity and redundancy are focal concepts in social-ecological systems research broadly, yet few studies here examined how redundancy, rather than diversity, in social interactions may positively influence adaptive capacity, collaboration, or behavior (Orchard et al. 2015, Salpeteur et al. 2016). Social network theory from organizational behavior and other disciplines suggests that dense, overlapping ties provide the social context required for non-codified or tacit information to spread (Reagans and McEvily 2003, Burt 2007). On the other hand, exposure to diversity through networks provides the social context for innovation. Depending on the desired function then, both diversity and redundancy in social interactions serve important functions for improving the adaptive capacity of social-ecological systems.

Achievement studies

Studies falling into the achievement category generally found that social interactions enabled adaptive capacity or resilience, but not always, yet the mechanism driving this outcome was sometimes unclear. Quantifying social interactions through the lens of resource exchange may be a helpful way to reduce the latency of social capital and clarify its underlying mechanism. Several binary metaphorical studies did this well, using items in a survey or questions in an interview to measure how social interactions helped an individual achieve their goals or provide monetary/resource support if needed (Fernández-Giménez et al. 2015, Lockwood et al. 2015, Malherbe et al. 2020). Other studies used group membership to quantify social capital (Cutter et al. 2014, Cinner et al. 2015, Fernández-Giménez et al. 2015, Dapilah et al. 2020, Satumanatpan and Pollnac 2020), which tends to obscure the underlying mechanism. While group membership is linked to adaptive capacity or resilience in most of these studies, understanding what benefits group membership conveys to adaptive capacity or resilience is hard to know with this measure alone. Structurally explicit studies tended to be more clear in their definitions of social capital and the underlying mechanisms that influence adaptive capacity or resilience. Studies that clearly asked respondents who they interact with for the purposes of specific goals (e.g., obtaining funding) were the most direct at measuring the underlying mechanism driving achievement (Fischer and Jasny 2017). Furthermore, by quantifying specific positions, tie types, and tie configurations, it was more clear how and why social capital influences an individual or a collective's adaptive capacity/resilience (Ramirez-Sanchez and Pinkerton 2009, Fischer and Jasny 2017) or ecological effects (Barnes et al. 2016).

Cooperation studies

Cooperation is probably the most difficult to quantify of the social interactions described here. Cooperation and all or most of its antecedents are fairly intangible and intertwined. For example, does social cohesion lead to cooperation in environmental management, or does cooperation lead to social cohesion, or are they inseparable, and what is social cohesion anyway? This issue, in part, may explain why results from studies examining the relationship between social cohesion and cooperation are variable, particularly for binary metaphorical studies. Cohesion, reciprocity, trust, leadership, community, and bonding/bridging ties are all concepts that tend to get mixed in this literature (Sherrieb et al. 2012, Kulig et al. 2013, Akamani and Hall 2015, Fernández-Giménez et al. 2015, Lockwood et al. 2015, Eakin et al. 2016, Paveglio et al. 2017). To some degree, this blurring is to be expected when these concepts are highly interrelated and there is limited space on a survey for multi-item scales. Nonetheless, many of these concepts have been studied extensively, such as trust (Siegrist et al. 2000, Stern and Coleman 2015), and building off of previous work may help improve the validity and reliability of these constructs.

Structurally explicit studies offer an alternative approach to understanding cooperation, though they are often limited by small sample sizes and thus causality is very difficult to infer. Comparing different cooperative arrangements, including their network measures and outputs (Sandström and Rova 2010, Yu et al. 2014, Alexander et al. 2015), helps clarify which measures may be driving which outcomes, though not definitively. Similarly, examining one cooperative arrangement over time provides insight into how different structural measures may serve different purposes at different points in a project (Ernstson 2011, Chaffin et al. 2016*a*). Most studies point to specific network shapes and combinations of bridging and bonding ties that best enable cooperative groups under different settings (Sandström and Rova 2010, Ernstson 2011, Yu et al. 2014, Alexander et al. 2015, Chaffin et al. 2016*a*, Lubell et al. 2017), though there is no "one-shape/tie fits all." Studies examining the extent to which individuals in a communication network participate in collaborative action are also illuminating. Because not everyone in the network is a collaborative participant, these studies reveal the extent to which network positions and actor attributes lead to an individual's collaborative engagement. Social network studies also offer an opportunity to explicitly study reciprocity, such as when the direction of ties goes both ways between two nodes, yet no social-ecological systems studies in this review examined how structural reciprocity influences cooperation or cooperative outcomes. While reciprocity is measured through binary metaphorical approaches with Likert style questions about the extent to which community members support one another (usually from the perspective of an individual), in structurally explicit approaches, reciprocity is measured based on the direction of the ties between two nodes from the perspective of every node in the network. When both people nominate one another as being trustworthy, for example, then the tie is said to be reciprocal, whereas non-reciprocal ties are said to be directed (e.g., person A finds person B trustworthy, but person B does not find person A trustworthy). A common criticism of formal collaborative arrangements is that they are rarely evaluated for achieving social justice or ecological outcomes. Although no studies in this review linked formal collaborative efforts with these goals, two studies related network structure to legal protections/agreements (Ernstson 2011, Chaffin et al. 2016*a*) and two studies related power asymmetries based on network position to the failure to develop collaborative strategies for regulating resource extraction (Crona and Bodin 2006, 2010), all of which presumably have both social and ecological ramifications.

Criticisms and opportunities

Although structurally explicit studies are increasing rapidly in social-ecological systems research, they still remain in their infancy. Other researchers have identified several common issues in environmental network analysis, including methodological and statistical problems and a disconnect between network theory, questions, and analysis (Guerrero et al. 2020). In addition to these criticisms, some of the social network analysis of social-ecological systems research reviewed here used terms inconsistently, imprecisely, or incorrectly and often focused on mechanisms that are falling out of favor in social network analysis more broadly. With respect to inconsistent terminology, several studies used the term “network exposure,” but this term had different meanings depending on the study. In Barnes et al. (2020), they use this term to refer to a homophily mechanism, whereas others used this term to mean the number of organizations to which someone has access (Lubell and Fulton 2008), while others still describe the number of different organizations to which someone has access as “vertical ties” (Alexander et al. 2015). In social network analysis studies of organizational behavior, the number of different people a person has access to is referred to as “range.” Language around ties is particularly confusing. Studies refer to vertical and horizontal ties, bridging and bonding ties, and linking ties are not always consistent across studies. In particular, bridging and bonding ties may refer to the characteristics of the nodes connected by the tie, the strength of the relationship between the nodes, or to structural elements of the network. In organizational behavior, the focus has moved towards the structural elements of the network rather than on tie or node characteristics. One study refers to the degree centrality of ego networks, though they mean ego network degree or size (Orchard et al. 2015) because the centrality of ego networks is pointless to measure (by definition, the ego is always at the center of the network). Similarly, another study uses ego network range and ego network centrality interchangeably (Tindall and Robinson 2017). One study used two-mode data of villages participating in community forestry and created a measure of cross-institutional links to understand the proportion of households in a community forest that participated in multiple community forests simultaneously (Yu et al. 2014). Another way to approach this analysis would have been to convert these interactions into one-mode data, by assuming linkages between villages that participate in the same community forest. Another study refers to the number of ties among alters in an ego's network as "ties," which is a poor approximation for density because it doesn't normalize for the size of the ego network (Saint Ville et al. 2016). Furthermore, in whole network studies, it is important to specify exactly what kind of centrality measure was used, as there are many and they are related to different mechanisms (Bodin et al. 2006). Two studies did not discuss a constraint mechanism operating through high density and/or bonding ties (strong, personal) that could be affecting their results (Isaac and Dawoe 2011, Wang et al. 2021). Another study found that perceptions of community engagement in collective action and solidarity were strong predictors of climate change concerns, perhaps more so than formal sources of information, but did not examine the underlying social mechanisms driving those beliefs – that is social influence or social selection (Jacobs and Cramer 2017).

Social interaction definitions, measures, and mechanisms were often inconsistent or unclear. Part of the challenge, as alluded to above, is that many social interactions and their outcomes are latent constructs and thus extremely difficult to quantify. Several studies described the concept they were measuring, but did not provide specific items (Prior and Eriksen 2013, Bennett et al. 2014, Akamani and Hall 2015, Nagel 2020, Witinok-Huber and Radil 2021) or methods clarifying how they got from concept to measurement to results (Wickes et al. 2015, Marshall et al. 2016, Jacobs and Cramer 2017, García de Jalón et al. 2018, Schramski et al. 2018, Afkhami et al. 2021, Amadu et al. 2021, Wongbusarakum et al. 2021). These problems were most apparent in binary metaphorical approaches, which used broad definitions of social capital and a variety of measures. While definition and measurement flexibility accommodates the wide variety of contexts in which quantitative social scientists work and is to be expected given the diverse contextual settings of the studies reviewed, these issues point to a need for creating some alignment in definitions and measures, and requiring that measurement (e.g., item scales) and analysis information is provided in published articles or accessible supplemental material. I am not suggesting that we need one definition or measurement scale for every social construct. Rather, improving the reliability and validity of these latent measures can, at the very least, start with clear definitions of the construct, the underlying mechanism being tested, and the specifics of the analysis, as well as referencing previous studies. Although this review aimed to improve clarity and provide references for measures and empirical relationships, it was not exhaustive and is likely biased towards social network analysis as well as studies in agriculture, fisheries, and forestry. One group who seems primed to take on a more exhaustive endeavor is the Society for Conservation Biology's Social Science Working Group. At a minimum, this group or one like it could come up with best practices for publishing repeatable quantitative social science studies, and at a maximum, this group could develop a database of measures with a summary of empirically established relationships. Such a guideline/database would enable researchers to produce repeatable studies and build off of previous work with the intention of improving our field.

There are several other opportunities for advancing the quantification of social interactions in social-ecological systems research. Much social science research in this field is criticized for lacking in cross-scalar analyses (Vallury et al. 2022). Depending on how the study is designed, structurally explicit approaches provide a means of understanding the perspectives of individuals and emergent collective outcomes through a social relational lens. For example, Yu et al. (2014) examined how forest management transforms due to pressures of globalization, finding that transformations to cooperative arrangements (rather than private gains) are more likely when forest commons have lower membership, reducing transaction costs, and more connections to other forest commons, increasing cross-institutional knowledge sharing. While this study does not use classic social network analysis language per se, it provides a structurally explicit analysis of the factors that influence the development of cooperation at the local level in the context of cross-institutional exchange and international pressures. Furthermore, this study provides an excellent example of how mixed methods – that is both quantitative analyses and rich qualitative descriptions informed by archival reports (in this case) – can complement one another for a more complete understanding of the context and mechanisms at play. Another great example of a structurally explicit cross-scalar study is from Rockenbauch et al. (2019), who examined how different approaches to information sharing influence agricultural innovation, finding that extension advice from government level sources only permeates as far as elite farmers, whereas migration in lower class farmers is strongly related to innovative behavior, suggesting that trans-local forces of information sharing are more important for many farmers to adapt to change.

While whole network analysis is time consuming for respondents and often requires specific statistical techniques most social scientists are not trained in, ego network analysis offers an opportunity to undertake structurally explicit studies that pair nicely with standard survey design and statistical techniques. Furthermore, ego network design does not have the same anonymity issues as whole network design. Ego network analysis is relatively underutilized, with only a few examples in the review here (Isaac and Dawoe 2011, Tindall et al. 2011, Orchard et al. 2015, André et al. 2017, Tindall and Robinson 2017, Barnes et al. 2020). Ego network design is particularly appropriate when researchers are interested in understanding how a person's immediate social contacts influence particular outcomes, noting that network position cannot be measured in ego network studies though size, composition, structure, and tie characteristics can. Another strength of ego network studies is that the sample size can be quite large, allowing for causality to be inferred in some study designs (Crossley et al. 2015). Other methods for improving causal inference include using permutations and simulations of whole network data (Crona and Bodin 2006, Nagel 2020), performing longitudinal studies (Ernstson 2011, Chaffin et al. 2016*a*), or assessing interventions (of which there were no studies in this review).

A major gap in social-ecological systems more broadly is that few studies explicitly examined the outcomes of social-social or social-ecological interactions. While much of the research reviewed here alluded to the effects of social interactions on ecological outcomes, only two examples explicitly measured these outcomes. These include work by Barnes et al. (2016), who studied how social-social interactions have major implications for conserving marine biodiversity, and Isaac and Dawoe (2011), who studied the effects of ego-network density on improved farm biodiversity through information diffusion mechanisms. Similarly, few studies examined the role that agency and power play for social equity outcomes. Some studies in this review examined social equity by looking at how disparities in network position caused differential access to resources (Barnes-Mauthe et al. 2013, 2014, Barnes et al. 2016, Chaudhury et al. 2017) or to social influence (Crona and Bodin 2006, 2010). Another study used Likert style questions about individual perceptions of power in combination with social network analysis to understand the drivers of adaptive and transformative behavior. They found that individuals were influenced by their peers to engage in adaptive and transformative behavior, but that individuals with high perceptions of their own power were more likely to adapt (protecting the status quo) than transform (changing underlying power structures) in response to climate change (Barnes et al. 2020).

Being able to reliably and validly quantify social interactions in social-ecological systems is important for understanding how to navigate rapid global change. Considerable progress has been made in the last 20 plus years, with more opportunities for progress into the future. Not only will improving our ability to quantify these interactions enable growth within our own singular disciplines, it may enable us to better collaborate with biophysical scientists on social-ecological studies by advancing more integrative quantitative techniques. Furthermore, finding opportunities to combine quantitative and qualitative approaches will make for ever more convincing arguments when the evidence of both reliable numbers and rich narratives is difficult to refute, even for the most positivist of policy makers. Improving our ability to quantify social interactions is a critical gap in the study of social-ecological systems towards being more intentional about how we navigate change and achieve both social and ecological goals.

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Chapter 3: Social networks and disturbance influence adaptive and transformative behaviors in a social-ecological system

Social network elements of adaptive capacity are mobilized in the face of disturbance to influence behavior of agricultural producers experiencing a widespread regime shift

Abstract

Social relations are critical for the adaptive capacity of social-ecological systems to maintain resilience or transform in the face of change. Yet few studies use structurally explicit social measures, which help clarify underlying mechanisms, to examine how disturbance mobilizes adaptation or transformation in social-ecological systems. One system that is undergoing a rapid and difficult to reverse regime shift is the North American Great Plains, where the westward encroachment of eastern redcedar (*Juniperus virginiana*) is transitioning the plains from grasslands to woodlands. Agricultural producers must adapt or transform in response to changing conditions if their operations are to survive this vegetation transition. Although producer adaptation has been studied in the context of individual risk perceptions and assets, we know little about how producers navigate change through their social networks. We sought to understand how producers' adaptive capacity, in combination with their experience of disturbance, influences their adaptive and transformative responses to cedar encroachment. We focused on producers' immediate communication networks to understand how social relations may be enabling or constraining behavior regardless of the level of disturbance to which producers are exposed. We administered an ego-network survey to producers in Nebraska, built logistic regressions, and leveraged landcover data to understand how individuals' social networks and exposure to disturbance influence their adaptive and transformative behavior. Our findings revealed that social network variables are important predictors of behaviors to manage vegetation transitions and that social network variables are more important than disturbance variables for predicting transformative behavior. In particular, we found that network homophily, heterogeneity, information access, and group involvement were predictive of prescribed burning, a behavior that we characterized as transformative.

On the other hand, network density and local exposure to vegetation transitions were predictive of mechanical removal of cedars, a behavior that we characterized as adaptive. This research represents a novel attempt to understand how patterns in social relations enable or constrain the behaviors of producers facing widespread ecological change. These findings improve understanding of how producers navigate change with transformative behavior through their social networks, which may help managers encourage behaviors to limit the extent of this regime shift and other regime shifts around the world.

Introduction

Social processes are an essential component of social-ecological systems, enabling people to adapt or transform in response to change. While social processes that foster social learning, trust, and collective action are regularly cited as important for sustainable environmental governance and adaptation (Berkes and Folke 1998, Dietz et al. 2003, Armitage and Plummer 2010, Berkes and Ross 2013), few studies use structurally explicit measures that help clarify the underlying mechanisms that enable such desirable outcomes (Bodin and Prell 2011), which may have hindered our ability to understand and manage the social complexities inherent to social-ecological systems. Furthermore, we have a limited understanding of how ecological disturbance mobilizes individuals toward adaptive or transformative behavior through their social networks (Wickes et al. 2015). Structurally explicit measures, such as through social network analysis, may enable a deeper understanding of how social processes are mobilized by ecological disturbance. Clarifying the mechanisms that act through social relations may provide much needed insight for those seeking to enable adaptive capacity in the face of global change. Adaptive capacity is the latent ability to respond to or manifest change (Gunderson 2000, Carpenter et al. 2001, Walker et al. 2006, Cinner and Barnes 2019). In other words, adaptive capacity enables resilience, such that a social-ecological system retains the “same function, structure, feedbacks, and therefore identity” (Walker et al., 2006, p. 2) through adaptation, or it enables a transition into a different, more desirable (or at least acceptable) state through transformation. A social-ecological system is comprised of social and ecological components that are linked through complex feedbacks and across scales to generate emergent properties (Colding and Barthel 2019). A social-ecological system's adaptive capacity has been characterized in numerous different ways, but essential elements described in the literature often include learning (Carpenter, Walker, Anderies, & Abel, 2001; Gunderson, 2000; Walker et al., 2006), social capital (Folke et al. 2005), social memory (Olsson et al. 2004), trust, equity, diverse sources of income, livelihood stability, demographics like mobility and migration, collective action (Adger 2000, Adger et al. 2000), community values cohesion, wealth generation, infrastructure, community understanding of risk, health (Cutter et al. 2008*a*), fairness (Cutter 2016), agency, and self-efficacy (Berkes and Ross 2013). Several scholars have produced frameworks for characterizing how different dimensions of adaptive capacity interact across scales to promote adaptation and transformation (Gupta et al. 2010, Whitney et al. 2017, Cinner and Barnes 2019). Cinner and Barnes (2019) conceptualized adaptive capacity as six interacting dimensions: agency, which includes both the power and ability act; assets to which people have access, including economic, infrastructure, and health services; flexibility and diversity of adaptation options; learning new information; social organization, which can enhance trust, cooperation, and collective actions; and socio-cognitions like beliefs, risk attitudes, and perceived social norms. Adaptive behavior enables system resilience and maintains the status quo, and transformative behavior changes the nature of the system including underlying power structures and paradigms (Walker et al. 2004, Leach 2008, Beymer-Farris et al. 2012, Cote and Nightingale 2012, Taylor 2015, Chaffin et al. 2016, Blythe et al. 2018, Scoones et al. 2018).

While there has been considerable growth in the study of adaptive capacity over the last few decades (Siders 2019, Vallury et al. 2022), elements that remain underexplored include the role of structurally explicit social interactions as a component of adaptive capacity that enables or constrains behavior and the role of disturbance in mobilizing adaptive capacity toward behavior. Although social scientists have demonstrated that social connections and communication are important to producer/landowner capacity and behavior (Lubell et al. 2013, Marshall and Smajgl 2013, Eakin et al. 2016, Marshall et al. 2016, Niemiec et al. 2016, Lubeck 2018), few have performed structurally explicit social network analysis, instead relying on metaphorical or descriptive approaches (Bodin et al. 2011). Structurally explicit approaches illuminate a deeper understanding of the social mechanisms that influence behavior and thus may allow researchers to provide more specific advice on how to encourage adaptive or transformative behavior. For example, structurally explicit approaches help test whether social interactions provide information that enables innovative behavior, social bonds that enable cooperation, or resource flows that provide more tangible assets. Furthermore, testing the relative importance of social networks and disturbance together enables an understanding of the specific combinations of social factors that enable or constrain behavior while controlling for actual change on the landscape. To our knowledge, examining the effect of both structurally explicit social interactions and disturbance on behavior has not been previously done but may be informative for practitioners trying to identify the most effective levers of change. For example, if social factors are more important than disturbance for influencing behavior, this finding may be good news for practitioners because social factors may be responsive to policy interventions encouraging proactive behavior, whereas reactionary responses to encroachment are often too late.

Network design research studies how actors (i.e., nodes) are connected to one another through different kinds of interactions or relationships (i.e., ties). Ego network designs (also called personal, ego centered, or egocentric network designs) allow the study of interpersonal relationships of an ego, that is the person of focus, and the people to whom ego is immediately connected (i.e., alters). With ego network design, the researcher is interested in how a person's immediate contacts influence an emergent outcome. Ego network approaches examine ego-alter and alter-alter ties, and can sample and study a set of egos from a population using standard survey design and statistical methods (Borgatti et al. 2013, Crossley et al. 2015). Ego network studies typically examine how characteristics of a network, such as its size (number of nodes), composition (frequency of node attributes), and structure (shape based on tie configuration) influence social processes and outcomes. Though few examples of ego network analyses exist in the environmental literature (Isaac and Dawoe 2011, Tindall and Robinson 2017, Barnes et al. 2020), Burt (2007) argues an ego network is more important than an extended whole network in terms of bridging structural holes and having access to diverse information and resources. In environmental management and conservation, individuals with access to larger networks may have access to novel information, more resources, and higher social support (Chaudhury et al. 2017, Waters and Adger 2017), such that larger networks have been associated with more conservation oriented behaviors (Lubell and Fulton 2008) and higher adaptive capacity (André et al. 2017). Heterogenous networks, characterized by ties between dissimilar people or groups, have been shown to improve communication, helping to spread novel information and innovation (Granovetter 1973, Hahn et al. 2006), improving adaptive capacity (André et al. 2017) and mobilizing resources (Sandström and Carlsson 2008) in environmental management. Homophilous networks, characterized by similarity between egos and their alters, have been shown to be influential to individual uptake of adaptive and transformative behaviors mitigating climate change (Barnes et al. 2020). Network structure has been shown to affect social influence and information diffusion across a number of disciplines (Granovetter 1973, Hansen 1999, Reagans and McEvily 2003, Hahn et al. 2006, Tindall et al. 2011) as well as in the study of whole networks in environmental management (Bodin and Crona 2009, Ernstson 2011, Sandström 2011).

The North American Great Plains, a temperate grassland biome, is an example of a social-ecological system undergoing rapid, wide-spread change, where individual adaptive capacity is being mobilized towards adaptive and transformative behavior. This system is not unique but part of a global pattern as grassland and savanna social-ecological systems experience profound change and the capacity of ranchers, pastoralists, and farmers to adapt to stressors is more essential than ever. Globally, grasslands and savannas support the grazing of approximately 360 million cattle and 600 million sheep and goats, and provide the soul source of income for 100 million people living in arid landscapes (FAO et al. 1999). Yet these grassland and savannah systems are often heavily degraded due to vegetation clearing, cropping, overgrazing, and climate change. Furthermore, vegetation state transitions, which occur when an ecosystem switches from one dominant vegetation state to another, threaten grasslands and savannahs across the globe. They can occur when landscapes shift from vegetated to bare ground (i.e., erosion and desertification), from herbaceous perennials, shrubs, and trees to annual grasses (i.e., exotic annual grass invasion), and from grasslands to woody plants (i.e., woody encroachment) (D'Antonio and Vitousek 1992, Chambers et al. 2014, Bestelmeyer et al. 2015, Lasslop et al. 2016). In the language of social-ecological systems science, these transitions constitute a regime shift, where once a new regime is established, it is extremely difficult to transition back to the prior regime (Walker et al. 2004, Uden et al. 2019). Although risk perceptions, assets, and attitudes are known to influence producer adaptation, we know little about the interplay between ecological disturbances and a producer social networks in influencing their behavior when responding to regime shifts. Understanding how agricultural producers adapt to or transform in response to these regime shifts may be essential for the survival of their livelihoods and the conservation of grasslands across the globe.

The North American Great Plains biome was historically characterized by grasslands, herbivores, humans, climate, and fire interactions (Rossum and Lavin 2000, Engle et al. 2008). As a grassland, the Great Plains biome provides habitat for numerous species which are in rapid decline, including grassland obligate species like the lesser prairie chicken (*Tympanuchus pallidicinctus*, Chapman et al. 2004, Roberts et al. 2022). The Great Plains is also home to a significant proportion of American cattle ranches, producing approximately 50% of American beef (Wishart 2004) in a $73 billion dollar industry (USDA ERS 2022). In the US, there are about 700,000 cattle farms, ranches, and feed yards, 80% of which are operated by families. Grazing operations use a total of 614 million acres – 27% of the American land base (National Cattlemen's Beef Association 2017), most of which exist in the Great Plains. For over 5000 years, the biome was dominated by grassland vegetation (Nordt et al. 2008, Cordova et al. 2011). However, altered interactions among these drivers have changed system dynamics such that woodlands, mostly Ashe juniper (*Juniperus ashei*) and Eastern redcedar (*J. virginiana,* hereafter "cedar"), are encroaching on the biome (Briggs et al. 2005, Van Oaken 2009). Decreased prevalence and intensity of both wild and anthropogenic fire across the landscape allow these fire-sensitive species to germinate and spread (Twidwell et al. 2013*a*). The issue is exacerbated by livestock overgrazing that removes the herbaceous layer necessary for grassland fires to advance, development that reinforces the need to prevent fire and simultaneously provides a seed source from wind breaks made of trees, and increased drought associated with climate change that enables cedar to outcompete other species (Briggs et al. 2005, Allred et al. 2012, Taylor et al. 2012, Twidwell et al. 2014). Without intervention, it is expected that the American Great Plains biome will be encroached upon by woody species by 2050 (D. Twidwell, personal communication). Where woody transitions occur, research has shown up to a 75% reduction in productivity for livestock forage (Fuhlendorf et al. 2008), prairie chicken avoidance at 2 trees/acre (Lautenbach et al. 2017) and no breeding with further encroachment (Merrill et al. 1999), reduced streamflows and groundwater recharge (Zou et al. 2018), higher intensity fires (Donovan et al. 2020), and the potential for reduced K-12 education funding, which grazing leases support in Nebraska (Lally et al. 2016). Understanding what elements of producers' adaptive capacity are mobilized towards promoting management behaviors is critical for increasing the collective action of individual producers to manage large landscapes and informing higher level policy initiatives.

Here, we investigate the relative importance of social networks and disturbance for influencing adaptive and transformative behaviors of Nebraska producers in response to cedar encroachment of the American Great Plains. Nebraska provides an opportune study location because the state has experienced a wide gradient of cedar encroachment, with considerable ongoing research on the ecological aspects of this regime shift and large opportunities for further engagement in social sciences. Additionally, there is a growing and shifting social response to this encroachment, from individual action, to small informal partnerships, to broader more institutionalized networks seeking to promote adaptation and transformation (Twidwell et al. 2013*b*). We administered an ego network survey to producers across Nebraska regarding the strategies they use to manage vegetation transitions on their operations, including mechanically removing cedars and using prescribed burning. We argue that mechanical removal is an adaptive behavior because it helps maintain social-ecological system resilience without challenging the status quo, while prescribed burning is a transformative behavior because it challenges the dominant fire suppression paradigm that are evident at all social levels. We asked questions about dimensions of their adaptive capacity with a particular focus on social organization as characterized by their immediate communication networks. We asked respondents with whom they communicate regarding the management of their operations and several questions about each of these contacts, including the types of information they provide to the respondent, how frequently they interact with the respondent, their occupation, and whether their contacts know one another. We also asked respondents questions about other dimensions of their adaptive capacity and quantified the level of disturbance they were locally experiencing through remote sensing data.

Using these survey responses we built logistic regressions to understand the relative importance of adaptive capacity and disturbance for explaining variation in mechanical removal and prescribed burning. We predicted producers with large networks (Lubell and Fulton 2008, André et al. 2017, Chaudhury et al. 2017, Waters and Adger 2017) and those with diverse networks (Sandström and Carlsson 2008, André et al. 2017) would be more likely to engage in adaptive and transformative behavior because of their increased access to novel information. We predicted producers with networks characterized predominantly by other producers (Blau 1977, Burt 1982, McPherson et al. 2001, Newig et al. 2010, Barnes et al. 2020) and frequent interaction with their contacts (Granovetter 1973, Hansen 1999, Uzzi 1999, Reagans and McEvily 2003, Hahn et al. 2006, Tindall et al. 2011) would be more likely to engage in adaptive and transformative behavior because of the social support they receive from their community. We predicted producers with networks characterized by a moderately dense structure would be most likely to engage in adaptive and transformative behavior because their network structure provides a "sweet spot" of novel information and social support (Hansen 1999, Uzzi 1999, Oh et al. 2004). Finally, we predicted the social organization dimension of adaptive capacity would be more predictive of transformative behavior than disturbance because of the social support required to enable transformative actions that challenge underlying paradigms (such as fire suppression). On the other hand, we predicted that both the social organization dimension and disturbance would be predictive of adaptive behavior.

Methods

Study area

This study was conducted in Nebraska, USA, which is in the American Great Plains biome. The Western High Plains ecoregion is in western Nebraska, dominated by shortgrass and mixedgrass prairie with a semi-arid to arid climate. Common land uses include dryland agriculture. The Central Great Plains ecoregion is in the south-central part of the state. Though most of this region has been converted to cropland, it was once dominated by mixedgrass prairie. In the north-central part of the state, there is the Northwestern Glaciated and Great Plains ecoregions, which are dominated by row crop agriculture, and the Nebraska Sand Hills ecoregion, which is home to cattle ranches and dominated by large, grass-stabilized sand dunes. The Western Corn Belt Plains ecoregion is in the eastern part of the state, with a 90% conversion rate from tallgrass prairie to cropland agriculture and livestock forage (Chapman et al. 2001). The state is experiencing wide-spread cedar encroachment from the east such that over a third of the state is in a high severity transition area (Natural Resources Conservation Service 2021).

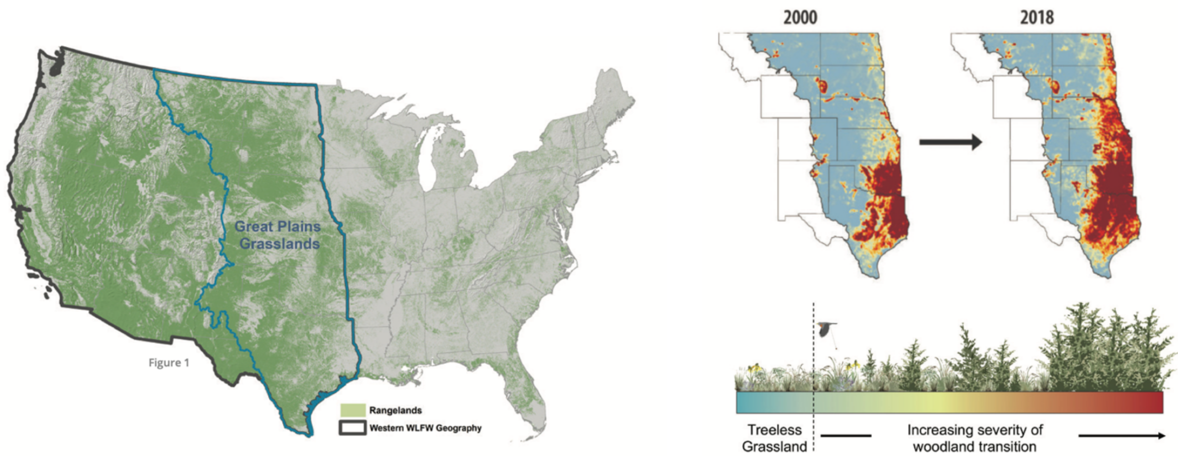
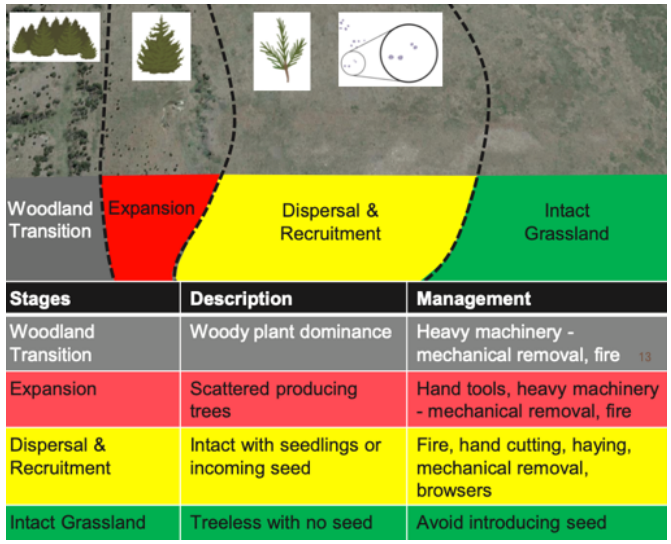


Figure 9: (A) The American Great Plains biome. (B) Cedar encroachment onto grasslands from 2000 to 2018 (from Natural Resources Conservation Service 2021).

Interventions to manage this regime shift vary depending on the stage of encroachment in a particular location (Figure 10). Where grasslands are intact, preventing contamination from seed sources is essential. In areas where seeds are dispersing, management interventions include mechanically removing the seed source and killing the seed bank with fire. In areas where active recruitment is occurring, eliminating seedlings before they reach maturity is essential, such as with fire, cutting, haying, and browsing. Once mature trees are encroaching on a site, a mix of interventions is required, including mechanical removal to thin the trees, which then enables high intensity fires (hot enough to kill the seed bank) to spread more readily through the matrix. In the final stage of encroachment, there has been a complete state transition from grasslands to woodlands and best management practices include strategically limiting the risk to nearby areas through tree removal and constant monitoring (Twidwell et al. 2021).



Stages	Description	Management
Woodland Transition	Woody plant dominance	Heavy machinery - mechanical removal, fire
Expansion	Scattered producing trees	Hand tools, heavy machinery - mechanical removal, fire
Dispersal & Recruitment	Intact with seedlings or incoming seed	Fire, hand cutting, haying, mechanical removal, browsers
Intact Grassland	Treeless with no seed	Avoid introducing seed

Figure 10: Interventions to manage woody encroachment at different stages (from Natural Resources Conservation Service 2021).

Data collection

Social data

We used a mail-back and online questionnaire (Appendix 3A) to Nebraska ranchers and farmers in 2021 (UNL IRB# 20086, UM IRB #235-19) to collect these data. We chose to administer a mail-back questionnaire based on previous experience with high online non-response with this demographic. Nine people piloted the questionnaire, including two graduate students, two faculty, three extension professionals, and two ranchers. We focused on 31 counties across a northwest to southeast cross-section of Nebraska, which represent a gradient of the vegetation transition (Figure 11). We bought names and addresses from Farm Market iD, a firm that provides producer data for agricultural marketing purposes. The purchased list constitutes the entire population of people who responded to the National Agricultural Survey in the counties we requested who self-identified as having >20 acres of pasture/rangeland (6546 people). Of this population, 3448 people had emails. We took a simple random sample of 4500 from the population of 6546 individuals. Of this sample, 2409 had emails. After duplicates were removed, the sample size was 4494. We administered the survey using a modified tailored design (Dillman et al. 2014) in May-July 2021. We sent three emails with a digital copy of the survey to those for which we had emails on June 4, June 23, July 23. We also sent three paper mailings, including a letter, and two questionnaire mailings, each approximately two weeks apart (May 26, June 11, June 24). The survey included questions about producers' behaviors, dimensions of adaptive capacity, demographics, and ego networks.

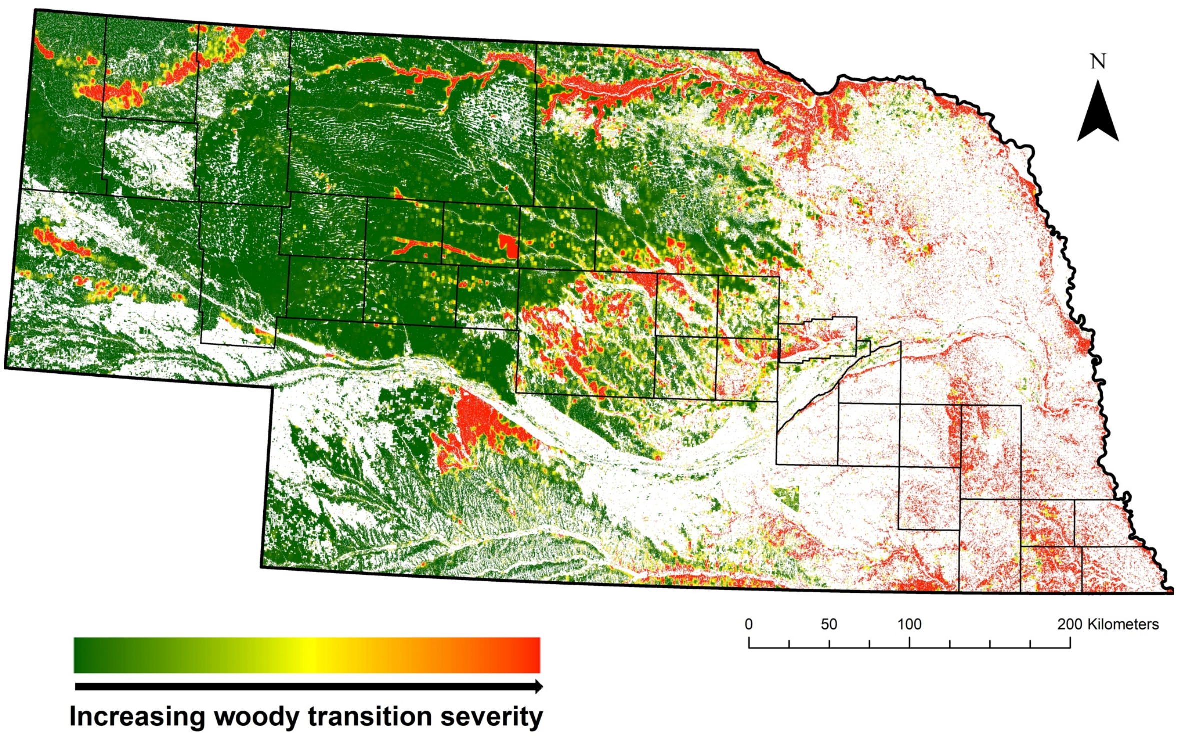


Figure 11: Map of Nebraska showing spatial covariance in 2020 in color. Counties that were sampled are shown and represent a gradient of the vegetation transition.

Ecological data

Ecological disturbance data were calculated based on vegetation classes in the Rangeland Analysis Platform v2.0 (RAP v2.0; USDA NRCS et al. 2019). We used spatial covariance to determine the intensity of spatial boundaries between two vegetation classes (perennial forbs/grasses and trees). Spatial covariance is calculated in a moving window approach and provides a measure of the extent to which two classes coexist in space (Uden et al. 2019). When one class increases while the other decreases across the window, covariance is negative, indicating that the two classes tend not to coexist with one another. When classes increase together the window, covariance is positive, indicating that the classes tend to coexist. When classes have no spatial relationship within the window, covariance is 0.

Spatial covariance in 2020 was computed between two RAP vegetation classes (perennial forbs/grasses and trees) over an 81 x 81 pixel moving window; the pixel size was 30 m. Cropland, water, and developed areas were excluded from analysis. More negative spatial covariance values indicate a greater intensity of spatial transition between forbs/grasses and trees (i.e., stronger/more boundaries). Spatial covariance of 0 indicates that there is no relationship between forbs/grasses and trees in that area (i.e., where there are no trees in a grassland regime or where there are no grasses in a forest regime; Uden et al. 2019). We calculated the spatial covariance at each respondent's location by averaging the spatial covariance of every pixel within their ~259 hectare section, as defined in the Public Land Survey System. This averaging was necessary because of the masking out of developed areas (where respondent addresses were often located) from spatial covariance images. In Chapter 4, we expanded on this approach by considering disturbance calculated at multiple spatial levels, rather than at just one level here.

Theoretical framing and measures

We tested the relative effects of different dimensions of adaptive capacity and levels of disturbance on producer behaviors used to manage vegetation transitions (i.e., mechanical removal and prescribed burning; Figure 12). To measure behaviors (i.e., response variables), we asked respondents how often they had used mechanical removal (an adaptive behavior) and prescribed burning (a transformative behavior) to manage vegetation transitions on their operation in the last three years (Table 10).

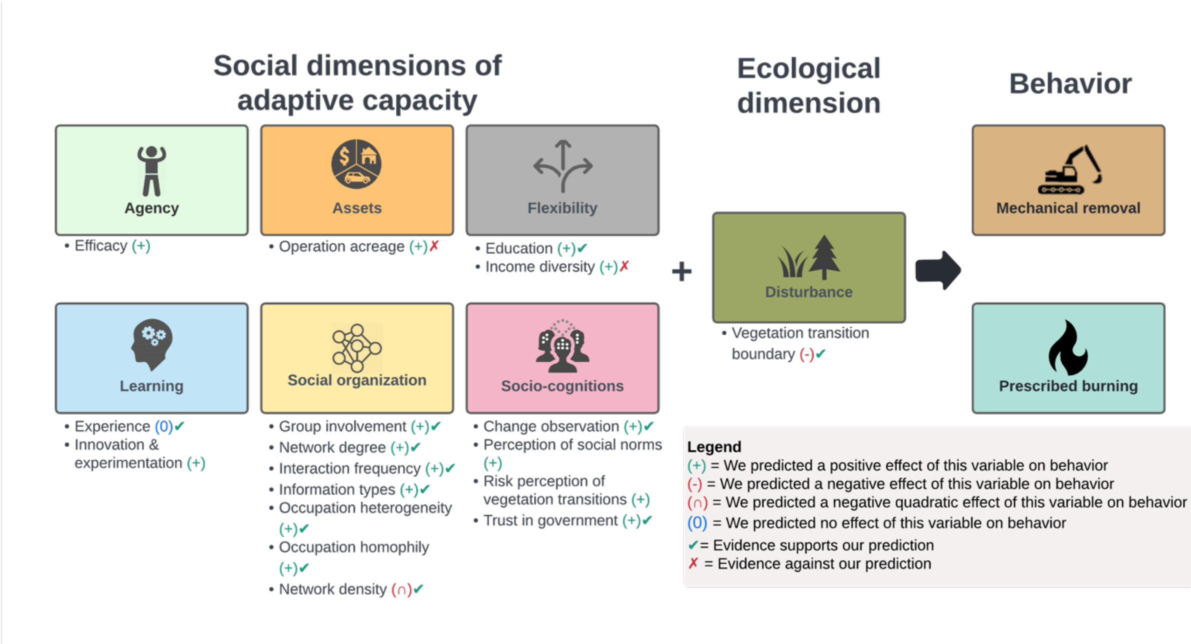


Figure 12: Conceptual model of the variables that may influence behaviors that manage vegetation transitions. The predicted effect of each variable on uptake of behavior is shown with a positive (+), negative (−), negative quadratic (∩), or null (O) sign next to each variable. Variables with both checks and xs indicate that our results show evidence in support and opposition of our prediction, depending on the behavior model. Variables without a check or x were not in any of the final models.

Adaptive capacity

We conceptualized adaptive capacity based on six dimensions from the framework developed by Cinner and Barnes (2019), including agency, assets, flexibility, learning, social organization, and socio-cognitions. Because adaptive capacity is a latent construct, researchers must measure it using proxies. We quantified each respondent's dimensions of adaptive capacity by asking questions in the survey that acted as proxies or indicators of each dimension (Table 10). Although adaptive capacity research has grown exponentially in the last 20 years, there is little consensus on its conceptualization and measurement (Siders 2019). Thus, we developed these indicators by modifying constructs and items in the adaptive capacity, collective action, rangeland management, and social network literature.

Agency

Agency, or the ability to act, was measured with the concepts of self-efficacy (Grothmann and Patt 2005, Marshall et al. 2016, Niemiec et al. 2016, Lubeck et al. 2019) and group efficacy (Marshall and Smajgl 2013, Niemiec et al. 2016, Lubeck et al. 2019). We predicted that those with higher perceptions of efficacy would be more likely to manage vegetation transitions (Grothmann and Patt 2005, Marshall et al. 2016, Niemiec et al. 2016, Lubeck et al. 2019).

Assets

To measure assets, we asked respondents how many acres they owned or rented for their operation (Lubell et al. 2013, Marshall and Smajgl 2013). Lubell et al. (2013) found that private acreage had a larger effect than leased acreage on whether a producer participated in conservation programs, while producers who operate more acres (both owned and rented) are likely to have higher profits and wider margins, and thus more flexibility to innovate. We tested whether total acreage of an operation influenced a producer's behaviors to manage vegetation transitions. We predicted that those who operated more land would be more likely to manage vegetation transitions while those who operated less land would be less likely to manage vegetation transitions, perhaps due to budget constraints (Thurow et al. 2000, Kreuter et al. 2004, Lubell et al. 2013). We also asked about income but had a low response rate so removed it from the analysis.

Flexibility

We measured a respondent's flexibility based on their level of education and the proportion of their income from other sources (i.e., not from agriculture; Lubell et al. 2013, Marshall and Smajgl 2013, Marshall et al. 2016). Education level may be indicative of how easily producers can diversify into other fields, navigate the red tape of conservation and financing programs, and access different sources of information (Kollmuss and Agyeman 2002). Producers who have more diverse income sources may have fewer budget constraints and thus more operating flexibility. Lubell et al. (2013) suggest that income diversity may also indicate other aspects of a producer's personality, including their willingness to innovate (Sorice et al. 2012). Thus, we predicted that producers with higher education and more diverse income sources would be more likely to manage vegetation transitions (Lubell et al. 2013, Marshall et al. 2016).

Learning

We measured learning through a respondent's years of experience and their level of innovation and experimentation in agriculture (Lubell and Fulton 2008, Engle and Lemos 2010, Marshall and Smajgl 2013, Marshall and Stokes 2014, Lockwood et al. 2015, Eakin et al. 2016, Marshall et al. 2016). Marshall et al. (2016) found that years of experience as a producer was negatively correlated with their ability to buffer their operation against the effects of climate change; yet, Lubell and Fulton (2008) found a weakly positive association between agricultural experience and participation in environmental practices. Lockwood et al. (2015) found a positive correlation between rural landholder's level of innovation and their perception of personal resilience; thus, we predicted no relationship between experience and managing vegetation transitions and a positive relationship between innovation/experimentation and managing vegetation transitions.

Social organization

We quantified social organization measures for each respondent based their level of involvement in local groups and on characteristics of their ego network. We asked each respondent their level of involvement in local rangeland management groups (Bennett et al. 2014, Cinner et al. 2015, Marshall et al. 2016). We predicted that those more involved in such groups would be more likely to manage vegetation transitions. We designed the ego network questions following methods in Burt

(1992, 1997, 2004). We used a name generator prompt (Crossley et al. 2015) and asked the respondent (i.e., ego) to list up to 15 contacts (i.e., alters) with whom they work, communicate, and seek management advice. We then asked questions about the alters' occupations, how frequently ego interacts with each alter, the kinds of information ego gets from each alter, and whether ego's alters know each other. Based on these questions, for each respondent, we measured the size of their network (i.e., number of alters), how frequently they interacted with their alters on average (as a measure of tie strength), and the number of information types they received from their alters on average. We also measured occupation diversity among their alters (i.e., occupation heterogeneity) and the degree to which they held the same occupations as their alters (i.e., occupation homophily). We measured network structure based on the density of ties among alters.

Egos with access to larger networks may have access to novel information, more resources, and higher social support (Chaudhury et al. 2017, Waters and Adger 2017), such that larger networks have been associated with more conservation oriented behaviors and higher adaptive capacity. For example, Lubell and Fulton (2008) found a positive association between an orchard grower's policy network size and their participation in environmental practices. André et al. (2017) found that the size of forest owner's knowledge sharing networks was positively correlated with their perceptions of climate change risk and their own adaptive capacity. Thus, we predicted that producers with a larger network would be more likely to manage vegetation transitions.

Tie strength, particularly in combination with network structure, has been shown to affect social influence and information diffusion across a number of disciplines (Granovetter 1973, Hansen 1999, Uzzi 1999, Reagans and McEvily 2003, Hahn et al. 2006, Tindall et al. 2011). Strong ties are likely to occur between people who are more similar and trust one another based on shared life experiences or values (Granovetter 1973, McPherson et al. 2001). People with strong ties are more likely to influence one another. Thus, we believed that tie strength, measured as interaction frequency in our study, would be positively associated with behavior uptake to manage vegetation transitions.

Access to information is regularly cited as an important mechanism that operates through social networks (Borgatti et al. 2009, Borgatti and Halgin 2011). We measured access to information directly and predicted that those with more information sources on average would be more likely to manage vegetation transitions (Lubell et al. 2013) because they likely have access to more novel, diverse information about the risks of vegetation transitions and the ways they can be managed. Heterogenous networks, such that there are ties between dissimilar people or groups, have been shown to improve communication and understanding, helping to spread novel information and mobilize behavior (Granovetter 1973, Hahn et al. 2006). In environmental research, André et al. (2017) found that heterogeneity in forest owners' networks was positively correlated with their perceptions of climate change risk and their own adaptive capacity. In a study of higher education policy networks, Sandström and Carlsson (2008) found that heterogenous networks were positively associated with mobilizing resources. Thus, we predicted that those with more heterogenous occupation networks among their alters would be more likely to manage vegetation transitions based on their access to novel information and resources. Homophily is the degree to which an ego is similar to their alters across a trait or value. Alters who are more similar to ego are more likely to influence ego to adopt new behavior (Burt 1982, McPherson et al. 2001, Newig et al. 2010). Alternatively, egos may select to interact with alters who are more similar to them (Blau 1977, McPherson et al. 2001). These mechanisms are difficult to tease apart and scholars have suggested that perhaps both occur simultaneously (Robins et al. 2001). Barnes et al. (2020) found that homophily positively influenced adaptive and transformative behavior, either through processes of social influence (similar people being more influential) or social selection (people selecting people who behave similarly to them) in coastal communities in Papua New Guinea. Similarly, we predicted that those with more homophilous networks would be more likely to manage vegetation transitions.

Network density and individual behavior may have a fairly complex relationship. Some studies from organizational behavior suggest that density eases knowledge transfer and helps diffuse information (Reagans and McEvily 2003). Most environmental social science research has shown that density increases interaction, information sharing, and trust, resulting in an increase in adaptive behavior and collective action (King 2000, Conley and Udry 2001, Isaac et al. 2007, Bodin and Crona 2009). However, some environmental social science research has found that at high densities, social homogenization and constraint may occur, reducing innovation and the ability to respond adaptively (Bodin and Norberg 2005, Bodin et al. 2006, Little and McDonald 2007, Bodin and Crona 2009, Isaac and Dawoe 2011), which would be more consistent with Burt's classic work on structural holes (Burt 1982, 2004). Indeed, several studies from organizational behavior suggest a quadratic relationship is possible (Hansen 1999, Uzzi 1999, Oh et al. 2004). We tested for this quadratic relationship between density and behavior, predicting that adaptive and transformative behavior would be highest at moderate densities.

Socio-cognitions

For socio-cognitions, we measured each respondent's change observation, perception of social norms to manage vegetation transitions, risk perception of vegetation transitions, and trust in the government to manage vegetation transitions. We predicted that observing vegetation transitions would increase behavior to manage them, much like the positive effects of risk salience on adaptation in farmers (Azadi et al. 2019) and the value of engaging in weed control behaviors in landholders (Lubeck et al. 2019). Social norms can be powerful influences on human behavior (Ajzen and Fishbein 1980, Griskevicius et al. 2008, Fishbein and Ajzen 2010), and include descriptive social norms, which are perceptions of what other respected (or similar to you) people are doing (what "is"), and injunctive social norms, which are perceptions of what those people believe you should be doing (what "ought"; Cialdini et al. 1991). In the context of rangeland and environmental management, social norms have been shown to affect behaviors to control weeds (Lubeck et al. 2019) and invasive trees (Niemiec et al. 2016), as well as ranchers' intentions to engage in wildlife management (Willcox et al. 2012). Thus, we predicted that those who perceived social norms around preventing vegetation transitions would be more likely to do engage in preventative behavior themselves. Risk perception has been shown to positively influence adaptive behavior, including in farmers adapting to climate change (Azadi et al. 2019), residents living in flood prone landscapes (Grothmann and Patt 2005), and residents managing invasive trees (Niemiec et al. 2016). Thus, we predicted that those who perceived high risks of vegetation transitions to rangeland profitability, ecosystems, and productivity would be more likely to manage for these transitions. Trust in the information that the government provides and government involvement in conservation has been shown to positively influence adaptive and conservation oriented behaviors (Lubell et al. 2013, Azadi et al. 2019). Although trust may have the opposite effect sometimes, perhaps by alleviating responsibility on the individual to act (Stern and Coleman 2015), because producers actively manage their land to be in business, we predicted that increased trust in government would increase behaviors to manage vegetation transitions in this demographic.

Disturbance

We also tested the effects of disturbance on each behavior. To our knowledge, few studies of adaptive capacity rooted in social-ecological systems science approaches have examined the effect of actual ecological disturbance on adaptive or transformative behavior; rather, most studies have focused on the observation of this disturbance or the perception of its risk on behavior. Research from the community hazard/disaster resilience literature is a notable exception, which incorporates ecological components into community/spatial resilience (Cutter et al. 2008*b*, Frazier et al. 2013). Another exception is research on adaptive capacity rooted in vulnerability approaches, which conceptualizes vulnerability as a function of exposure and sensitivity to a hazard, and the capacity to adapt to exposure or modify sensitivity (McCarthy et al. 2001, Ford et al. 2006). Because adaptive capacity is by definition a latent ability to adapt, we predict that it is mobilized into behavior by disturbance, and the intensity of this disturbance would influence the extent of uptake in behavior. Because spatial covariance is more negative as the intensity of the boundary between forbs/grasses and trees increases, we predicted a negative relationship with behavior such that behavior is most frequent at the most intense boundaries. We predicted that as the boundary approaches (i.e., the wave of cedars gets closer to a producer), behaviors would increase in response to the visual threat. However, after the boundary has passed (i.e., the wave of cedars has encompassed a producer), we predicted that behaviors would diminish as they become more futile.

Table 10: Variables included in models and their scale, question wording, mean and standard deviation (SD), Cronbach's alpha, and citation. Median (*) is shown for operation acreage.

Behavior / dimension	Variable	Scale	Scale description	Question	Question #	Mean (SD)	Alpha	Citation
Behavior	Mechanical removal	0, 1	0 = Never or rarely; 1 = Occasionally or always as appropriate	Please rate how often you have [used mechanical removal] to manage vegetation transitions on your operation in the past three years.	7d	0.76 (0.43)		D. Twidwell, personal communication
	Prescribed burning	0, 1	0 = Never or rarely; 1 = Occasionally or always as appropriate	Please rate how often you have [used prescribed burning] to manage vegetation transitions on your operation in the past three years.	7b	0.3 (0.46)		D. Twidwell, personal communication
Agency	Efficacy	1-5	1 = Strongly disagree; 2 = Somewhat disagree; 3 = Neither; 4 = Somewhat agree; 5 = Strongly agree	If I take actions to manage vegetation transitions, it will inspire other producers to do so. (group efficacy, reciprocity) I doubt that other producers and I can collectively prevent vegetation transitions at a regional scale. (group efficacy, collective effects on region [reverse coded]) If nearby producers take actions to manage vegetation, it will also reduce the chance of vegetation transitions on my operation. (group efficacy, collective effects on operation) I do not think I can personally do anything about vegetation transitions on my operation. (self-efficacy, personal [reverse coded]) I believe my actions on my operation can significantly reduce vegetation transitions happening on the greater landscape. (self-efficacy, cross-boundary effects) Through effective planning, I can overcome risks to my operation from vegetation transitions. (self-efficacy, planning)	8a 8b 8c 8e 8f 11b	3.79 (0.51)	0.61	Grothmann & Patt 2005; Lockwood et al. 2015; Lubeck et al. 2019; Marshall et al. 2016; Marshall & Smajgl, 2013; Niemiec et al. 2016
Assets	Operation acreage	Continuous	Acres owned + rented (logged for analysis)	Please estimate the acreage of your operation in 2020 (owned acres; acres rented from others).	3a 3b	890*		Lubell et al. 2013; Marshall & Smajgl, 2013
Disturbance	Vegetation transition boundary	Continuous	Spatial covariance between forbs/grasses and trees in 2020, averaged at the section-level; more negative values indicate a greater	Not in survey - Spatial covariance was computed between two RAP (v2.0) vegetation classes (perennial forbs and grasses; trees) over an 81 x 81	NA	-159.5 (141.82)		Cutter et al. 2008; Frazier et al. 2013

Behavior / dimension	Variable	Scale	Scale description	Question	Question #	Mean (SD)	Alpha	Citation
			intensity of spatial transition between vegetation groups within that section (i.e., stronger/more boundaries)	pixel moving window; the pixel size was 30 m; covariance was averaged at the section-level for each respondent				
Flexibility	Education (recoded)	0, 1	0 = Some college / vocational training or less; 1 = 2-year college or more	What is the highest level of school you have completed? (recoded)	25	0.58 (0.5)		Bennett et al. 2014; Lubell et al. 2013; Marshall et al. 2016
	Income diversity (recoded)	0-100	0-100%; recoded from ordinal to midpoint of each range and converted to 100 - proportion from agriculture	Approximately what percentage of your household income came from agriculture in 2019? (recoded)	22	42.25 (31.1)		Bennett et al. 2014; Lubell et al. 2013
Learning	Experience	Continuous	Years	How many years have you personally been ranching or farming?	2	35.14 (15.08)		Engle et al. 2010; Lubell & Fulton, 2008; Marshall et al. 2016
	Innovation & experimentation	1-5	1 = Strongly disagree; 2 = Somewhat disagree; 3 = Neither; 4 = Somewhat agree; 5 = Strongly agree	I frequently look for information about new ranching/farming techniques to prevent vegetation transitions on my operation. I implement test plots to evaluate new ranching/farming practices to prevent vegetation transitions on my operation. I like to experiment with new management practices to overcome risks to my operation from vegetation transitions.	9a 9b 11a	3.13 (0.79)	0.63	Eakin et al. 2016; Lockwood et al. 2015; Marshall & Smajgl, 2013; Marshal & Stokes, 2014
Social organization	Network degree	1-15	Network size or number of alters	Please list the people who you work with on your operation, you communicate with about operating your ranch or farm, and you go to for rangeland management advice. (name generator)	13	5.53 (3.03)		Andre et al. 2017; Lubell & Fulton, 2008
	Interaction frequency	1-6	Average interaction frequency with alters (reverse coded); 1 = Less than once/month; 2 = monthly; 3 = 2-3 times/month; 4 = weekly; 5 = 2-3 times/week; 6 = daily	How frequently do you interact with each person?	17	3.08 (1.28)		Granovetter, 1973; Hansen 1999; Reagans & McEvily, 2003; Taylor 2011; Uzzi 1999
	Information types	1-5	Average number of information types received from alters	What kinds of information do you mainly receive from each person?	16	1.72 (0.85)		Lubell et al. 2013
	Occupation heterogeneity	0-1	Index of qualitative variation (IQV) based on occupation; a measure of categorical heterogeneity in alters; ranges from 0 to 1, where 0 = all in one category and 1 = evenly dispersed among categories	What is each person's primary occupation?	14	0.7 (0.36)		André et al. 2017; Sandström & Carlsson, 2008
	Occupation homophily	-1-1	Similarity with alters' occupations (-[EI index]); ranges from -1 to 1, where -1 = all ties are external to the group and 1 = all ties are internal to the group. We assumed respondents were producers because of how we drew the sample.	What is each person's primary occupation?	14	-0.03 (0.6)		Burt, 1982; McPherson et al. 2001; Newig et al. 2010; Barnes et al. 2020

Behavior / dimension	Variable	Scale	Scale description	Question	Question #	Mean (SD)	Alpha	Citation
	Network density	0-1	Number of ties / number of possible ties; ranges from 0-1, where 0 = no ties between alters and 1 = all ties between alters	This question is to find out whether your contacts know each other.	18	0.53 (0.37)		Bodin et al. 2006; Bodin & Norberg 2005; Bodin & Crona, 2009; Conley & Udry 2011; Crona & Bodin, 2006; Crona 2006; Hahn et al. 2006; Hansen et al. 1999; Isaac et al. 2008; Isaac & Dawoe, 2001; King, 2000; Little & McDonald, 2007; Oh et al. 2004; Ruef, 2002; Regans & McEvily, 2003; Uzzi, 1999
	Group involvement (recoded)	0-4	0 = There are no groups in my area who discuss rangeland management; 1 = I am not involved in any groups; 2 = I am minimally involved with at least one group; 3 = I am moderately involved with at least one group; 4 = I am heavily involved with at least one group; recoded from original survey	Are there groups of people in your area that regularly meet to discuss rangeland management? What's the extent of your involvement with these groups? (recoded)	20a 20b	0.39 (0.99)		Bennett et al. 2014; Cinner et al. 2015; Marshall et al. 2016
Socio-cognitions	Change observation	1-5	1 = Strongly disagree; 2 = Somewhat disagree; 3 = Neither; 4 = Somewhat agree; 5 = Strongly agree	I have noticed that vegetation has transitioned from mostly grasses to mostly shrubs/trees	5a	2.44 (1.3)		Azadi et al. 2019; Bennett et al. 2014; Lubeck et al. 2019
	Perception of social norms	1-5	1 = Strongly disagree; 2 = Somewhat disagree; 3 = Neither; 4 = Somewhat agree; 5 = Strongly agree	Most producers like me believe it's important to prevent vegetation transitions. (injunctive) Most producers like me are taking actions to prevent vegetation transitions. (descriptive)	12a 12b	3.62 (0.92)	0.76	Lubeck et al. 2019; Niemiec et al. 2016; Willcox et al. 2012
	Risk perception	1-5	1 = Strongly disagree; 2 = Somewhat disagree; 3 = Neither; 4 = Somewhat agree; 5 = Strongly agree	Vegetation transitions will harm the profitability of rangelands in the long term. Vegetation transitions will harm rangeland ecosystems. Vegetation transitions are not a significant challenge to future agricultural productivity. (reverse coded)	6a 6b 6c	4.08 (0.87)	0.72	Azadi et al. 2019; Bennet et al. 2014; Grothmann & Patt, 2005; Niemiec et al. 2016
	Trust in government	1-5	1 = Strongly disagree; 2 = Somewhat disagree; 3 = Neither; 4 = Somewhat agree; 5 = Strongly agree	I trust the government to effectively manage vegetation transitions.	12c	1.83 (1.01)		Azadi et al. 2019; Lubell et al. 2013; Marshall et al. 2016

Analysis

We used several different scales for different question items on the survey and recoded several question items before beginning analyses (Table 10). We dichotomized the response variables (i.e., behaviors) from a 4-point ordinal scale because each level of the scale meant different frequencies depending on the behavior and we wanted to make comparisons between behaviors. We reverse coded several items that were stated in the negative (group efficacy, collective effects on region; self-efficacy, personal; interaction frequency; risk perception to productivity). To generate the operation acreage variable, we summed the number of acres owned and rented, and took the log. We dichotomized the education variable from a 6-point ordinal scale to ease interpretation. To generate the income diversity variable, we asked respondents what proportion of their income came from agriculture (0-19%, 20-39%, 40-59%, 60-79%, 80-100%), took the midpoint of each proportion range, and subtracted that from 100. To generate the group involvement variable, we combined responses from two questions about whether those groups existed and their level of involvement if such groups exist and created a 5-point scale. Experience (in years) and spatial covariance were on continuous scales. All other items, except the ego network variables described below, were measured on a 5-point Likert scale (strongly disagree to strongly agree). All variables except the responses (i.e., behaviors) and education were treated as continuous and standardized.

Network measures

We used E-Net v0.5 (Borgatti 2006) to operationalize respondents' ego network variables. We measured each respondent's network size using degree, which is a count of the number of people (alters) each respondent named as network contacts. We asked each respondent how frequently they engaged with each of their alters on a six-point scale. For each respondent, we averaged interaction frequency across alters. We asked each ego what types of information they received from each of their alters. The respondent could select up to five types of information (i.e., ranch or farm operations, ranch or farm technology, conservation practices, financial or insurance programs, non-operations) from each ego. We summed the number of information types from each alter. For each ego, we averaged the number of information types received from their alters. We measured information types as the average number of information types each ego received from their alters. We asked each ego to report on the occupation (i.e., producer; scientist or researcher; government agency manager or conservationist; other conservation professional; farm financier; other) of each of their alters. We assumed each respondent was a producer because of how we drew the sample.

We measured occupation heterogeneity among ego's alters with Agresti's index of qualitative variation (IQV):

$$IQV = \frac{1-\sum p^2}{1-\frac{1}{k}},$$

where p is the proportion in each category and k is the number of categories. IQV ranges from 0 to 1, where 0 occurs when all alters have the same occupation and 1 occurs when alters are evenly dispersed among occupations (Agresti and Agresti 1977, Borgatti et al. 2013).

We measured occupation homophily as the inverse of Krackhardt and Stern's external-internal (EI) index:

$$EI = \frac{b-a}{b+a},$$

where a is the number of alters that have the same occupation as ego and b is the number of alters that have a different occupation from ego (Krackhardt and Stern 1988, Borgatti et al. 2013). Taking the inverse of EI, occupation homophily measures similarity between an ego and their alters, where -1 occurs when all alters have a different occupation from ego, and 1 occurs when all alters have the same occupation as ego.

We measured density as the number of ties divided by the number of possible ties among alters:

$$Density = \frac{\#\ of\ ties}{\#\ of\ pairs\ (aka\ possible\ ties)},$$

where 0 occurs when there are no ties among alters and 1 occurs when all possible ties among alters exist (Borgatti et al. 2013).

Factor analysis and logistic regressions

We performed factor analysis to reduce the number of variables in the analysis (Table 10). We used exploratory factor analysis to generate the efficacy and learning variables, and confirmatory to generate the norms and risk perception variables. We used the fa.parallel function (psych package; Revelle 2019) in R (version 3.6.1; R Core Team 2019) and found minimum residuals through ordinary least squares with a varimax rotation. For composite variables, we measured scale reliability with Cronbach's alpha, using a cut-off of 0.6 (Vaske 2008). To generate composite variables, we took the average of responses. We removed all respondents with incomplete data after generating composite variables.

We built logistic regression models to test the relationship between adaptive capacity / disturbance variables and each behavior, building one model for each behavior. We fit saturated models with all of the explanatory variables in Table 10. We performed backward, forward, and iterative model selection, measuring model fit with Akaike's Information Criterion (AIC) using the stepAIC function (MASS package; Venables and Ripley 2002), to come up with a candidate set of models for each behavior; however, each procedure resulted in the same model (i.e., the "final model") for each behavior.

We examined model diagnostics to check assumptions and model fit. We examined plots of the logit versus the predicted value for each continuous variable in the final models. We found no evidence of non-linearity except for the heterogeneity variable in the prescribed burning model, likely because it is both 0 and 1 inflated. We identified potentially influential observations with Cook's distance greater than 4/n and high leverage observations with hat values greater than 2p/n and did not find any unusual observations or standardized residuals above 3, and thus no evidence of influence or leverage. We found no evidence of multicollinearity among our explanatory variables in both the saturated and reduced models as all variance inflation factors were below 2.6 (Ott and Longnecker 2015). We determined whether each final model was significantly different from its saturated and null models using likelihood ratio tests. We used Hosmer-Lemeshow tests (ResourceSelection package, hoslem. test function; Lele et al. 2019) to test goodness of fit, using a range of group numbers (4-15) due to the test's sensitivity to group number. We used McFadden's pseudo-R^2 (pscl package, pR2 function; Jackman 2017) to approximate explained variation in our logistic regressions. We report model accuracy and model accuracy with cross-validation. We placed 60% of the data into a training set, which we used to parameterized the model, and determined how well the model predicted the remaining 40% of the data in the testing set.

Results

Overview of sample

We received 573 responses and 176 refusals for a response rate of 12.8% (sample size of 4494). There were no significant differences between our respondents and non-respondents for acres in production for beef, dairy, pasture/range, soybeans, and wheat. However, respondents had significantly less planted acres, gross farm income (GFI), and acres in corn production than non-respondents, indicating that caution should be used when inferring our results to the largest operations (acres >5000, GFI >$2.5 million, acres in corn production >2500). There were no significant differences in demographics (age, gender, education, income) between the paper and email prompts. We received 338 at least partial responses for the ego network part of the survey. After removing incomplete responses, we had 191 responses for this analysis. All descriptive statistics and analyses reported are for this sample of 191 responses. Though a small sample for population-level inference, model diagnostics and fit indicate we can use these data to answer our research questions. Our respondents were 91% male and 7% female with the remaining identifying as other or preferred not to disclose. Respondents most commonly had a 4-year college degree (26%) or some college / vocational training (25%) and made $50-99,999/year (31%) or $100-149,999/year (24%). The average age of respondents was 62 in 2021 at the time the survey was administered. Respondents operated between 38 and 84,000 acres, with a median of 890 acres. 39% of respondents said that 0-19% of their income came from non-agricultural sources, 13% of respondents said that 20-39% of their income came from other sources, 14% of respondents said that 40-59% of their income came from other sources, 16% of respondents said that 60-79% of their income came from other sources, and 18% of respondents said that 80-100% of their income came from other sources. Our respondent profile has a slightly higher income than the average Nebraskan farmer, slightly higher education level than that of the state (Western Economics Services 2021), and a larger farm size than the state average (USDA NASS 2021), which we would expect for ranchers compared to other kinds of agricultural production.

The majority of respondents used mechanical removal but not prescribed burning to manage vegetation transitions (Figure 13). In particular, 35% of respondents always mechanically removed trees as appropriate, 41% occasionally did, 12% rarely did, and 12% never did. Whereas 11% of respondents used prescribed fire always as appropriate, 19% occasionally used fire, 17% rarely used fire, and 53% never use fire.

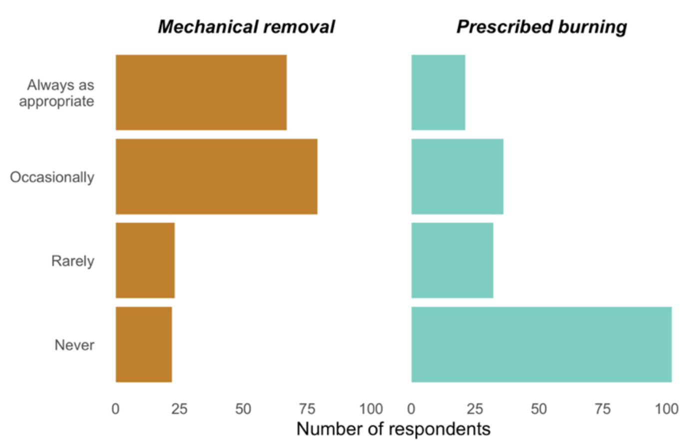


Figure 13: Frequencies of respondent adoption of each behavior in the past three years (at the time the survey was administered).

On average, respondents had 6 contacts in their ego networks (mean degree), interacted with them about 2-3 times/month (mean interaction frequency of 3), got 1.7 different kinds of information from their contacts (mean information type of 1.72 from alters), had moderate to high heterogeneity in their networks (mean occupation heterogeneity of 0.7, where 0 is all in one category and 1 is evenly dispersed), moderate homophily with their contacts (mean occupation homophily of -0.03, where -1 is all ties are to non-producers and 1 is all ties are to producers), and moderate density in their networks (mean density of 0.53, where 0 occurs when there are no ties between alters and 1 occurs when all possible ties exist between alters; Table 10). The vast majority of respondents were not involved in rangeland management groups, mostly because no groups existed in the area (83%). Respondents experienced a mean spatial covariance of -159.5 (where 0 indicates there are either no trees in a grassland regime or there no grasses in a forest regime and -663 is the most severe boundary in the sample).

Model fit

All final models significantly predicted behaviors and had little to no evidence of lack of fit (Table 11). Variables were significant predictors of behavior (P<0.05 for LR test of null versus final model) and reduced models performed just as well as their saturated models (P>0.05 for LR test of saturated versus final model). None of the 12 Hosmer-Lemeshow tests conducted for each model were significant, providing little evidence of poor model fit. McFadden's pseudo-R^2 ranged from 0.16 to 0.29, accuracy ranged from 74-83%, and prediction accuracy using cross-validation ranged from 62-68% across models.

Table 11: Fit and diagnostics for each model; n = sample size, df = degrees of freedom, AIC = Akaike's Information Criterion, LR test = likelihood ratio test, HLGOF = Hosmer-Lemeshow goodness-of-fit, VIF = variance inflation factor.

	Mechanical removal	**Prescribed burning**
n	191	191
df	183	183
AIC (saturated)	183.32	231.97
AIC (reduced)	163.5	212.54
AIC (null)	210.56	234.84
McFadden's R^2	0.29	0.16
LR test (null)[a]	< 0.001	< 0.001
LR test (saturated)[a]	0.98	0.97
HLGOF tests (number of tests where P<0.05)[b]	0	0
Prediction accuracy	83%	74%
Prediction accuracy with cross-validation	68%	62%
VIF (saturated)	1.1-1.9	1.2-2.6
VIF (reduced)	1.13-2.08	1.04-1.53

[a] Likelihood ratio (LR) tests against the null indicate model significance (when P<0.05), whereas LR tests against the saturated model indicate that there is no significant difference between the reduced model and the saturated model (when P>0.05).
[b] We used the Hosmer-Lemeshow goodness-of-fit (HLGOF) test with 4–15 groups per model to test lack of fit—the number reported here is the number of times out 12 that the test was significant (i.e., evidence of lack of fit).

Model results

Explanatory variables in top models varied by behavior (Figure 14, Table 12, Table 13). The most ubiquitous predictor of behavior was change observation. Change observation had a moderate effect size (log odds = 0.5, CI = [0.04, 1]) on mechanical removal, such that a one unit increase in observation increased the odds of mechanical removal by 1.47 times on average, all else being equal. Whereas for prescribed burning, change observation (log odds = 0.61, CI = [0.25, 1]) had a moderate to large effect, such that a one unit increase in observation increased the odds of prescribed burning by 1.6 times on average, all else being equal.

For the mechanical removal model, all variables in the final model had moderate to large effect sizes and confidence intervals above or below 0. The largest effects were of operation acreage measured on a log-scale (log odds = -1.22, CI = [-1.84, -0.66]), such that a 2.75 acre increase (log(2.75)=1) in operation size decreased the odds of removing trees mechanically by 56% on average, all else being equal, and income diversity (log odds = -0.87, CI = [-1.45, -0.34]), such that every 20% increase in income from other sources decreased the odds of mechanical removal by 3% all else being equal. Vegetation transition boundaries had also had an effect, such that for every 100 unit increase in spatial covariance, indicating decreasing boundary severity, producers were 50% less likely to mechanically remove trees, all else being equal [log odds = -0.69, CI = [-1.31, -0.15]). For network density, the presence of the linear (log odds = -0.63, CI = [-1.09, -0.2]) and quadratic (log odds = -0.69, CI = [-1.25, -0.17]) terms indicate that the relationship between mechanical removal and density is non-linear, such that mechanical removal is most likely at moderate densities, and is least likely at low and high densities. Finally, interaction frequency had a moderate effect size (log odds = 0.48, CI = [0.04, 0.95]), such that a one unit increase in interaction frequency increased the odds of mechanical removal by 1.45 times on average, all else being equal.

The final model for prescribed burning had the largest number of social organization and socio-cognitive variables of the two models tested. Group involvement (log odds = 0.5, CI = [0.17, 0.84]) and occupation homophily (log odds = 0.49, CI = [0.07, 0.96]) had moderate effect sizes and confidence intervals not spanning 0. A one unit increase in group involvement increased the odds of prescribed burning by 1.65 times on average, all else being equal, and a one unit increase in homophily increased the odds of prescribed burning by 2.25 times on average, all else being equal. Occupation heterogeneity (log odds = 0.33, CI = [-0.08, 0.79]) and information types (log odds = 0.31, CI = [-0.04, 0.66]) also had moderate effects, such that a one unit increase in heterogeneity increased prescribed burning by 2.5 times on average all else being equal, and for every information type received from alters, odds of prescribed burning increased by 1.43 times on average all else being equal. Trust in government (log odds = 0.43, CI = [0.09, 0.77]) had a moderate effect, such that a one unit increase in trust increased the odds of prescribed burning by 1.53 times on average all else being equal. Education (log odds = 0.62, CI = [-0.1, 1.38]) also had a large effect, such that the odds of using prescribed burning increased by 1.86 times on average for those with a 2-year college degree or more, compared to those with less education.

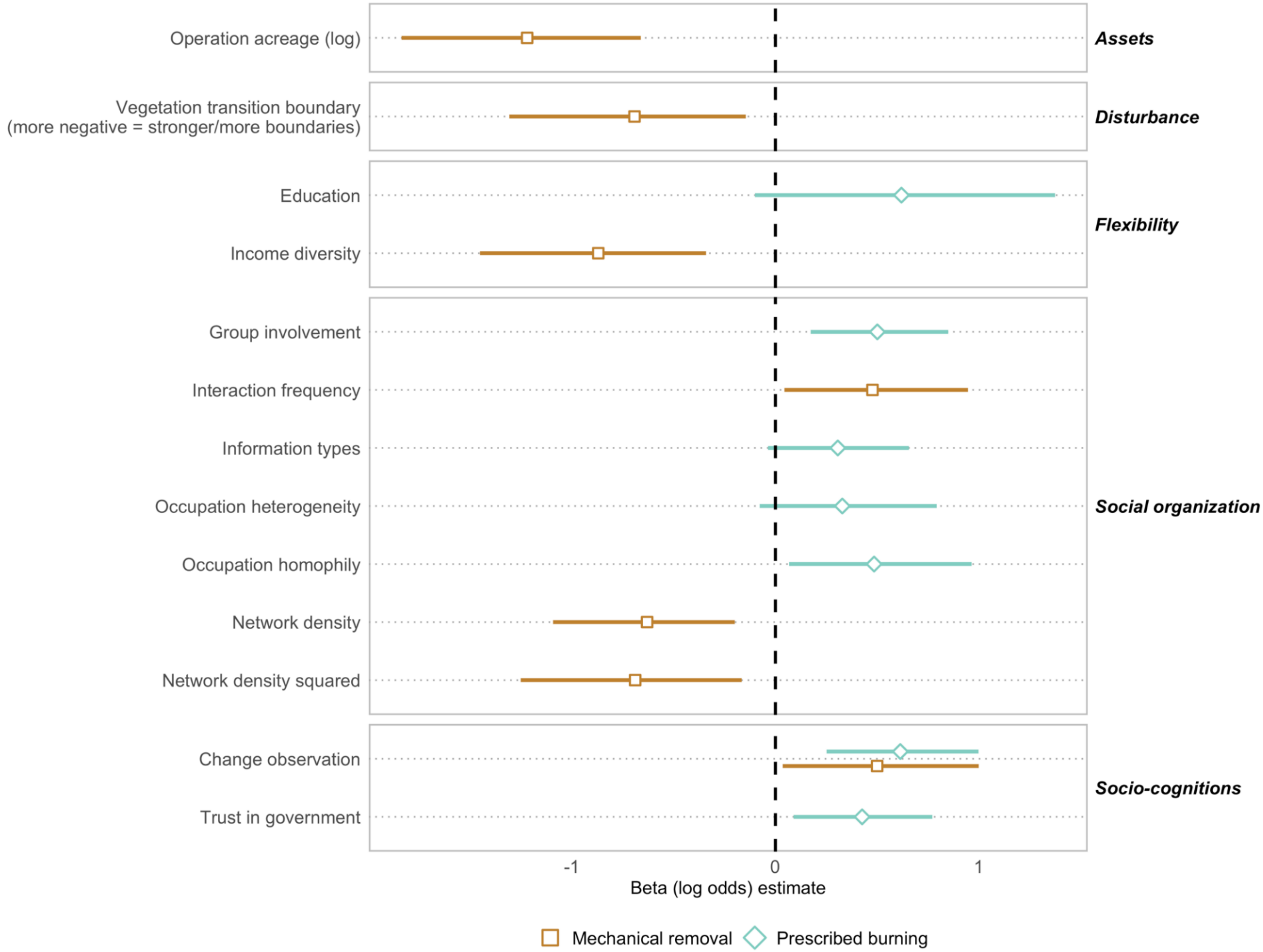


Figure 14: Log odds estimates for parameters in each reduced model (based on Akaike's Information Criterion) predicting mechanical removal and prescribed burning. The square and diamond symbols denote the point estimate and the bars denote the 95% confidence interval.

Table 12: Log odds estimates and 95% confidence intervals (CIs) for standardized parameters in each reduced model (based on Akaike's Information Criterion) predicting mechanical removal and prescribed burning. Numbers correspond to those shown in Figure 14.

Dimension	Variable	Mechanical removal		Prescribed burning	
		Log odds (95% CI)	**Wald P**	**Log odds (95% CI)**	**Wald P**
	Intercept	2.44 (1.67, 3.34)	< 0.001	-1.39 (-2.02, -0.83)	< 0.001
Assets	Operation acreage (log)	-1.22 (-1.84, -0.66)	< 0.001		
Disturbance	Vegetation transition boundary	-0.69 (-1.31, -0.15)	0.02		
Flexibility	Income diversity	-0.87 (-1.45, -0.34)	0.002		
	Education			0.62 (-0.1, 1.38)	0.098
Social organization	Group involvement			0.5 (0.17, 0.84)	0.003
	Network degree				
	Interaction frequency	0.48 (0.04, 0.95)	0.04		
	Information types			0.31 (-0.04, 0.66)	0.08
	Occupation heterogeneity			0.33 (-0.08, 0.79)	0.13
	Occupation homophily			0.49 (0.07, 0.96)	0.03
	Network density	-0.63 (-1.09, -0.2)	0.005		
	Network density squared	-0.69 (-1.25, -0.17)	0.01		
Socio-cognitions	Change observation	0.5 (0.04, 1)	0.04	0.61 (0.25, 1)	0.001
	Trust in government			0.43 (0.09, 0.77)	0.01

Table 13: Odds estimates and 95% confidence intervals (CIs) for unstandardized parameters in each reduced model (based on Akaike's Information Criterion) predicting mechanical removal and prescribed burning. Numbers correspond to those in the text.

Dimension	Variable	Mechanical removal		Prescribed burning	
		Odds ratio (95% CI)	**Wald P**	**Odds ratio (95% CI)**	**Wald P**
	Intercept	394.61 (11.78, 18402.31)	< 0.001	0.01 (0, 0.05)	< 0.001
Assets	Operation acreage (log)	0.44 (0.29, 0.64)	< 0.001		
Disturbance	Vegetation transition boundary	0.995 (0.99, 1)	0.02		
Flexibility	Education			1.86 (0.9, 3.96)	0.098
	Income diversity	0.97 (0.95, 0.99)	0.002		
Social organization	Group involvement			1.65 (1.19, 2.34)	0.003
	Network degree				
	Interaction frequency	1.45 (1.04, 2.09)	0.04		
	Information types			1.43 (0.96, 2.16)	0.08
	Occupation heterogeneity			2.5 (0.81, 9.1)	0.13
	Occupation homophily			2.25 (1.12, 4.99)	0.03
	Network density	42.04 (0.73, 2904.23)	0.005		
	Network density squared	0.01 (0, 0.29)	0.01		
Socio-cognitions	Change observation	1.47 (1.03, 2.16)	0.04	1.6 (1.21, 2.16)	0.001
	Trust in government			1.53 (1.09, 2.15)	0.01

Discussion

Our results demonstrate that dimensions of adaptive capacity – especially social organization and socio-cognitions – and ecological disturbance influence adaptive and transformative behavior to manage regime shifts in a threatened grassland social-ecological system. Social organization and socio-cognitive variables were particularly predictive of prescribed burning, a transformative behavior that is arguably one of the most effective at managing vegetation transitions at large spatial scales. Furthermore, while ecological disturbance at the local level was predictive of mechanical removal, it was not for prescribed burning, suggesting that social connections and cognitions, though often under-theorized/quantified, are critically important for influencing transformative behavior. Given that both prescribed burning and mechanical removal are necessary treatments to manage cedar encroachment, often in tandem, these findings have direct implications for those seeking to both increase landowner responses to the encroachment and elevate this issue to higher levels of governance for policy intervention. These findings have implications for the study and management of social-ecological systems more broadly, highlighting that social networks play a critical role in adaptive and transformative responses to ecological change. Leveraging an understanding of social networks may help practitioners across the globe encourage behaviors that enable sustainable management of our social-ecological systems.

Our prescribed burning model provides evidence that this highly effective behavior for managing cedar encroachment (Twidwell et al. 2013*a*, 2021, Roberts et al. 2022) is influenced by social organization and socio-cognitive processes. Prescribed burning, though not a new technique, is having a resurgence as the Eurocentric paradigm of fire suppression begins to shift in recognition of the essential role disturbance plays for the resilience of social-ecological systems, including grasslands (Russell-Smith and Thornton 2013, Twidwell et al. 2013*b*). 30% of the producers in this study used fire to manage their operation on an occasional or more frequent basis, compared to 76% who mechanically removed trees. Thus, for this demographic at least, prescribed burning is novel and innovative. There is a long tradition from the social network analysis literature studying how innovation spreads throughout a network (Coleman et al. 1957, DiMaggio and Powell 1983, Hansen 1999, Valente and Davis 1999, Podolny 2001, Obstfeld 2005, Davis 2016) – and our research is consistent with this larger body of work. Innovative behaviors like prescribed burning increase with access to novel information when networks are diverse (i.e., heterogeneity) and when the person of focus is more similar to their networks (i.e., homophily). While these heterogeneity and homophily mechanisms may seem contradictory, they are not. Heterogeneity and homophily are measuring similar, but different concepts and were mildly negatively correlated in our study (r = -0.36). We suspect that different mechanisms are at play for different types of producers – those with heterogenous networks and those with homophilous networks – and both of these mechanisms are important. Those with heterogeneous networks have access to more information and resources (Sandström and Carlsson 2008, André et al. 2017), while those with homophilous networks are more influenced by their close knit communities (Burt 1982, McPherson et al. 2001, Newig et al. 2010, Barnes et al. 2020).

Not only is prescribed burning innovative, it also usually requires more than one person to accomplish via coordinated collective action. For such actions, it makes intuitive sense that social variables would be important predictors (Olson 1965). For example, involvement in rangeland management groups, the kind required to manage fire on the landscape, is an important predictor of prescribed burning. Furthermore, close knit communities of producers (with high homophily), are more likely to support and influence one another (McPherson et al. 2001) to come together to use fire on the landscape. Coordinated collective action is also supported in heterogenous, educated networks, which have access to the information and resources (Granovetter 1973, Hahn et al. 2006, Sandström and Carlsson 2008, Lubell et al. 2013) required to undertake such an onerous activity, both in terms of the work on the landscape as well as acquiring the necessary permits (Twidwell et al. 2013*b*, 2015). Because prescribed burning requires permits and government agency involvement, we suspect that those who use this tool either already trust the government or develop trust with the government as interactions with government employees increase (Lubell et al. 2013, Stern and Coleman 2015, Azadi et al. 2019).

Importantly, social organization and socio-cognitive variables were strongly associated with prescribed burning behavior, as was the extent to which disturbance was observed by the producer, but severity of the vegetation transition boundary at the local level was not. Social connections and cognitions are more important for prescribed burning than actual local change on the landscape, which suggests at least two different mechanisms are driving producers' behaviors, or some combination thereof. First, social organization and socio-cognitions, manifesting in low social support and information access, may act as significant constraints to a producer hoping to implement prescribed burning even when vegetation transition boundaries are locally severe. Based on pervasive perceptions of fire risk and the significant litigious and bureaucratic hurdles in place around prescribed burning (Russell-Smith and Thornton 2013, Twidwell et al. 2015, Weir et al. 2016), this mechanism seems likely. The second possibility is that producers receive information about regional scale ecological change, through their social networks, which is more important to their behavior than local ecological conditions. In other words, perhaps these social connections are encouraging proactive behavior as producers begin to notice and prepare for the "cedar wave" if they have contacts in already affected areas or in government/research/conservation already confronting the problem. Based on social innovation and diffusion theory (Obstfeld 2005), this mechanism also seems likely. An interesting avenue for future research would be to determine what scale of biophysical change influences producers' decisions about prescribed burning, if at all. Another unanswered question is whether this finding is confounded by the effectiveness of the behavior at addressing the challenge. For example, if prescribed burning is effective at keeping cedar encroachment at bay on a producer's operation, spatial covariation wouldn't indicate that cedar are present even though the threat is there and is just being managed. Indeed, producers who use prescribed burning may not have actual cedar recruitment on their operation, but may be using fire to kill the seedbank (Twidwell et al. 2021).

Producers who interacted more frequently with their contacts, had moderately dense social networks, and experienced and observed vegetation transitions at the local scale were more likely to mechanically remove trees on their operation. Frequency of interaction may indicate a lack of isolation from the surrounding community and more access to information (Uzzi 1999, Reagans and McEvily 2003, Amadu et al. 2021). The finding that adaptive behavior peaks at moderate densities is consistent with social network research on organizational behavior – at low densities access to information is weak, yet at high densities, social constraint mechanisms prevent behavioral change or behaviors that are inconsistent with the rest of the network. In this case, an optimized network would have some combination of ties that provide both access to novel information and social support (Uzzi 1999, Oh et al. 2004). Furthermore, knowledge transfer has been found to be influenced by network structure – while tacit knowledge transfer requires dense networks, knowledge transfer enabling innovative behavior happens more often in open networks (Hansen 1999). Given that mechanically removing trees is hardly tacit, it seems reasonable that this type of behavior would transfer readily through open, moderately dense networks. Different from prescribed burning, mechanical removal was more likely for producers who experienced and observed increasing local vegetation transitions. As mechanical removal by definition means that saplings or trees are present, it makes sense that local experience and observation would occur in tandem to drive this behavior.

Contrary to our predictions, mechanical removal was less likely among producers with large operations or more diverse income streams. This finding may be indicative of the spatial and temporal constraints producers must navigate. Producers with large operations may find mechanical remove infeasible or impractical due to the large spatial extent they have to cover with their management. Similarly, producers with diverse income streams may not have the time to mechanically remove trees from their operation. On the other hand, given that observation of vegetation transitions was predictive of mechanical removal, it could be that less observation takes place in producers with large operations or diverse income streams due to spatial/temporal limitations in their capacity.

Producers understand the risks of cedar encroachment, but that understanding does not translate into adaptive or transformative behavior, suggesting that other social factors are constraining them more than their general knowledge of the issue. In particular, risk perceptions of cedar encroachment were not predictive of prescribed burning or mechanical removal and most producers perceived high risks from cedar encroachment. Together, these two results suggest that a deficit of risk information is not the issue (Heberlein 2012) – the issue is more likely a deficit of social support and socio-cognitions. For example, not understanding how to use fire and mechanical treatments to manage cedar, not having enough people to manage a treatment area, not having social support to use fire and fearing the social repercussions, and not being able to navigate the bureaucracy around burning (Russell-Smith and Thornton 2013, Twidwell et al. 2015, Weir et al. 2016) are likely limiting behavior more than an understanding of risk. This result also suggests that "information out" campaigns have likely been effective at improving producers' understanding, but not changing their behavior. Thus, campaigns that provide social support and target socio-cognitive constraints may be more effective at changing behavior (Heberlein 2012), particularly for prescribed burning (Twidwell et al. 2015, Weir et al. 2016).

There are a few caveats to our research that require consideration. Though normal for this demographic, our response rate was low and our sample demographic was slightly more educated and affluent than the target population (Western Economics Services 2021). We were also unable to sample the largest operations (acres >5000, GFI >$2.5 million) in our target population from the National Agricultural Survey. Based on budgetary limitations, we were unable to sample the entire state, so we sampled a cross-section of Nebraska that is representative of the vegetation transition gradient, constraining the extent of our inference. However, after vetting our results with several producers and conservation professionals across the state, our results appear to be consistent with their experiences, at least anecdotally.

Our research adds to the body of evidence that cedar encroachment is a large scale threat to the American Great Plains biome (Uden et al. 2019) that requires a matching scale of social response (Weir et al. 2016). Our findings may be informative for those seeking to encourage producers to manage vegetation transitions on their operations or to encourage collective action among producers on the larger landscape. There is a considerable, ongoing effort by extension professionals, non-profits, researchers, and agencies to support producers managing vegetation transitions. For example, extension professionals connect interested producers with partners who can support them in writing burn plans and engaging in cost-share programs for mechanical removal (but typically not prescribed burning because of legal concerns; Twidwell et al. 2015). Non-profits in the form of conservation organizations and prescribed burn associations provide information, resources, and a community of people to help producers burn their land. Researchers are working on diagnostic tools to provide early detection of problem areas and enable more proactive, strategic management (Uden et al. 2019), while agencies are releasing best management guidelines and running workshops to teach producers how to limit the risk of cedar encroachment on their operations (Natural Resources Conservation Service 2021, Twidwell et al. 2021). Some of these efforts clearly target the constraints we have identified in this study – providing physical human labor, information, and resources are essential. Yet these efforts treat this problem on an individual landowner basis which is clearly not effective at scale because the encroachment continues (Twidwell 2022). Our research shows that implementing prescribed burning is a collective action problem that requires considerable social support at levels beyond the individual (Twidwell et al. 2013*b*, Weir et al. 2016). In particular, we demonstrate that networks and rangeland management groups are strongly related to prescribed burning. Supporting groups like prescribed burn associations with further capacity and building extensive prescribed burn networks through higher level policy initiatives may be effective. Given that trust was also predictive of prescribed burning, increasing trust in government, such as with consistent messaging across agencies and levels (Lachapelle and McCool 2012, Stern and Coleman 2015) or other means, may also be effective. For example, eliminating Natural Resource Districts' cost-sharing programs for establishing cedar wind breaks and updating their guidelines to manage cedar wind breaks where they exist (Nebraska Association of Resources Districts 2021) would be more consistent with management guidelines released by the USDA to manage cedar risk (Natural Resources Conservation Service 2021). While it is possible this change may improve trust in government, without question it would reduce seed sources across the state.

This research also illuminates further questions for exploration that may help inform higher level policy to manage vegetation transitions at scale. For example, it may be helpful to understand the scale of disturbance that influences individual producers to use prescribed burning on their operation and whether social networks across broader landscapes play a role in disseminating information and influencing behavior. If spatially dispersed networks do play a role, campaigns that connect producers across the state with diverse cedar encroachment experiences may be beneficial. Producers sharing narratives of their own challenges and learnings in areas that have experienced the transition may be highly influential for producers who are still on the front end of the wave. It may also be helpful to better understand the preconditions and ongoing interactions that enable effective behaviors at scales that actually make a difference through in-depth case studies. For example, the Loess Canyons Rangeland Alliance is a burn group that has near 100% producer participation in an area of about 100,000 acres, enabling them to manage the land strategically and with capacity (University of Nebraska 2021). Performing a whole network analysis on such a group, paired with qualitative analyses such as interviews and document review, may reveal barriers and opportunities for creative policy makers to implement interventions across the state.

Given the rapid global change and sustainability issues we continue to face, understanding how people can create or maintain the social-ecological systems in which they want to live is essential (Higuera et al. 2019). This research provides a quantitative example of how social organization plays a critical role in enabling adaptive and transformative responses to widescale regime shifts. We use a relatively novel ego network approach that is compatible with standard survey design and statistical procedures and which can be illustrative for other researchers interested in measuring structurally explicit aspects of social organization. Furthermore, we demonstrate how disturbance at one spatial scale mobilizes adaptive capacity for adaptive but not transformative behavior. This finding points to the important, but rarely quantified interaction between social and ecological variables, suggesting that social barriers can substantially limit transformative behavior despite both the presence of an ecological threat and an understanding of the consequences of inaction. We add to the limited, but growing, body of work quantifying both social and ecological aspects of adapting to global change. We believe these approaches and findings are broadly applicable to both the theory of social ecological systems science and management.

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Chapter 4: Scalar mismatches in a social-ecological system experiencing a regime shift

Ecological disturbance interactions across spatial levels and collective efforts influence individual behavior to manage regime shifts in a system dominated by private land ownership

Abstract

Scalar mismatches occur when the alignment between the level of an ecological process and the level of society responsible for managing that process results in major disruptions or losses to the social-ecological system. How scalar mismatches specifically manifest to affect social-ecological system management is not well understood but may provide insight into how system alignment could further enable sustainability. The American Great Plains biome provides an opportune study system to examine scalar mismatches and their effects on wide-spread social-ecological change. Mismatches in this social-ecological system may be hindering efforts to limit the westward encroachment of eastern redcedar (*Juniperus virginiana*), which has the potential to result in a system-wide regime shift and the complete collapse of the biome. We asked how scalar mismatches manifest to influence individual behaviors to manage regime shifts. We examined the effects of cross-level spatial interactions of ecological disturbance and engagement in collective action on individual landowner behaviors of mechanical tree removal and prescribed burning. We used data from a mail-back/online questionnaire and a rangeland landcover raster dataset to build logistic regressions predicting landowner behavior. We found that spatial interactions and collective factors influence individual management, with practical implications for managing cedar encroachment in Nebraska and the surrounding states, and theoretical implications for the study of scalar dynamics and interactions in social-ecological systems threatened by scalar mismatches and regime shifts globally.

Introduction

Disturbance is an essential component of any resilient social-ecological system because it maintains diversity and processes for learning (Berkes et al. 2003). Yet ecological disturbance can overwhelm adaptive and transformative human responses such that social-ecological systems undergo wide-spread regime shifts, whereby a system switches from one regime to another persistent regime through hysteresis (Walker et al. 2004). Regime shifts are evident in ecosystems across the globe – including when aquatic communities reorganize or nutrient levels drive shifts in watersheds (Gunderson et al. 2017, Gilarranz et al. 2022); when changing atmospheric conditions, altered food web dynamics, or habitat loss drive shifts in marine environments (deYoung et al. 2008); and when desertification, exotic annual grass invasion, or woody encroachment drive shifts in grasslands (D'Antonio and Vitousek 1992, Chambers et al. 2014, Bestelmeyer et al. 2015, Lasslop et al. 2016). How ecological disturbance mobilizes individual human behavior may be important for understanding how to limit the extent and effects of regime shifts, particularly in contexts where individual behavior is one of the only social levels through which management can be implemented (i.e., in regions with extensive private land ownership). However, we know little about how ecological disturbance interactions and collective social forces together influence individual behaviors to manage regime shifts, an understanding of which may reveal opportunities for policy interventions that promote better scalar alignment between disturbances and how society manages them.

A social-ecological system contains coupled social and ecological components that interact within and across scales and levels to generate emergent properties (Colding and Barthel 2019). Resilience is when a social-ecological system retains the "same function, structure, feedbacks, and therefore identity" (Walker et al., 2006, p. 2) despite disturbance. The ability to respond to or drive change is a system's latent adaptive capacity (Gunderson 2000, Carpenter et al. 2001, Walker et al. 2006, Cinner and Barnes 2019), which can be mobilized toward adaptation such that the system is maintained as is, or transformation such that the system shifts into a different, presumably more desirable regime (Walker et al. 2004, Leach 2008, Beymer-Farris et al. 2012, Cote and Nightingale 2012, Taylor 2015, Chaffin et al. 2016, Blythe et al. 2018, Scoones et al. 2018, Higuera et al. 2019). While it is widely recognized that disturbance plays a critical role in maintaining the adaptive capacity of a social-ecological system by promoting learning, flexibility, and diversity (Holling 1986, Gunderson and Holling 2002, Berkes et al. 2003), few scholars to our knowledge have examined how disturbance interactions at different spatial levels influence social responses that ultimately act as feedbacks on the ecological component of the system.

Organization or pattern is an emergent property of structures and processes interacting within and across different scales and levels, thus scales and levels are a critical consideration in the study of social-ecological systems. Though "scale" and "level" have numerous definitions and are often conflated, we follow Gibson et al. (2000) and define scale as "the spatial, temporal, quantitative, or analytical dimensions used to measure and study any phenomenon" and levels as the "units of analysis that are located at the same position on a scale." Ecological phenomena are typically studied in the context of their spatial and temporal scales, where levels might include small and large areas on a spatial scale and short and long durations on a temporal scale. Social phenomena can be studied on spatial and temporal scales, and are also often studied in terms of their analytical dimension, which might include individual, municipal, state, federal, and institutional levels. How one scale or level affects another in social-ecological systems is the central tenant of panarchy, whereby adaptive cycles of collapse, reorganization, growth, and conservation interact across scales/levels (Gunderson and Holling 2002). Initially conceptualized in ecology, each adaptive cycle is part of a nested hierarchy of cycles typically based on spatial and temporal scales where slow, large-area processes are at the top of the hierarchy, and fast, small-area processes are at the bottom. Disturbance can propagate across levels to affect emergent outcomes of the social-ecological system. Constraints at higher levels may influence what is possible at lower levels (e.g., salmon stock depletion in ocean fisheries limits the number of salmon that spawn in a local watershed) whereas lower-level changes can propagate through a system to higher levels, particularly when that system is brittle and vulnerable to collapse (e.g., aquatic species invasion causing complete ecosystem reorganization). Furthermore, the unique combination of cross-level interactions dictates how a system reorganizes following collapse (e.g., recolonization of salmon from a neighboring watershed following dam removal; Peterson 2000).

Scalar mismatches occur when the alignment between the level of an ecological process and the level of society responsible for managing that process results in major disruptions or losses to the social-ecological system (Berkes and Folke 1998, Gunderson and Holling 2002, Cumming et al. 2006). Social and ecological processes can be misaligned spatially, temporally, or functionally. These mismatches occur when interactions across scales and levels change, resulting in a loss in adaptive capacity and resilience. Cumming et al. (2006) argue that the primary social cause for scalar mismatches is with respect to land tenure, including the rights and rules around land access and use, while the primary ecological cause for scalar mismatches is with respect to changing resources. Misalignment of coupled social-ecological processes is a result of changing interactions between these two components, whereby misaligned feedback dynamics, rather than dynamics internal to either the social or ecological component, are driving losses to system resilience. Resolving these mismatches requires identifying where and how misalignment has occurred, removing institutional barriers, and creating enabling conditions such that principles of adaptive co-management, polycentric governance, and collective action can emerge (McGinnis 19991, Dietz et al. 2003, Folke et al. 2005, Cumming et al. 2006, da Silveira and Richards 2013).

The American Great Plains biome provides an excellent example of how cross-scalar/level interactions influence emergent outcomes in a social-ecological system. Although this biome has been in a grassland state for several millennia (Nordt et al. 2008, Cordova et al. 2011), changing interactions among key drivers, including grasses, herbivores, humans, climate, and fire (Engle et al. 2008), have enabled eastern redcedar (*Juniperus virginiana*, hereafter "cedar") woodlands to encroach on grasslands (Briggs et al. 2005, Van Oaken 2009) with the potential to force a system-wide regime shift (Walker et al. 2004, Uden et al. 2019). This regime shift is likely the consequence of both high-level constraints on low-level processes and low-level changes that propagate rapidly to the highest levels of this currently vulnerable system. For example, the highest constraint with effects across scales and levels is likely the colonial fire suppression paradigm, which permeates all social levels, affects wide spatial areas, has existed for a long period of time, and enables fire-sensitive cedar to germinate and spread (Twidwell et al. 2013). Climate-change induced drought, which makes cedar more competitive, and state-endorsed tree planting programs further constrain adaptive capacity at the system's lower levels. On the other hand, low-level local processes include cedar recruitment from windbreaks, fire suppression, overgrazing, and micro-climate and topography where these trees are more competitive (Briggs et al. 2005, Allred et al. 2012, Taylor et al. 2012, Twidwell et al. 2014). Because the system is highly brittle, driven by changes across multiple scales and levels, these processes, together, "scale-up" such that "islands" of cedar in a "sea" of grass become "continents." At some point, the higher level processes began to overwhelm those at the lower level and cedar is now spreading progressively from east to west (Briggs et al. 2005, Van Oaken 2009, Natural Resources Conservation Service 2021). While these scalar processes have been well-studied, predominantly in the context of the ecological component of the system, we know little about how different levels of ecological disturbance across space may influence the social component of the system that is, at least hypothetically, capable of limiting the pace and extent of this regime shift.

Scalar mismatches may be a critical barrier to managing cedar encroachment and limiting the extent of a wide-spread regime shift in the state of Nebraska, US (Roberts et al. 2018). Of the 50 states, Nebraska has the third most private land in the country (tied with Iowa), with 97.4% of the land area in private holdings (Headwaters Economics 2019). Because the state is almost exclusively private land, policy makers frequently describe and treat cedar encroachment as a landowner issue (D. Twidwell, personal communication). The vast majority of management actions must be funnelled through individual landowners (or managers) even though the spatial scale of encroachment exceeds even the state. With only the ability to manage their own properties, producers at an individual level are attempting to manage an ecological process that is occurring at much larger spatial extents. While individuals may be successful at limiting encroachment on their own properties, they are currently unsuccessful at halting the encroachment occurring across the state. Thus, a low-level social process of individual land tenure is likely mismatched with a high-level ecological process of woodland encroachment. Taken together with the high-level constraints (pervasive fire suppression paradigm, climate change, and tree cost-share programs) and low-level processes (local recruitment, fire suppression, overgrazing, and micro-climate/topography) that alter social-ecological feedbacks, it is perhaps not surprising that cedar encroachment continues. However, collective efforts exist to support landowners seeking to manage this encroachment, including federal initiatives, conservation non-profit organizations, prescribed burn associations, and other less formal rangeland management groups. Investigating how different spatial levels of disturbance combined with different social levels of support may influence individual landowners' management actions toward encroachment may reveal windows of opportunity to increase voluntary management of cedar in the Great Plains.

Here, we asked how scalar mismatches between social and ecological components of the system are manifesting to influence management of wide-spread regime shifts. We assessed the relative effects of different spatial levels of disturbance, their interaction, and involvement in rangeland management groups on the probability that a landowner engages in behaviors to manage cedar encroachment in Nebraska. Using data from a mail-back/online questionnaire and a rangeland landcover raster dataset, we built two logistic regressions predicting landowner engagement in mechanical removal of cedar and prescribed burning of property to eliminate seed dispersal and recruitment. We calculated disturbance as the change in mean percent tree cover from 1990 to 2020 in a 1 km (local) and 100 km (regional) radius around each respondent's geocoded location. We hypothesized that a mismatch between ecological disturbance and the social levels responsible for management would occur such that i) regional-level disturbance would have a larger effect on individual behavior than local-level disturbance, ii) the effect of local-level disturbance on an individual's behavior would be dependent on the extent of regional-level disturbance, and iii) collective efforts would significantly increase the likelihood of individual behavior to manage encroachment. Alternatively, if scales were matched, local-level disturbance would have a larger effect on individual behavior than regional-level disturbance, there would be no interaction effect, and collective efforts would not increase the likelihood of individual behavior to manage encroachment. How mismatches manifest has implications for managing this particular regime shift as well as implications for the study of scalar mismatches and regime shifts in social-ecological systems globally.

Methods

Study area

This study was conducted in Nebraska, USA, which is in the American Great Plains biome. Nebraska consists of grassland ecoregions characterized by substantial row crop agriculture and ranching (Chapman et al. 2001). Wide-spread cedar encroachment has resulted in high severity transition areas in over a third of the state (Natural Resources Conservation Service 2021). Landowners can use a variety of interventions to manage this regime shift depending on the stage of encroachment. Preventing seed source contamination is the best way to protect intact grasslands. Once seed dispersal and/or recruitment has occurred, management options include mechanical removal of seedlings and fire to kill the seedbank. In active recruitment zones, removing trees before they reach maturity is recommended. Areas within an estimated 183 meters (200 yards) of a seed source need to be managed for recruitment and prevent dispersal. If trees reach maturity, thinning and prescribed burning are the most effective techniques for managing the encroachment. Where complete regime shifts have occurred such that the area is in a total woodland regime, management options are limited to monitoring and tree removal to contain the area and prevent neighboring contamination (Twidwell et al. 2021). For more description of Nebraska's ecoregions and management of cedar encroachment, see Chapter 3's study area section.

Data collection

Social data

In 2021, we administered a mail-back and online questionnaire (Appendix 3A) to producers in Nebraska (UNL IRB# 20086, UM IRB #235-19) to collect these data. Two graduate students, two faculty, three extension professionals, and two ranchers piloted the questionnaire. Our study area included 31 counties across a gradient of the vegetation transition (Figure 15). We purchased producer address information from Farm Market iD, a data marketing company in the agricultural industry. We requested addresses within our study area counties for all of the respondents to the National Agricultural Survey who self-identified as having >20 acres of pasture/rangeland (6546 people with mailing addresses, 3448 of which had emails). After taking simple random sample of 4500 from this population and removing duplicates, we had a sample size of 4494 individuals, 2409 of which with emails. Using a modified tailored design (Dillman et al. 2014), we sent three emails (June 4, June 23, July 23) and three paper mailings, including a letter, and two questionnaire mailings (May 26, June 11, June 24). The survey included questions about producers' behaviors and group involvement.

Ecological data

Ecological disturbance data were calculated based on percent tree cover in the Rangeland Analysis Platform v2.0 (RAP v2.0; USDA NRCS et al. 2019). We calculated the mean percent tree cover at each respondent's location by averaging the percent tree cover of every pixel within a 1 km radius and a

100 km radius of their address in 1990 and in 2020 (Figure 15). To calculate the change in mean percent tree cover, we subtracted the 1990 mean percent tree cover values from the 2020 mean percent tree cover values for each respondent. We chose a 1 km radius because it results in an area of 3.14 km^2, which is 776 acres and close to the average farm size in Nebraska of 1000 acres (USDA NASS 2021). We chose a 100 km radius because it is far enough to include average commute times for every county in the state, which range from 10-30 minutes (Index Mundi 2018). Assuming a driving speed of 130 km/h (80 mph), it would take a person about 30 minutes to drive 70 km. Additionally, change in mean percent tree cover calculated at a 100 km radius was not highly correlated with change in mean percent tree cover calculated at a 1 km radius (r = 0.36) such that we could include both variables in a model and not have issues with multicollinearity.

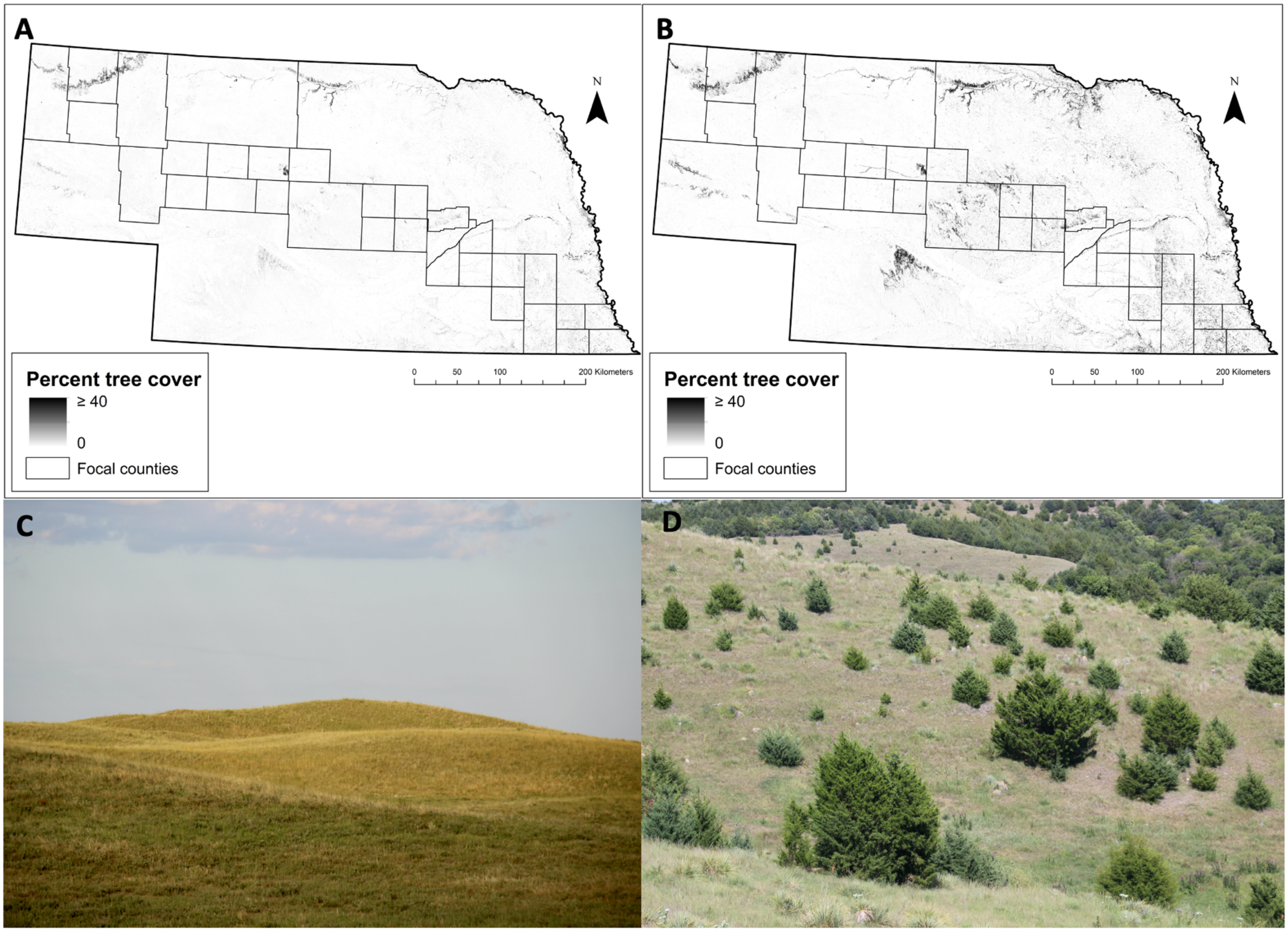


Figure 15: Percent tree cover in 1990 (A) and 2020 (B) in greyscale; counties that were sampled are highlighted and represent a gradient of the vegetation transition. Photos of 0% tree cover (C) and 5-10% tree cover in the foreground (D).

Theoretical framing and measures

The social and ecological components of a system are linked through social factors that affect ecosystems and ecological factors that affect society (Berkes and Folke 1998, Anderies et al. 2004, Ostrom 2009). In Nebraska's Great Plains biome, relationships within the social component of the system lead to collective (coordinated and uncoordinated) and individual factors that must be funnelled through individual behavior because most of Nebraska's land area is held in private property (Figure 16). These individual behaviors seek to prevent regime shifts in the ecological component of the system. Relationships within the ecological component result in local- and regional-level landscape changes that interact with one another to influence the social component of the system. Instead of focusing our study within the social or ecological components, we focused on the relationships (i.e., solid arrows) that connect these two components.

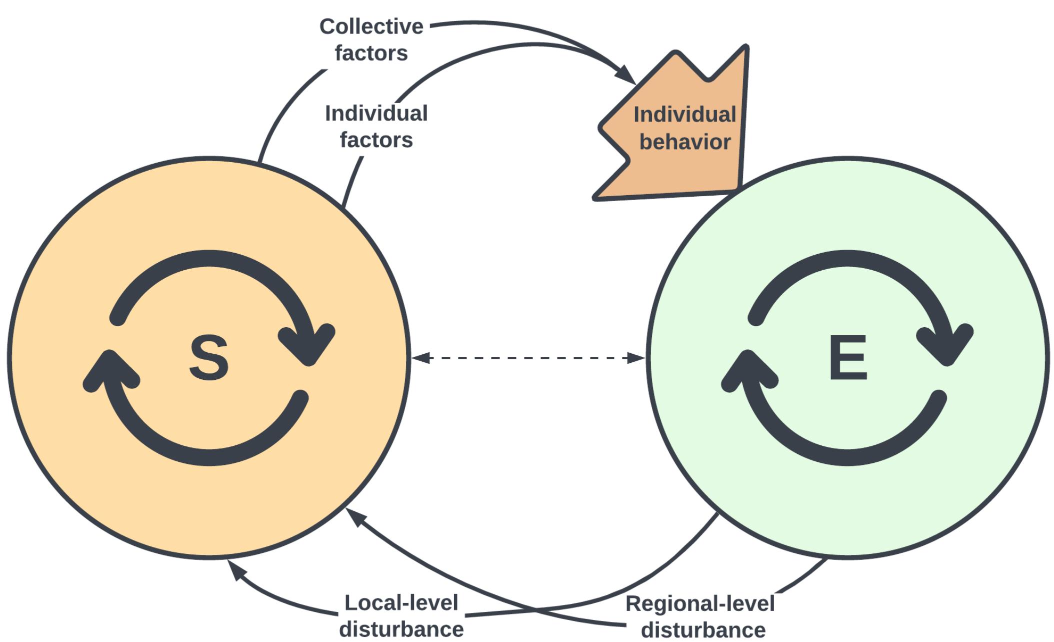


Figure 16: Conceptual diagram of our theoretical framing. In Nebraska's Great Plains Biome social-ecological system, social (S) collective and individual factors are funneled through individual behavior in a landscape that is predominantly privately owned to influence the ecological (E) component, whereas local- and regional-level disturbance interact to influence the social component. The dashed arrow indicates that there are many other connections between social and ecological components that were not studied here.

We tested the relative effects of involvement in rangeland management groups, local- and regional-level changes in mean percent tree cover, and the interactions across these spatial levels on the probability that a producer uses mechanical removal or prescribed burning to manage vegetation transitions. To measure behaviors (i.e., response variables), we asked respondents how often they used mechanical removal and prescribed burning to manage vegetation transitions on their operation in the last three years (Table 14).

We also asked each respondent their level of involvement in local rangeland management groups (Bennett et al. 2014, Cinner et al. 2015, Marshall et al. 2016). We hypothesized that individual behavior to manage encroachment would be more likely for those involved in collective efforts than those not involved. Additionally, the effect of group involvement would be greater for prescribed burning than mechanical removal. Prescribed burning is a collective action requiring more than one person to accomplish (Olson 1965), whereas mechanical removal is generally not. Thus, group involvement may provide the support necessary to safely manage a burn, whereas it may have little to do with mechanical removal. If social and ecological components were aligned, there would be no effect of group involvement on either behavior because individuals would be capable of managing the ecological disturbance alone. In other words, encroachment would be readily managed at the local-level by exclusively individual-level behavior. Group involvement may also be indicative of collective social factors, like normative influences and information access through social connections, that affect an individual's behavior (Willcox et al. 2012, Lubell et al. 2013, Niemiec et al. 2016, Lubeck et al. 2019). If these collective factors are influencing individual behavior, it would indicate opportunities for higher social levels to engage in cedar management through, for example, collective support systems.

We tested the effects of disturbance at different spatial levels and the interaction of these levels on each behavior. We hypothesized that regional-level disturbance would have a larger effect on individual behavior than local-level disturbance and the effect of local-level disturbance on an individual's behavior would be dependent on the extent of regional-level disturbance. If social and ecological components were aligned, local-level disturbance would have a larger effect on individual behavior than regional-level disturbance and there would be no interaction effect because individuals would be responding to encroachment on their property with little concern for regional-level disturbance.

Table 14: Variables included in models and their scale, source, mean and standard deviation (SD).

Type	Variable	Scale	Scale description	Source	Mean (SD)
Response	Mechanical removal	0, 1	0 = Never or rarely; 1 = Occasionally or more frequently	Survey to producers: Please rate how often you have [used mechanical removal] to manage vegetation transitions on your operation in the past three years.	0.76 (0.43)
	Prescribed burning	0, 1	0 = Never or rarely; 1 = Occasionally or more frequently	Survey to producers: Please rate how often you have [used prescribed burning] to manage vegetation transitions on your operation in the past three years.	0.25 (0.43)
Explanatory	Group involvement	0, 1	0 = I am not involved in any groups; 1 = I am involved with at least one group	Survey to producers: What's the extent of your involvement with rangeland management groups?	0.07 (0.26)
	Local-level change in percent tree cover from 1990 to 2020	Continuous	Ranges from -10% to 29%	Rangeland analysis platform: Percent tree cover in 1990 and 2020 for a 1 km radius around each respondent	2.4 (4.0)
	Regional-level change in percent tree cover from 1990 to 2020	Continuous	Ranges from -0.1% to 10%	Rangeland analysis platform: Percent tree cover in 1990 and 2020 for a 100 km radius around each respondent	3.2 (2.5)

Analysis

We used several different response scales for question items on the survey and recoded many question items before beginning analyses (Table 14). We dichotomized the response variables (i.e., behaviors) from a 4-point ordinal scale because each level of the scale meant different frequencies depending on the behavior and to enable comparisons between behaviors. To generate the group involvement variable, we combined responses from two questions about whether those groups existed and their level of involvement if such groups exist and created a dichotomized variable. Mean percent tree cover was on a continuous scale, which we standardized.

We built logistic regression models to test the relative importance of mean percent tree cover change at 1 and 100 km, the interaction between mean percent tree cover change at 1 and 100 km, and group involvement on each behavior (i.e., the saturated model). We focused on the saturated model for this analysis, but compared Akaike's Information Criterion (AIC) for all possible variable combinations to examine the relative performance of the model compared to simpler models. We examined plots of the logit versus the predicted value for the mean percent tree cover change variables in the saturated model and found some evidence of non-linearity. We identified potentially influential observations with Cook's distance greater than 4/n and high leverage observations with hat values greater than 2p/n, but did not find any unusual observations or standardized residuals above 3, and thus no evidence of influence or leverage. We found no evidence of multicollinearity among our explanatory variables as all variance inflation factors were below 2 (Ott and Longnecker 2015). We determined whether each saturated model was significantly different from its respective null model using likelihood ratio tests. We used Hosmer-Lemeshow tests (ResourceSelection package, hoslem. test function; Lele et al. 2019) to test goodness of fit, using a range of group numbers (4-15) due to the test's sensitivity to group number. We used McFadden's pseudo-R^2 (pscl package, pR2 function; Jackman 2017) to approximate explained variation in our logistic regressions. We report model accuracy and three different cross-validation outputs. In the first cross-validation approach, we placed 60% of the data into a training set, which we used to parameterized the model, and determined how well the model predicted the remaining 40% of the data in the testing set. In the second cross-validation approach, we used k-fold cross-validation with 10 folds. In the third approach, we used leave-one-cluster-out spatial cross-validation with 10 folds.

Results

Overview of sample

There were 573 responses and 176 refusals to our survey (response rate of 12.8%) and no significant differences in demographics (age, gender, education, income) between respondents to the paper versus email prompts. Respondents and non-respondents were statistically the same ($p>0.05$) for acres in production for beef, dairy, pasture/range, soybeans, and wheat, but respondents had fewer planted acres, less gross farm income (GFI), and fewer acres in corn production than non-respondents. After removing incomplete responses for the variables in this analysis, we were left with 383 respondents used to generate all descriptive statistics and conduct analyses reported here. Our respondents were 91% male and 8% female with the remaining identifying as other or preferred not to disclose. Respondents most commonly had some college / vocational training (25%) or a 4-year college degree (25%) and made $50-99,999/year (34%) or $100-149,999/year (20%). The average age of respondents was 64 in 2021 at the time the survey was administered. Respondents owned between 0 and 84,000 acres (median = 466) and rented between 0 and 20,000 acres (median = 340). Although this profile is more affluent and educated, and has a larger operation than the average Nebraskan producer (USDA NASS 2021, Western Economics Services 2021), this profile is consistent for ranchers compared to other producers.

The majority of respondents used mechanical removal but not prescribed burning to manage vegetation transitions, and the vast majority were not involved in rangeland management groups (Figure 13A). In particular, 76% of respondents always or occasionally mechanically removed trees, while 24% rarely or never did. Whereas 25% of respondents always or occasionally used prescribed burning, while 75% rarely or never did. 7% of respondents were involved in rangeland management groups and 93% were not.

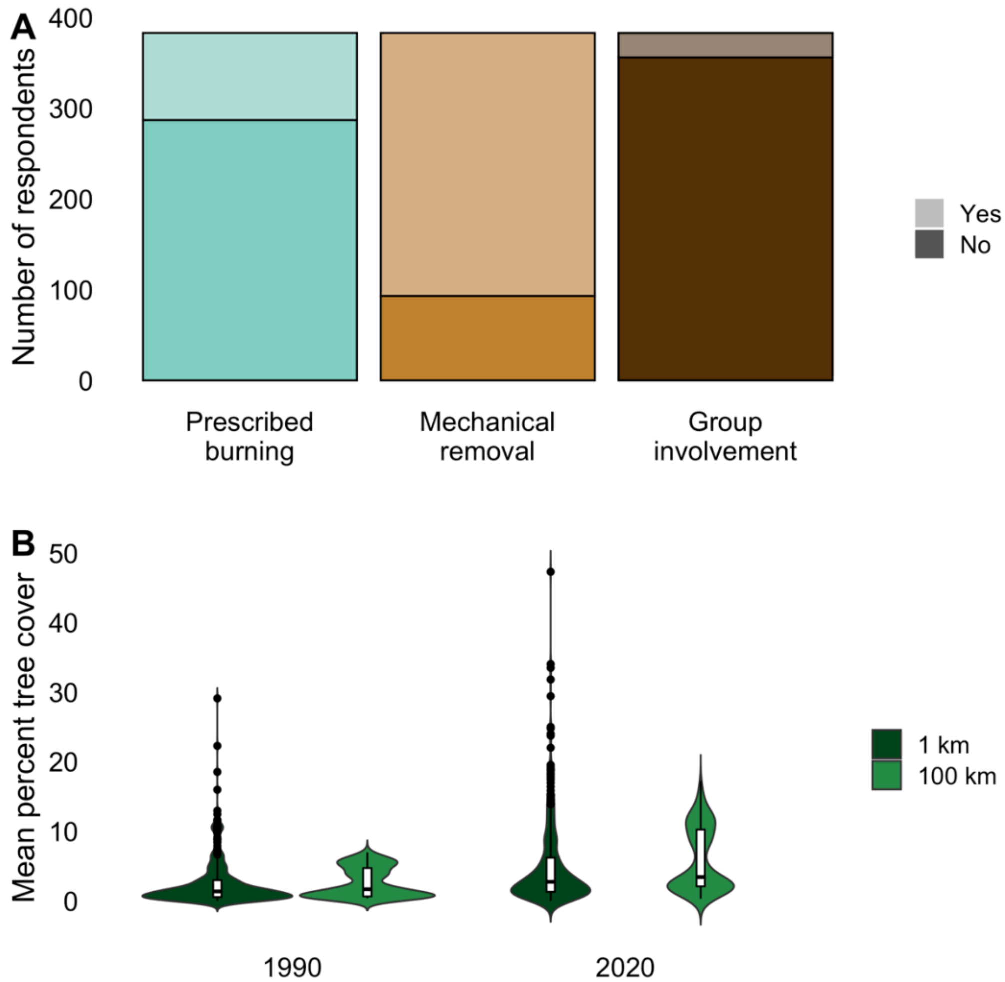


Figure 17: (A) Frequencies of respondent adoption of each behavior and group involvement in the past three years (at the time the survey was administered). (B) Violin plots illustrating the distribution of mean percent tree cover in 1990 and 2020 calculated at a 1 km and 100 km radius. The width of the violin plots illustrates the kernel density of the data distribution such that the wider violins indicate where more data cluster. Boxplots are also shown indicating the median (thick middle line), the 25th and 75th percentiles (top and bottom lines of box), the 75th percentile plus 1.5(interquartile range) (the lines on the top and bottom of the box), and potential outliers beyond the lines.*

Mean percent tree cover calculated at a 1 km and 100 km radius is shown in Figure 13B in distribution format for 1990 and 2020 and in Figure 18 in time series format from 1990-2020. Average mean percent tree cover for respondents in 1990 was 2.6% at both the 1 and 100 km level and increased in 2020 to 5% at the 1 km level and 5.8% at the 100 km level. In 1990, respondents experienced a range of 0 to 29% tree cover at the 1 km level, and 0.3 to 7% at the 100 km level. In 2020, respondents experienced a range of 0 to 47 mean percent tree cover at the 1 km level, and 0.3 to 17 mean percent tree cover at the 100 km level. From 1990 to 2020, respondents experienced an increase of 2.4 in mean percent tree cover at the local-level on average, ranging from a decrease of 10% to an increase of 29%. Respondents experienced an increase of 3.2 in mean percent tree cover at the regional-level on average, ranging from a decrease of 0.1% to an increase of 10%. Figure 19 and Figure 20 show the spatial distributions of these data across the state.

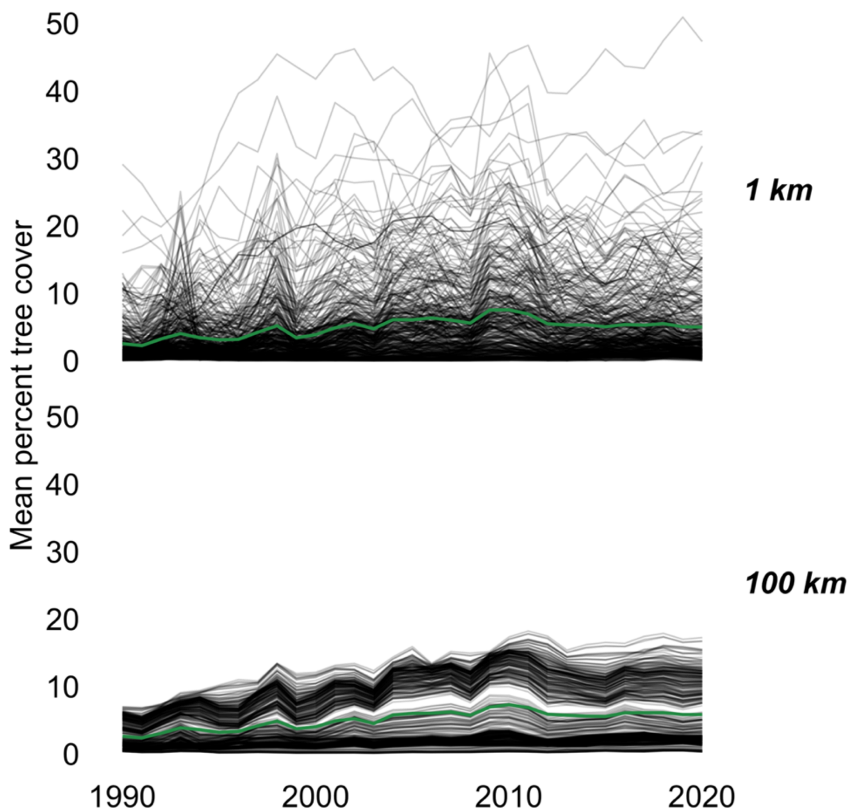


Figure 18: Mean percent tree cover at each spatial level for each respondent. Each black line is a respondent and the green line indicates the average across respondents.

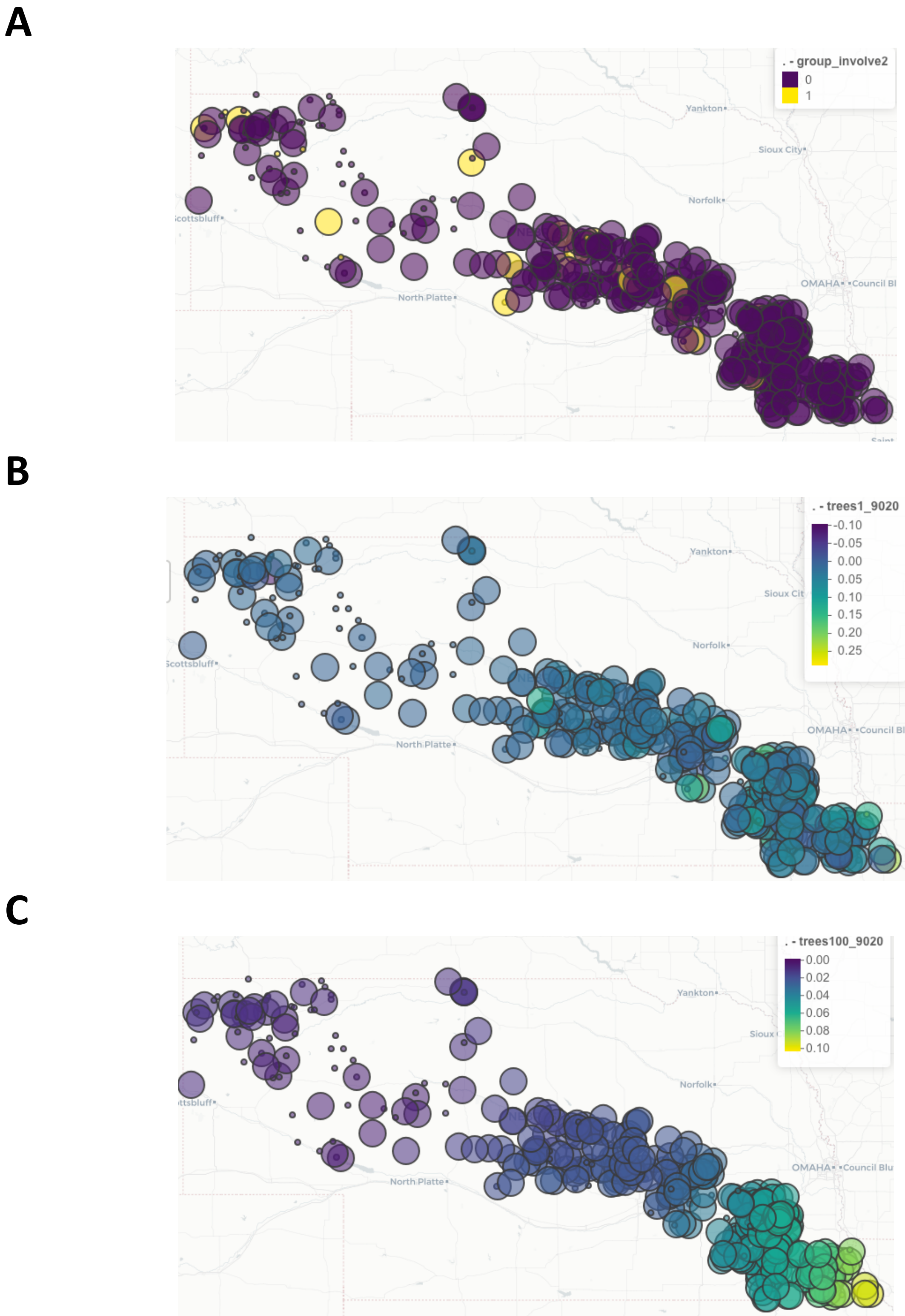
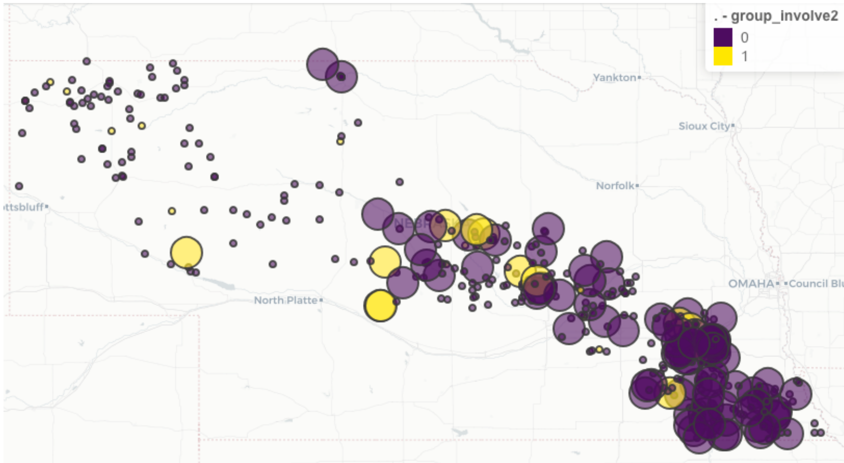
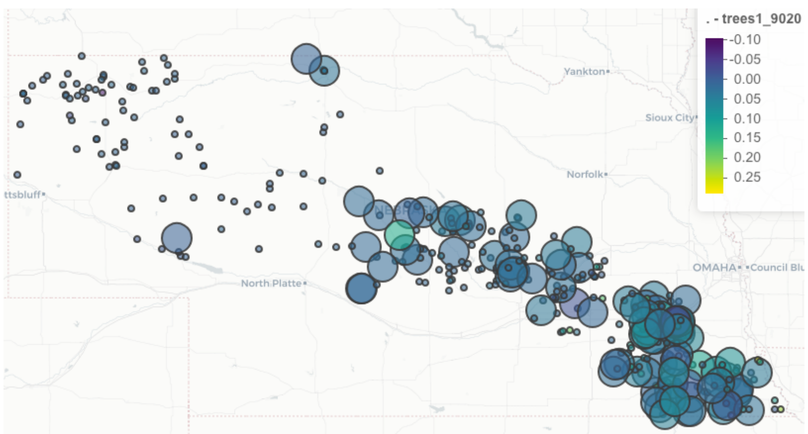


Figure 19: Respondents in this analysis who have used mechanical removal (large point) or not (small point) and (A) whether they are involved in rangeland management groups (yellow) or not (purple); (B) the change in mean percent tree cover they experienced from 1990 to 2020 at the local-level (color); and (C) the change in mean percent tree cover they experienced from 1990 to 2020 at the regional-level (color).

A



B



C

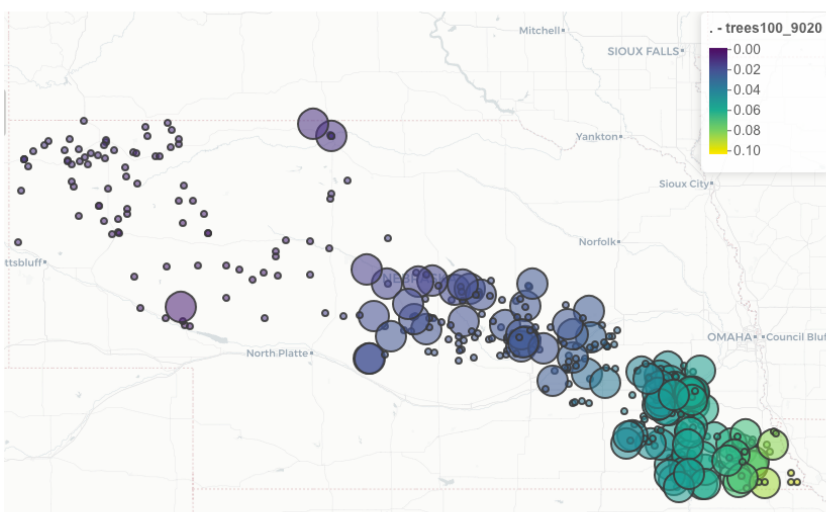


Figure 20: Respondents in this analysis who have used prescribed burning (large point) or not (small point) and (A) whether they are involved in rangeland management groups (yellow) or not (purple); (B) the change in mean percent tree cover they experienced from 1990 to 2020 at the local-level (color); and (C) the change in mean percent tree cover they experienced from 1990 to 2020 at the regional-level (color).

Model fit

Model fit and cross-validation are shown in Table 15. Of the models tested, the model with both spatial levels and the interaction had the most support predicting mechanical removal (AIC = 391.9), and the model with both spatial levels, the interaction, and group involvement had the most support predicting prescribed burning (AIC = 393.5). Variables were significant predictors of behavior ($p<0.05$ for LR test of null versus saturated model). All of the 12 Hosmer-Lemeshow tests conducted for the mechanical removal model were significant, providing strong evidence of poor model fit, while only 3 of the tests were significant for the prescribed burning model, providing little evidence of poor model fit. McFadden's pseudo-R^2 ranged from 0.10 to 0.11 and accuracy ranged from 74-76%. Cross-validation indicated weak performance for the mechanical removal model (27-73% accuracy) and strong performance for the prescribed burning model (70-74%). Spatial cross-validation indicated that the mechanical removal model performed better in the eastern part of the state and poorly in the west, while the prescribed burning model generally performed well across the state, with slightly higher performance in the west compared to the east (Figure 21).

Table 15: Fit and cross-validation for each model; n = sample size, df = degrees of freedom, AIC = Akaike's Information Criterion, LR test = likelihood ratio test. The models with the most AIC support are ***bolded****.*

	Mechanical removal	**Prescribed burning**
n	383	383
AIC (df)	trees100*trees1+group: 393.9 (5) **trees100*trees1: 391.9 (4)** trees100+trees1+group: 398.0 (4) trees100+group: 396.8 (3) trees1+group: 428. 1 (3) trees100: 394.8 (2) trees1:426.5 (2) group: 428.2 (2) null: 426.6 (1)	**trees100*trees1+group: 393.3(5)** trees100*trees1: 404.2 (4) trees100+trees1+group: 396.3 (4) trees100+group: 398.4 (3) trees1+group: 430.0 (3) trees100: 409.3 (2) trees1: 435.3 (2) group: 428.0 (2) null: 433.3 (1)
McFadden's pseudo-R^2	0.10	0.11
LR test (null)	P < 0.001	P < 0.001
HLGOF (number of significant tests (P < 0.05) out of 12)	12	3
Accuracy	76%	74%
Cross-validation		
60/40 – accuracy predicting 40%	73%	73%
10-fold – mean accuracy across folds (SD)	27% (4%)	74% (4%)
Spatial leave one cluster out – mean accuracy across folds (SD)	29% (16%)	70% (15%)

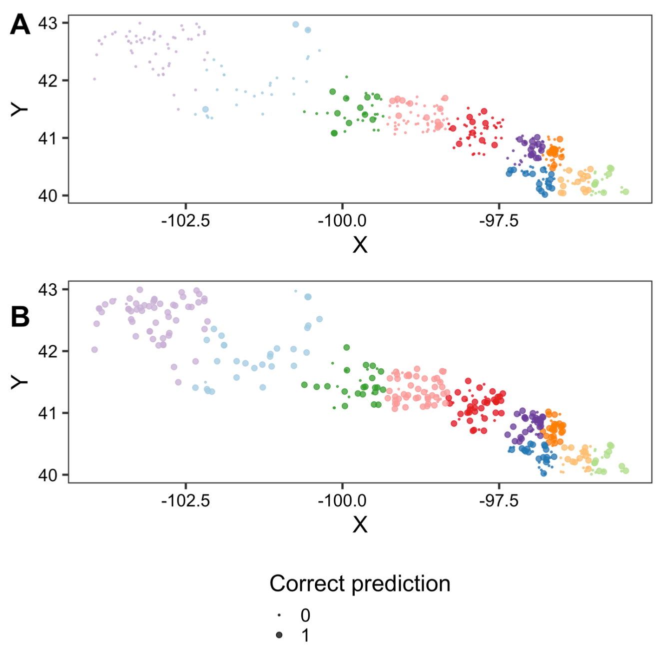


Figure 21: Leave one cluster out spatial cross-validation results for (A) mechanical removal and (B) prescribed burning models. 0 is an incorrect prediction and 1 is a correct prediction. Predictions were deemed correct if the probability of a behavior was above 0.5 and the respondent exhibited that behavior, or if the probability was 0.5 and below and the respondent did not exhibit that behavior. X is the longitude and Y is the latitude of Nebraska.

Model results

The effect size and confidence intervals of explanatory variables varied by behavior (Figure 22, Table 16). Regional-level change in mean percent tree cover and the interaction between local- and regional-level change in mean percent tree cover were the most ubiquitous explanatory variables in both models. In particular, the log odds of using mechanical removal increased by 0.83 (CI = [0.5,1.18]) and the log odds of using prescribed burning increased by 0.72 (CI = [0.45, 1.00]) for every standardized unit increase in regional-level change on average, all else being equal. The log odds of the interaction effect for mechanical removal was -0.27 (CI = [-0.50, -0.06]) and for prescribed burning was -0.34 (CI = [-0.69, -0.04]. In other words, the probability of using mechanical removal or prescribed burning increased when local-level change was high and regional-level change was low, or when local-level change was low and regional-level change was high. On the other hand, the probability of using mechanical removal or prescribed burning decreased when local- and regional-level change was high, or when local- and regional-level change was low (Figure 23). The effect of local-level change was uncertain in both the mechanical removal (log odds = 0.05, CI = [-0.28, 0.41]) and the prescribed burning (log odds = 0.02, CI = [-0.33, 0.35]) models and was lower than the effect of regional-level change, supporting our mismatch hypothesis. Thus, scalar mismatches can be characterized as occurring when ecological disturbances at regional-levels are being managed by local-level actors. The effect size of group involvement was highly uncertain in the mechanical removal model (log odds = -0.02, CI = [-0.88, 0.93]). However the effect was large for the prescribed burning model such that the log odds of using prescribed burning increased by 1.6 (CI = [0.74, 2.47]) on average for those who were involved in groups compared to those who were not, all else being equal (Figure 23), supporting the idea that collective forces may be more effective at managing encroachment, even though individual actors are the primary conduit of cedar management.

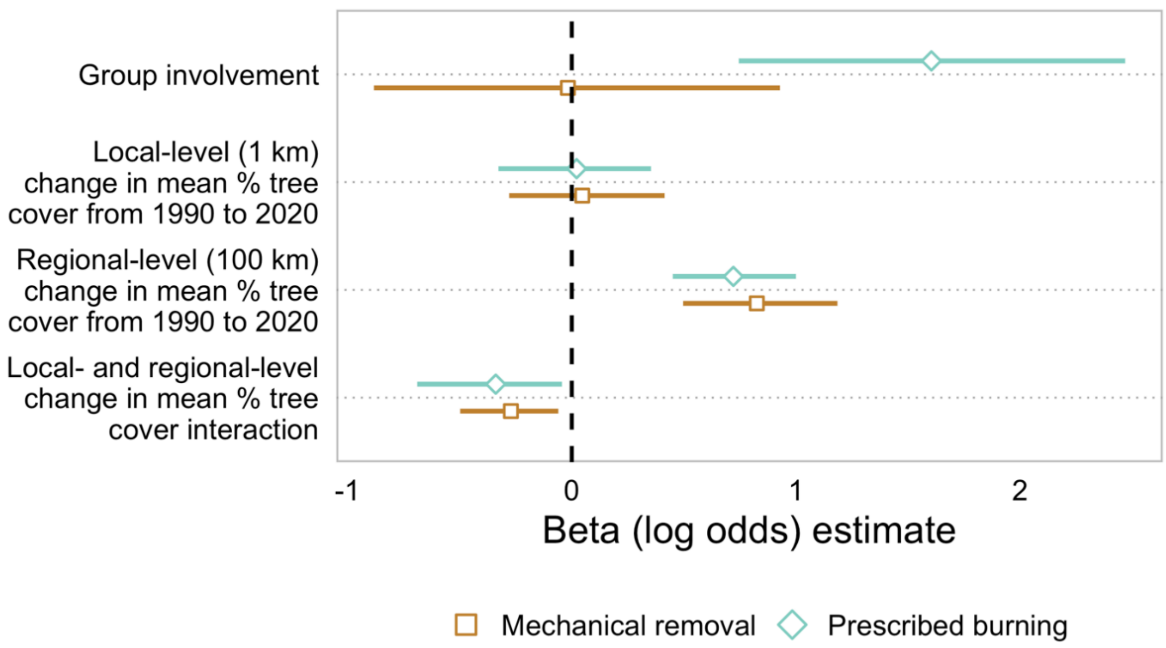


Figure 22: Log odds estimates for parameters in each model predicting mechanical removal and prescribed burning. The square and diamond symbols denote the point estimate and the bars denote the 95% confidence interval.

Table 16: Log odds estimates and 95% confidence intervals (CIs) for parameters predicting mechanical removal and prescribed burning. Numbers correspond to those shown in Figure 22.

Variable	Mechanical removal		Prescribed burning	
	Log odds (95% CI)	**Wald P**	**Log odds (95% CI)**	**Wald P**
Intercept	1.42 (1.13, 1.73)	< 0.001	-1.25 (-1.55, -0.97)	< 0.001
Group involvement	-0.02 (-0.88, 0.93)	0.97	1.6 (0.74, 2.47)	< 0.001
Local-level (1 km) change in mean percent tree cover from 1990 to 2020	0.05 (-0.28, 0.41)	0.79	0.02 (-0.33, 0.35)	0.9
Regional-level (100 km) change in mean percent tree cover from 1990 to 2020	0.83 (0.50, 1.18)	< 0.001	0.72 (0.45, 1.00)	< 0.001
Local- and regional-level change in mean percent tree cover interaction	-0.27 (-0.50, -0.06)	0.01	-0.34 (-0.69, -0.04)	0.04

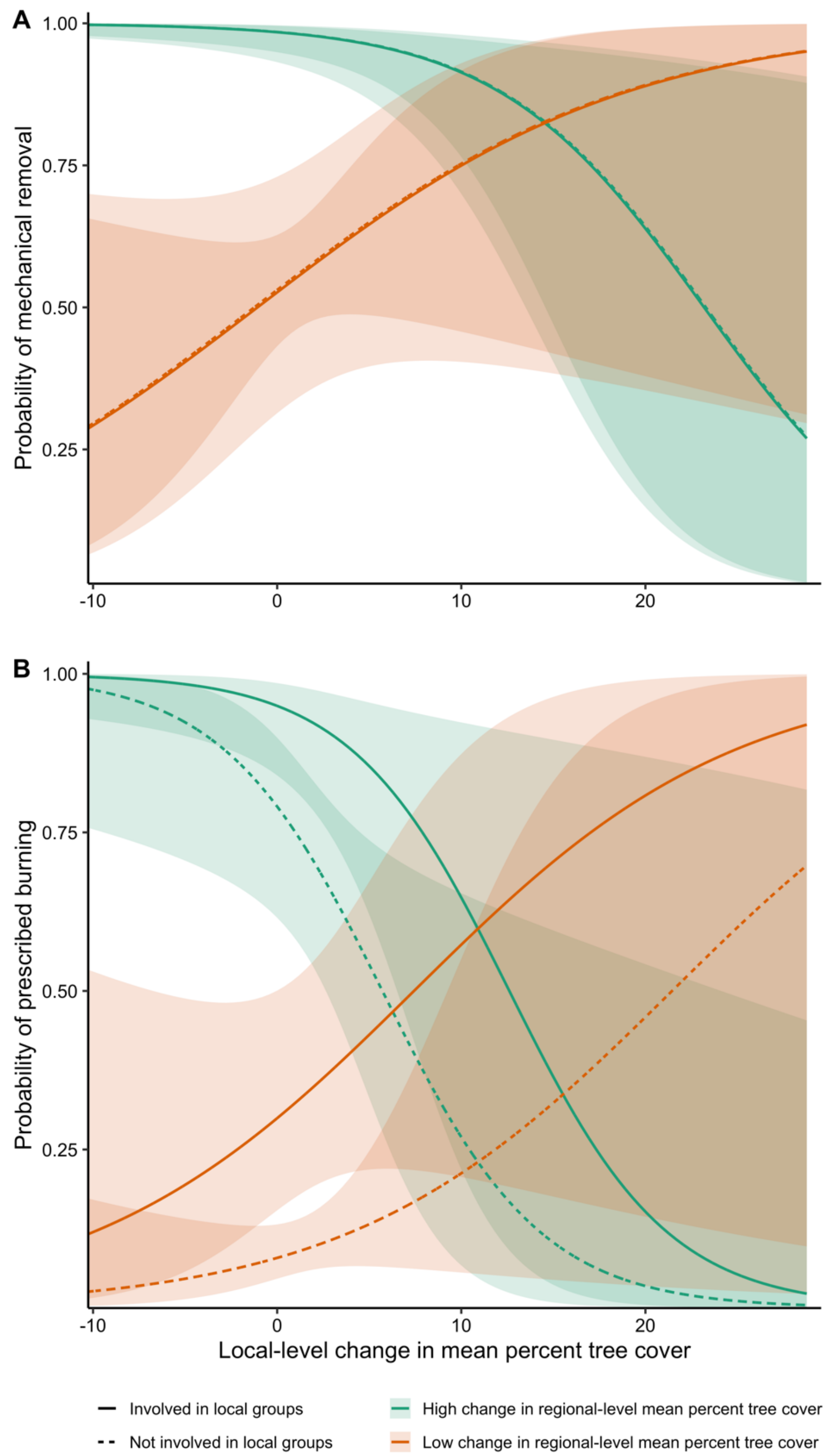


Figure 23: The interaction of local-level change in mean percent tree cover and regional-level change in mean percent tree cover for the (A) mechanical removal and (B) prescribed burning models. Because change in mean percent tree cover from 1990 to 2020 is on a continuous scale, we had to make dichotomous predictions for one of the spatial levels to illustrate the interaction. We defined "high change" as the maximum amount of change (i.e., 10%) and "low change" as the minimum amount of change (i.e., 0%) experienced by our respondents at the 100 km level between 1990 and 2020. Lines indicate the mean prediction while translucent colors represent the 95% confidence intervals around the mean. Solid lines indicate the prediction for those who are involved in local groups while dashed lines indicate the prediction for those who are not involved in local groups.

Discussion

Our results demonstrate that scalar mismatches between ecological disturbance and social management are occurring in one of the largest grassland social-ecological systems in the world, the American Great Plains biome. These mismatches are likely contributing to a wide-spread regime shift that could result in the collapse of the biome. In particular, we show that the behavior of individual producers to voluntarily manage regime shifts on their private properties is influenced by ecological disturbance interactions across spatial levels and their engagement with coordinated collective efforts. We illustrate that cross-level ecological interactions and multi-level social factors together influence individual behaviors that act as feedbacks on the ecological component of the system. Individuals responding to these higher-level processes suggests there may be opportunities for corresponding social efforts at similar levels to better match regional-level ecological disturbance. We posit that if higher levels of the social component were engaged in managing regime shifts, there would be better alignment with regional-level ecological disturbance and thus more effective system-wide management.

Both cognitive risk assessment and perceived normative pressure have been shown to have large effects on individual behavior in the context of agriculture (Grothmann and Patt 2005, Willcox et al. 2012, Azadi et al. 2019), weed management (Niemiec et al. 2016, Lubeck et al. 2019), and other conservation areas (Lubell et al. 2007, Nesbitt et al. 2021). In our study, the effect of ecological disturbance at the local-level on producer behavior was dependent on the extent of ecological disturbance at the regional-level such that producers were most likely to use management interventions when they were on one of two “islands” and least likely when they were on one of two “continents.” The two islands where producers were most likely to manage encroachment include a grassland island surrounded by cedar (i.e., no local-level change, but high regional-level change; top left in Figure 23) and a cedar island surrounded by grasslands (i.e., high local-level change, but no regional-level change; top right in Figure 23). We suspect that producers on the grassland island, witnessing encroachment on their neighbors' properties and losses to their neighbors' operations, are responding to the immediate risks to their livelihoods. In contrast, producers on the cedar island are responding to descriptive and injunctive norms around them. Regarding descriptive norms, if the cedar island landowner believes his neighbors are managing their property to eliminate cedar, he may feel pressure to do the same. Regarding injunctive norms, if the cedar island landowner believes her neighbors think she should manage the cedar on her property, she may feel social sanctioning to do so.

Research on environmental campaigns and messaging indicates that the concept of futility and normative influences are powerful inhibitors of conservation oriented behavior (Griskevicius et al. 2008, Heberlein 2012). In our study, the two continents where producers were least likely to manage encroachment include a grassland continent with no regional cedar (i.e., no local- or regional-level change; bottom left in Figure 23) and a cedar continent with no regional grasslands (i.e., high local- and regional-level change; bottom right in Figure 23). On the grassland continent, there is no sign of disturbance and thus no reason to manage it because there are no risks or social pressures to act. On the cedar continent, management is futile – no intervention can eliminate the encroachment because it is everywhere. Normative pressures, though not measured here, may have the opposite effect from those on cedar islands – if it is clear neighbors are not managing cedar, why would any other individual actor?

The large effects of the cross-level disturbance interaction and regional-level disturbance on behavior demonstrate that individual landowners are responding to more than just the disturbance on their land – instead, they are taking into account changing conditions on the surrounding landscape, perhaps both ecologically and socially, and incorporating that information into decisions about how to manage their own operation. This finding shows that low-level social processes are responding to and managing high-level ecological processes. Additionally, it demonstrates how individuals are likely responding to coordinated collective social efforts, exactly the type of factors that could be better leveraged to encourage more voluntary behavior on private lands. Certainly, normative and identity appeals are evident in current prescribed burn campaigns (Figure 24), which may help encourage voluntary management of encroachment, but more effort at higher levels of the social system beyond non-profits, for example, is likely the appropriate match for this level of disturbance.

Figure 24: Marketing strategies with normative and identity appeals from the (A) Loess Canyons Rangeland Alliance (Loess Canyons Rangeland Alliance 2022)*, a prescribed burn association, and (B) the Sandhills Task Force* (Sandhills Task Force 2022)*, a working lands conservation non-profit organization.*

Collective factors, such as group involvement, are important drivers of behaviors that both require collective action and socio-cognitive support to overcome institutionalized barriers to transformation. Group involvement may be a proxy for information access, whereby those with readily available information are more likely to exhibit adaptive or transformative behavior managing their rangelands (Lubell et al. 2013, Chapter 3). Similarly, group involvement may be a proxy for the influence of social norms, whereby normative influences encourage respondents to manage vegetation transitions through the behaviors (i.e., descriptive norms) and expectations (i.e., injunctive norms) of their peers (Willcox et al. 2012, Niemiec et al. 2016, Lubeck et al. 2019). We found that those more involved in rangeland management groups were more likely to manage vegetation transitions with prescribed burning, but not with mechanical removal, perhaps for two reasons. First, prescribed burning requires the support of others to implement safely, whereas mechanical removal can be accomplished alone. Second, prescribed burning is a transformative behavior that goes against the fire suppression paradigm engrained in the status quo. Social support may enable a person to overcome the barriers of the status quo to burn landscapes, whereas it may be less important for mechanical removal of cedar, which while adaptive, is aligned with the status quo. The effect of group involvement was large for producers on cedar islands (top right in Figure 23) compared to those on grassland islands (top left in Figure 23), further supporting that normative pressure, as described above, plays a role in transformative responses. Thus, even where private property predominates, collective action can be enabled toward transformation. Either mechanism, or likely some combination, lends credence to the idea that cedar encroachment is a collective action problem, requiring collective forces, both through human labor and socio-cognitive support, to address.

Research on cedar encroachment from roadside seed sources (Hogan et al. 2022) also provides evidence of a free-rider effect, which occurs when actors abstain from contributing to collective action when the collective good can be achieved without their participation (Olson 1971, Sandler 2015). Right-of-ways, from the edge of the road to the private property boundary, are an average of 5.8 meters wide in this area of Nebraska and put as much as 44% of rangelands in the study area at risk of seed dispersal and cedar recruitment (Hogan et al. 2022). While roadside cedar management is usually under the county's purview, when these areas go unmanaged, risks to private properties increase. Thus, cross-boundary ecological effects are occurring because of a gap in management at higher social levels. Taken together with the strong effect of group involvement on prescribed burning, it is clear that multiple social levels are required to match the ecological levels of encroachment and prevent a wide-spread regime shift.

While the land tenure system of Nebraska, dominated mostly by private land, limits the ability of higher social levels to manage encroachment, the history of fire management and tree planting (and their success at eliminating fire and creating woodlands) highlights that higher social levels have and can bolster adaptation and transformation. If higher level social programs are among the forces driving this regime shift, there's a social and ecological justice argument to be made for actors at these higher levels to share accountability for the shift in addition to individual landowners. In particular, the pervasive fire suppression paradigm, which is demonstrated in codified institutions such as legal practices and fire permits and informal social norms of fearing and eliminating fire (Taylor et al. 2012, Russell-Smith and Thornton 2013), and cost-share programs offered through the state's Natural Resource Districts to promote the planting of cedar for windbreaks (Nebraska Association of Resources Districts 2022) are among the driving forces enabling this regime shift. Though a primary motivation for private property rights is to entangle individual interests with the sustainable management of public goods and common pool resources (Freyfogle 2007), when faced with ecological disturbance at the highest spatial levels, property owners are ill-equipped to meet the challenge without substantial support. To be clear, considerable efforts are underway, including those of local prescribed burn associations and non-profits, the US Department of Agriculture Natural Resource Conservation Service's (USDA NRCS) cost-share programs for tree removal and prescribed burning with $8.6 million spent in Nebraska from 2004-2013 (Simonsen et al. 2015), and the federal government, with $177 million spent from the last Farm Bill on cedar encroachment (Twidwell 2022*a*). Given that no county has restored lost agricultural yield after significant woody encroachment (Twidwell 2022*b*), building off of these efforts is likely appropriate if investments are to be worthwhile.

It is important to consider a few caveats to our research. Our sample demographic had a higher education and income level than the target population (Western Economics Services 2021), our response rate was low, though typical for this demographic, and we did not sample the entire population of Nebraska. Therefore, we can only make inference to producers in sampled counties and caution should be used when inferring to the largest operations. Nonetheless, our results appear to be consistent with the experiences of producers and conservation professionals with whom we have engaged. Another caveat is that our mechanical removal model had relatively low accuracy, thus behavioral predictions based this model are ill-advised. Instead, this model should be considered as a starting point to understand the relative importance of different variables in influencing mechanical removal. Clearly other variables not considered in this study are important for predicting mechanical removal, whereas this relatively simple model of cross-level spatial interactions and group involvement performed well for prescribed burning. Because mechanical removal is very common and likely not limiting the effectiveness of cedar encroachment management, a substantial barrier to managing cedar encroachment, the performance of this model is less consequential than that of prescribed burning.

This research is an early step to understand how cross-level and multi-scalar social-ecological factors influence behavior, yet the approach and results highlight several possible avenues for future inquiry. For example, we considered group involvement a collective factor in this research, though it may be better characterized as an individual engaging in coordinated collective behavior. It may be helpful for future research to investigate how higher social levels, particularly those institutionalized in policy, can influence behavior as well. For example, although most of the state’s Natural Resource Districts engage in cost-share programs to provide cedar windbreaks to producers, two Districts (Twin Platte and Upper Loup) have ended their cedar program (USDA NRCS 2019) and others may be considering releasing more thorough guidelines on how to manage land around cedar windbreaks to limit seedling recruitment (D. Wilcox, personal communication). It would be interesting to see if these institutional policy changes had an effect on individual behavior. Because the Natural Resource District funding model relies heavily on the conservation tree program for revenue, a deeper analysis on these organizations may be an illuminating case study on institutionalized adaptation barriers. The USDA NRCS could also be included in that analysis, which recently updated some of their guidelines by flagging some applications for cost-share of cedar seedlings as low priority (USDA NRCS 2019).

Two other collective levels that might be useful to consider in future studies include fire districts and non-profit organizations. Fire districts, which vary substantially in their policies and staff, may have a large effect on whether producers are able to navigate bureaucratic hurdles, get fire permits, and take advantage of burning weather windows. There are over 1000 fire districts in the state (State of Nebraska 2022), so considering them in any modeling approach would likely require scraping of publicly available data, though interviews and focus groups may also provide coded data on the support/barriers of fire districts for prescribed burning. The state also has numerous non-profits, including prescribed burn associations (Pheasants Forever 2016, Great Plains Fire Science Exchange 2022), actively supporting mechanical removal and prescribed burning to manage cedar encroachment. Understanding their role, particularly in the context of building networks and providing resources and information, may highlight how organizations at levels beyond the individual step in when state and municipal levels of government are risk averse to transformative change.

Future studies could examine how ecological change over different time periods influences behavior. For example, do individuals respond more to large changes over short or long periods of time (Stern 1992, Laland and Brown 2006, Young et al. 2006, Pahl et al. 2014). Additionally, how do ecological changes across different temporal scales interact with social campaigns to communicate the risks of cedar encroachment, and perhaps more importantly, change pervasive social norms around fire and producer behavior. Understanding when these social campaigns began in earnest may reveal lags between ecological change and social efforts to manage it, as well as inflection points where social change begins to respond more rapidly. Although a temporal scalar dimension was included in this study (mean percent tree cover change from 1990 to 2020)., it was not the primary focus.

Our findings may be helpful for those seeking to encourage prescribed burning on private lands across the state, particularly where capacity is low and taking a "low hanging fruit" approach is necessary. For example, with the help of diagnostic tools available online (USDA NRCS et al. 2019), practitioners may be able to identify grassland or cedar islands (i.e., low local-level change and high regional-level change or vice versa) that are prime for managing encroachment from a behavioral perspective and strategically contact producers in these areas. Currently, non-profits wait for landowners to contact them because they do not have the capacity to do more than respond (A. Garrelts and E. Hubbs, personal communication), but if more capacity became available through institutionalized efforts at the municipal or state level, an approach like this may be possible. Our results also demonstrate a large group involvement effect on prescribed burning behavior. Investing in pre-existing groups with resources, capacity building, and networking opportunities may be another example of strategic engagement that is effective without having to reinvent the wheel. Finally, more policy and investment from higher levels of government is needed. Initiatives could include ending Natural Resource District cedar cost-share programs, providing state-wide guidelines and funding that enable fire districts to support prescribed burns on private lands, and county-level management of roadside cedar.

Scalar mismatches severely limit our ability to manage social-ecological systems and prevent wide-spread regime shifts. Our research demonstrates that scalar mismatches are occurring in one social-ecological system, with implications for the theory and management of social-ecological systems globally. While few studies explicitly examine how cross-scalar/level dynamics influence the adaptive capacity and resilience of social-ecological systems (Siders 2019, Vallury et al. 2022), we illustrate a straight forward approach for assessing interactions across levels and the relative effects of different scales on human behavior. We focus our efforts on the linkages between social and ecological components of a social-ecological system, rather than the dynamics within each component, to better understand how feedbacks occur across scales. For example, while disturbance is widely recognized as an important element of resilient social-ecological systems, few studies examine how ecological disturbance, particularly at different spatial levels, influences human behaviors that can manage that disturbance as part of a feedback. We also highlight the importance of understanding the nuances of collective action, particularly in the context of enabling social-ecological transformation. From a practical standpoint, we provide specific recommendations for better aligning social and ecological components of the American Great Plains biome in Nebraska. More broadly, research on scalar mismatches helps identify where those mismatches occur and provides policy makers with quantitative evidence and strategic guidance on how to resolve these mismatches in the long-term towards more sustainable management of our social-ecological systems.

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Chapter 5: Summary and conclusions

Throughout my PhD, I studied the "social side" of social-ecological systems science in an effort to understand how society can collectively adapt or transform in response to wide-spread social-ecological change. As we continue to witness increasingly severe change, it is clear that our current approaches to understanding and managing social-ecological systems are inadequate. Though the social study of social-ecological systems science has continued to grow in the last several decades, there remain incredible opportunities for an expanded understanding and appreciation for feedbacks between social and ecological components of social-ecological systems. Through such expansion, my hope is that social science is taken seriously and used appropriately in the study and management of social-ecological systems.

The social study of social-ecological systems has been criticized for being under-theorized, with social interactions being inadequately measured or considered (Colding and Barthel 2019, Siders 2019, Vallury et al. 2022). My experience developing surveys and searching the literature for quantified relationships between social interactions and social-ecological systems outcomes was consistent with these criticisms of the field, yet few solutions were being offered or tangible steps being taken to support future researchers seeking to build off of these criticisms towards improved methods or theory. Because I believed a synthesis of quantified social interaction measures would be extremely helpful for building off of previous work more systematically, but was lacking, I decided to undertake a literature review on the quantification of social interactions in social-ecological systems science (Chapter 2).

In this literature review (Chapter 2), I had three main goals: (1) support theoretical development; (2) improve conceptual clarity; and (3) increase the complexity with which we treat social interactions in this field. To achieve the first goal, I asked how have researchers quantified social interactions and what relationships between social interactions and social-ecological systems outcomes have empirical support. I developed a database that describes how every article selected for my review measured social interactions (including data collection methods and specific measures) and evaluated relationships (including analysis techniques and findings). To achieve the second goal, I asked what are the underlying mechanisms influencing the relationship between social interactions and outcomes. I first classified each approach as binary metaphorical, descriptive, or structurally explicit (Bodin et al. 2011), and then applied a framework to distinguish the mechanism that's operating through social interactions (i.e., pipes vs. bonds) and the outcome (i.e., success vs. similarity), which results in four typologies based on social network theory (Borgatti and Halgin 2011). To achieve the third goal, I asked what opportunities are there for growth in the field. Based on my review, I highlighted several key findings and opportunities.

Although my findings were generally consistent with other criticisms, I have added several nuances to these criticisms as well as resources and opportunities for growth. I found that there was a broad suite of definitions and blending of terms for describing social interactions. While this is not problematic in and of itself, because of this diversity, it is important that researchers are clear about how they are defining social interactions and how they are measuring them, without which the precision/validity of their results is questionable. Guidelines for publishing repeatable quantitative social science in social-ecological systems research would be helpful. Furthermore, building off of the database I provided, which is likely biased towards social network analysis and agriculture/fisheries/forestry contexts, with a more exhaustive database on quantified social interactions/relationships would act as a resource for future researchers seeking to quantify social interactions in social-ecological systems science.

I also found that the mechanism acting through social interactions to influence outcomes is often not deeply interrogated. This finding builds on criticisms on the study of environmental governance from social network researchers (Bodin et al. 2011) who argue for using structurally explicit approaches, like social network analysis, to understanding socially embedded processes. While social network analysis may be one approach for interrogating mechanisms, more generally researchers can ask what specific aspects of social interactions result in specific outcomes. For example, pairing quantitative and qualitative methods may help triangulate the answer to this question more effectively than one method alone can (Denscombe 2008, UNAIDS 2010). The best examples of understanding social interaction mechanisms fell under the "social contagion" typology (Borgatti and Halgin 2011), whereby researchers asked how social interactions, acting as pipes of information, influenced individual behavior by enhancing social similarity with peers (e.g., Barnes et al. 2020). Where teasing apart mechanisms and outcomes is difficult, researchers may find the typology presented here for social-ecological systems science, based off Borgatti and Halgin (2011), helpful.

Finally, several questions regarding social interactions remain underexplored in social-ecological systems research. A few examples of studying ecological outcomes of social interactions (Ernstson 2011, Isaac and Dawoe 2011, Barnes et al. 2016, Chaffin et al. 2016), social justice outcomes of social interactions (Crona and Bodin 2006, 2010, Barnes-Mauthe et al. 2013, 2014, Chaudhury et al. 2017), and feedbacks across different social levels (Yu et al. 2014, Rockenbauch et al. 2019) exist but remain understudied. No examples in my review examined social outcomes of ecological interactions across levels, even though understanding such feedbacks is arguably critical for sustainable management.

In my subsequent chapters, I illustrated relatively straightforward approaches for studying two of the gaps identified in my literature review: interrogating the mechanisms that operate through social interactions using social network analysis (Chapter 3) and assessing feedbacks between social and ecological components of a system across levels using social and ecological data to study scalar mismatches influencing management (Chapter 4).

My study area was in Nebraska, where producers are facing a wide-spread regime shift from grasslands to cedar woodlands. Cedar is encroaching on grasslands from east to west. Once the encroachment occurs, it is extremely difficult to reverse. This system provided an opportune context for studying how individuals navigate ecological change through their social networks (Chapter 3) because of the persistent nature of this ecological shift (Briggs et al. 2005, Van Oaken 2009), the fact that it is quite well-studied from an ecological perspective (Merrill et al. 1999, Briggs et al. 2005, Fuhlendorf et al. 2008, Allred et al. 2012, Taylor et al. 2012, Twidwell et al. 2014, Lautenbach et al. 2017, Zou et al. 2018, Uden et al. 2019, Donovan et al. 2020) but not from a social perspective, and most importantly, there appears to be a changing social response to this regime shift (Weir et al. 2016). Additionally, because of Nebraska's unique governance and land tenure arrangement (Headwaters Economics 2019), the system was ideal for studying mismatches between management and ecological processes (Chapter 4).

In my social network analysis (Chapter 3), I examined how agricultural producers respond to wide-spread ecological change through their social connections. Using an ego network approach on producers, I asked how social networks, as a component of adaptive capacity, and disturbance, influence individual behavior to manage regime shifts. After building two logistic regressions with adaptive capacity proxies, including social network variables, and disturbance as predictors, I found that social interaction variables were predictive of behaviors to manage encroachment. In particular, I found that producers were more likely to use prescribed burning when their immediate communication network was composed of other producers (i.e., occupation homophily), they were members of rangeland management groups, they had access to diverse information sources through their networks (i.e., number of information sources and occupation heterogeneity), or they trusted the government. On the other hand, fewer social interaction variables were predictive of mechanical removal behavior among producers. Furthermore, producers who experienced local environmental change and/or understood the risks of cedar encroachment were not more likely to use prescribed burning, suggesting that a lack of information is not limiting behavior. In other words, current efforts to educate the public on cedar encroachment are likely improving producers' awareness of the issue, but this awareness is not translating into behavior change (Heberlein 2012). Other social factors are likely more limiting, such as not having enough social support to manage fire or navigate complex rules around fire. Given that prescribed burning is less common than mechanical removal but more effective at scale (Twidwell et al. 2013), these findings illustrate the importance of leveraging social connections to support effective management of cedar encroachment.

In my scalar mismatch analysis (Chapter 4), I examined the consequences of social and ecological mismatches on the management of cedar encroachment in Nebraska. I approached this analysis by considering the different social and ecological levels through which cedar encroachment is enabled and managed. Factors that have enabled cedar encroachment include the colonial fire suppression paradigm, which exists at all levels of society from the federal government to individuals being afraid of fire and its consequences and allows cedar to germinate and spread (Twidwell et al. 2013). Climate change induced drought, which makes cedar more competitive, and state-endorsed tree planting programs are also high-level drivers of cedar encroachment. At more local levels, cedar recruitment from windbreaks, fire suppression on private property, and overgrazing make these trees more competitive (Briggs et al. 2005, Allred et al. 2012, Taylor et al. 2012, Twidwell et al. 2014). From a management perspective, cedar encroachment is predominantly addressed through the actions of private property owners because over 97% of the land area in Nebraska is privately owned (Headwaters Economics 2019). When a fine social level is tasked with managing wide-spread ecological change, the consequences include unmanaged change, inconsistent management, and disruptions to the social system (Cumming et al. 2006). To resolve these mismatches, it is necessary to characterize them such that institutional barriers can be removed and collective action can emerge.

To be specific about how to remove institutional barriers that enable collective action, I asked what are the consequences of mismatches between social and ecological levels on the management of a wide-spread regime shift. I assessed the relative effects of different spatial levels of disturbance, their interaction, and landowner involvement in rangeland management groups on the probability that a producer manages cedar encroachment in Nebraska using logistic regressions and a combination of social and ecological data. I found that scalar mismatches were affecting management because individual behavior was responding to higher level social and ecological factors. In particular, producers were more likely to use prescribed burning and mechanical removal if they experienced low local-level ecological change and high regional-level change (i.e., a "grass island") or high local-level ecological change and low regional-level change (i.e., a "cedar island"). They were the least likely to use either treatment if they experienced low local- and regional-level change (i.e., a "grass continent") or high local- and regional-level change (i.e., a "cedar continent"). These results suggest areas that are prime for prescribed burning based on ecological interactions across spatial levels. Additionally, producers who were engaged in rangeland management groups were more likely to use prescribed burning, but not mechanical removal, indicating that collective factors likely enable management that is most effective at scale.

Taken together, Chapters 3 and 4 have numerous potential implications for managing cedar encroachment in Nebraska and generally all fall under support from higher social levels. First, because of the importance of social support for enabling highly effective management like prescribed burning, practitioners and policy-makers can seek to support prescribed burn associations, less formal rangeland management groups, and conservation non-profits with additional capacity. For example, by using diagnostic tools available online (USDA NRCS et al. 2019), practitioners may be able to strategically contact producers in grass or cedar islands who are most likely to engage in prescribed burning. Although non-profits currently do not have the capacity for such an approach, an influx of resources from institutionalized efforts may enable such strategic outreach. Second, because producers with a high proportion of other producers in their network were more likely to engage in prescribed burning, leveraging those existing networks and connecting with key players in close-knit communities may help prescribed burning behaviors spread through already established networks. Third, supporting partnerships among producers and non-producers with good, consistent information and resources may be helpful. As it is right now, there are mixed messages coming from different levels of government, which, not only is confusing, but also erodes trust in government. Given that trust was predictive of prescribed burning, taking steps to fortify relationships and build trust may enable more prescribed burning among producers. For example, making information consistent at different levels of government might include aligning messages from the Natural Resource Conservation Service and Natural Resource Districts on managing cedar windbreaks, or eliminating cost-sharing of cedar altogether. County-level management of cedar along roadsides may also improve trust while eliminating seed sources. Fourth, higher level social support in general is likely needed. This support might include removing institutional barriers that are codified into federal and state laws or enabling rural fire districts to support prescribed burning on private lands. Given the role of higher social levels in creating this regime shift, there is a social and environmental justice argument to be made for their involvement in managing it now.

My dissertation also has implications for the methods and theory of social-ecological systems science. As described briefly above, I made recommendations and provided resources for supporting theoretical development, improving conceptual clarity, and increasing the complexity with which we treat social interactions in this field based on my literature review. My subsequent analyses also highlighted methodological opportunities for growth in social-ecological systems science (i.e., ego network analysis, scalar mismatch analysis). Ego network analyses, although rare in social-ecological systems science, provide an opportunity for the structurally explicit study of social interactions, which helps distinguish mechanisms from outcomes and may ultimately enable more targeted interventions. My scalar mismatch analysis provides a relatively straightforward methodological approach for studying how different social levels and ecological levels of disturbance interact to influence behavior. Although methodological approaches that combine both multi-scalar (e.g., ecological, social) and multi-level (e.g., local to regional; individual to collective) data are rare, understanding these types of feedbacks is critical for a more complete understanding of social-ecological systems.

From a theoretical perspective, one of the most exciting contributions of this work is highlighting the importance of social interactions for enabling transformative behavior. Because prescribed burning challenges pervasive power structures and paradigms while simultaneously managing regime shifts effectively across larger spatial extents, it has the potential to be truly transformative for fire-prone ecosystems across the globe. Beyond the context of using fire to manage ecosystems, this finding has implications for the study of transformation in social-ecological systems science more broadly. Intuitively, it makes sense that challenging power dynamics through transformation requires social support, yet few empirical quantitative examples exist. Here, I presented a rare example of how social interactions enable such behavior through social support and diffusion. Understanding how social interactions enable transformative behaviors in other contexts (such as in resource management like fisheries or more broadly in land use planning and transportation) may be a critical next step for managing social-ecological systems for sustainability into the future. Combined with an understanding of how scalar mismatches manifest, studies such as these can provide strategic guidance for alleviating barriers to transformative behavior such that social and ecological components are aligned for sustainable management of our social-ecological systems.

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Appendices

Appendix 2

See "Nesbitt_Dissertation_Appendix2.xlsx":

- Appendix 2A is a table of all citations reviewed.
- Appendix 2B is a table of all quantitative measures included in the citations reviewed.
- Appendix 2C is a table of social network measures.

Appendix 3

Appendix 3A: Nebraska rangeland vegetation change survey

NEBRASKA RANGELAND VEGETATION CHANGE SURVEY

Working in Nebraska

1. Which of these options makes up the **largest proportion** of your operation?
(*Please choose only **one** option.)*

- ◯ Cattle ranching
- ◯ Other livestock (for example: dairy, pigs, poultry), please specify: ______________________
- ◯ Farming
- ◯ Specialty farm products (for example: bees), please specify: ___________________________
- ◯ Other, please specify: ____

2. How many years have you personally been ranching or farming?
Please enter a numeric value. _____________ years

3. Please estimate the acreage of your operation in 2020.
Please enter a numeric value. If none, please enter a zero.

Owned acres ______________ Acres rented from others _____________

4. In what county in Nebraska is the largest proportion of your operation located?

____

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Vegetation transitions and other changes on the landscape

The following questions ask about your experiences with changes on the landscape, including **"vegetation transitions"** on your operation. Specifically, we would like to know if you have noticed transitions from a mostly grassy landscape to one with more shrubs and trees.

5. Please indicate how strongly you agree or disagree with the following statements about **landscape changes in your area**. *(For each row, please choose only **one** option.)*

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
In my time managing my operation, I have noticed...					
...that vegetation has transitioned from mostly grasses to mostly shrubs/trees.	○	○	○	○	○
...more variability in precipitation.	○	○	○	○	○
...increased problems with invasive species on the landscape.	○	○	○	○	○
...more flooding at certain times of year.	○	○	○	○	○
...more severe drought at certain times of year.	○	○	○	○	○

6. Please indicate how strongly you agree or disagree with the following statements about **the general effects of vegetation transitions from mostly grasses to mostly shrubs/trees**. *(For each row, please choose only **one** option.)*

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
Vegetation transitions will harm the profitability of rangelands in the long term.	○	○	○	○	○
Vegetation transitions will harm rangeland ecosystems.	○	○	○	○	○
Vegetation transitions are not a significant challenge to future agricultural productivity.	○	○	○	○	○

7. Please rate how often you have taken the following actions to **manage vegetation transitions on your operation *in the past three years***. *(For each row, please choose only **one** option.)*

	Never	**Rarely**	**Occasionally**	**Always as appropriate**
Chemical application	○	○	○	○
Prescribed burning	○	○	○	○
Rotational grazing	○	○	○	○
Mechanical removal	○	○	○	○
Other vegetation controls	○	○	○	○

8. For this question, imagine for a moment that vegetation transitions are occurring on your operation. Please indicate how strongly you agree or disagree with the following statements about **managing vegetation transitions from mostly grasses to mostly shrubs/trees on your operation**. Please respond to these questions as if **vegetation transitions are occurring on your operation**. *(For each row, please choose only* ***one*** *option.)*

	Strongly disagree	**Somewhat disagree**	**Neither agree nor disagree**	**Somewhat agree**	**Strongly agree**
If I take actions to manage vegetation transitions, it will inspire other producers to do so.	◯	◯	◯	◯	◯
I doubt that other producers and I can collectively prevent vegetation transitions at a regional scale.	◯	◯	◯	◯	◯
If nearby producers take actions to manage vegetation, it will also reduce the chance of vegetation transitions on my operation.	◯	◯	◯	◯	◯
I can easily change practices on my operation to manage vegetation transitions.	◯	◯	◯	◯	◯
I do not think I can personally do anything about vegetation transitions on my operation.	◯	◯	◯	◯	◯
I believe my actions on my operation can significantly reduce vegetation transitions happening on the greater landscape.	◯	◯	◯	◯	◯

9. Please indicate how strongly you agree or disagree with the following statements about **trying different ranching/farming practices on your operation to prevent vegetation transitions from mostly grasses to mostly shrubs/trees**. *(For each row, please choose only **one** option.)*

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I frequently look for information about new ranching/farming techniques to prevent vegetation transitions on my operation.	○	○	○	○	○
I implement test plots to evaluate new ranching/farming practices to prevent vegetation transitions on my operation.	○	○	○	○	○
I am willing to adopt management practices on my operation to prevent vegetation transitions on my neighbors' properties.	○	○	○	○	○

10. Recent advances in digital technology make it possible to map different types of vegetation across the landscape. In some areas, these maps can provide information about how quickly vegetation is transitioning from grasses to shrubs/trees. This vegetation mapping can be used as an "early warning system" to help producers get ahead of vegetation transitions and ensure operation profitability. The next three questions ask about your views regarding this mapping technology.

Please indicate how strongly you agree or disagree with the following statements about **information provided by technology**. *(For each row, please choose only **one** option.)*

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I am willing to consider using vegetation mapping to manage vegetation transitions on my operation.	○	○	○	○	○
I would like more access to vegetation maps to help me manage vegetation transitions on my operation.	○	○	○	○	○
I would attend a workshop to learn more about using vegetation mapping to manage vegetation transitions.	○	○	○	○	○

11. Please indicate how strongly you agree or disagree with the following statements about **managing risk on your operation related to vegetation transitions from mostly grasses to mostly shrubs/trees**. *(For each row, please choose only **one** option.)*

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I like to experiment with new management practices to overcome risks to my operation from vegetation transitions.	○	○	○	○	○
Through effective planning, I can overcome risks to my operation from vegetation transitions.	○	○	○	○	○
I am willing to participate in **state funded** land conservation programs to reduce financial risks associated with vegetation transitions.	○	○	○	○	○
I am willing to participate in **federally funded** land conservation programs to reduce financial risks associated with vegetation transitions.	○	○	○	○	○
I am willing to participate in **privately funded** land conservation programs to reduce income risks associated with vegetation transitions.	○	○	○	○	○
If needed, I can rely on other producers in my community for assistance managing risks created by vegetation transitions on my operation.	○	○	○	○	○
The risks of adopting new technology to manage vegetation transitions on my operation outweigh the benefits.	○	○	○	○	○

12. Please indicate how strongly you agree or disagree with the following statements about **other people's efforts to manage vegetation transitions from mostly grasses to mostly shrubs/trees**. *(For each row, please choose only **one** option.)*

	Strongly disagree	**Somewhat disagree**	**Neither agree nor disagree**	**Somewhat agree**	**Strongly agree**
Most producers like me believe it's important to prevent vegetation transitions.	○	○	○	○	○
Most producers like me are taking actions to prevent vegetation transitions.	○	○	○	○	○
I trust the government to effectively manage vegetation transitions.	○	○	○	○	○
I believe current efforts to manage vegetation transitions in my area are **not** working well enough.	○	○	○	○	○

About your professional social network

We would like to ask you about the people who you go to for advice about rangeland management and the operations of your ranch or farm. Please list these people, but only use their **first names or initial**s to maintain privacy.

No one but the research team will see the names or initials you list and **we will never** use this information to identify or contact individuals.

As you answer these questions, **don't feel pressure to fill all 15 slots.** It's fine if people fit into multiple categories, but please make sure you ***only list each person once.***

13. First, think of the people with whom you work on your operation. Please list up to four people with whom you work.

Next, think of the people with whom you communicate about operating your ranch or farm. Please list up to four people with whom you communicate about your operation. Please consider people you have not already listed.

Next, think of the people to whom you go for rangeland management and operations advice. Please list up to four people with whom you consult for this information. Please consider people you have not already listed.

Finally, scan your list of contacts and decide: is anyone significant missing? If so, please add any additional people who should be included in your network of contacts regarding management activities on your operation.

10

The next few questions are about the people you just named. First, we will ask some questions about them, and then we will ask questions about your relationship with each person.

14. What is each person's **primary** occupation? *(For each person, please choose only **one** option.)*

	Rancher, farmer, or producer	Scientist or researcher	Government agency manager or conservationist	Other conservation professional	Farm financier	Other
1	○	○	○	○	○	○
2	○	○	○	○	○	○
3	○	○	○	○	○	○
4	○	○	○	○	○	○
5	○	○	○	○	○	○
6	○	○	○	○	○	○
7	○	○	○	○	○	○
8	○	○	○	○	○	○
9	○	○	○	○	○	○
10	○	○	○	○	○	○
11	○	○	○	○	○	○
12	○	○	○	○	○	○
13	○	○	○	○	○	○
14	○	○	○	○	○	○
15	○	○	○	○	○	○

12

15. How many years have you known each person? Please enter a numeric value for each person.

If you've known a person for less than one year, please write 1.

	Years known
1	
2	
3	
4	
5	
6	
7	
8	
9	
10	
11	
12	
13	
14	
15	

14

16. What kinds of information do you mainly receive from each person?

*(For each person, please select **all options** that apply.)*

Information about...

	Ranch or farm operations	Ranch or farm technology	Conservation practices (prescribed burning, weed control, etc.)	Financial or insurance programs (CRP, EQIP, etc.)	Non-operations
1	☐	☐	☐	☐	☐
2	☐	☐	☐	☐	☐
3	☐	☐	☐	☐	☐
4	☐	☐	☐	☐	☐
5	☐	☐	☐	☐	☐
6	☐	☐	☐	☐	☐
7	☐	☐	☐	☐	☐
8	☐	☐	☐	☐	☐
9	☐	☐	☐	☐	☐
10	☐	☐	☐	☐	☐
11	☐	☐	☐	☐	☐
12	☐	☐	☐	☐	☐
13	☐	☐	☐	☐	☐
14	☐	☐	☐	☐	☐
15	☐	☐	☐	☐	☐

16

17. How frequently do you interact with each person? Please include both face-to-face and electronic interactions.

*(For each person, please choose only **one** option.)*

	Daily	2-3 times per week	Weekly	2-3 times per month	Monthly	Less than once per month
1	○	○	○	○	○	○
2	○	○	○	○	○	○
3	○	○	○	○	○	○
4	○	○	○	○	○	○
5	○	○	○	○	○	○
6	○	○	○	○	○	○
7	○	○	○	○	○	○
8	○	○	○	○	○	○
9	○	○	○	○	○	○
10	○	○	○	○	○	○
11	○	○	○	○	○	○
12	○	○	○	○	○	○
13	○	○	○	○	○	○
14	○	○	○	○	○	○
15	○	○	○	○	○	○

This question is to find out whether your social contacts know each other. Feel free to copy the list of your contacts into the header row of the table opposite. Make sure that the names and numbers match.

18. Please look across each person's ROW. If the person in the row and the person above know each other, place a check in the appropriate box. For example, say you named John, Paul, George and Ringo as your social contacts. For this question, you would go across John's ROW and put checks under Paul, George and Ringo, because John and Paul know each other, John and George know each other, and John and Ringo know each other. For your contacts who don't know each other, leave the boxes between them blank.

Take your time and be as accurate
and complete as possible.

First Name or Initials														
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
		☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
			☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
				☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
					☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
						☐	☐	☐	☐	☐	☐	☐	☐	☐
							☐	☐	☐	☐	☐	☐	☐	☐
								☐	☐	☐	☐	☐	☐	☐
									☐	☐	☐	☐	☐	☐
										☐	☐	☐	☐	☐
											☐	☐	☐	☐
												☐	☐	☐
													☐	☐
														☐

20

First Names or Initials	
Person 1	
Person 2	
Person 3	
Person 4	
Person 5	
Person 6	
Person 7	
Person 8	
Person 9	
Person 10	
Person 11	
Person 12	
Person 13	
Person 14	
Person 15	

19. Due to COVID-19, communication with the people I listed above has been...

*(Please choose only **one** option.)*

- ○ ...very negatively affected.
- ○ ...somewhat negatively affected.
- ○ ...unaffected.
- ○ ...somewhat positively affected.
- ○ ...very positively affected.

20.a. Are there groups of people in your area that regularly meet to discuss rangeland management? *(Please choose only **one** option.)*

- ○ No → skip to **Question 21**
- ○ Yes → continue to **Question 20.b**

20.b. What's the extent of your involvement with these group(s)? *(Please choose only **one** option.)*

- ○ I am not involved in any groups. → skip to **Question 21**
- ○ I am heavily involved with at least one group. → continue to **Question 20.c**
- ○ I am moderately involved with at least one group. → continue to **Question 20.c**
- ○ I am minimally involved with at least one group. → continue to **Question 20.c**

20.c. What's the longest amount of time you have been involved in any of these groups? *(Please choose only **one** option.)*

- ○ Less than 1 year
- ○ 1-3 years
- ○ 4-10 years
- ○ 11-20 years
- ○ More than 20 years

Economic decision making

In this section, we want to understand a little about your approach to decision making. We will ask you five questions about a hypothetical opportunity to win a cash payment. In each question, you will be asked to choose one of two options.

21. Option A guarantees a payment of $25,000 in all five choices, while in option B there is a 50-50 chance of winning a certain amount. **Which option would you choose for each question?**

Although this is a hypothetical exercise and no real payments are involved, please think carefully before making your choice for each question. *(For each numbered row, please choose only **one** option.)*

Question	Option A		Option B
1.	○ $25,000	OR	○ 50% chance of $48,000, and 50% chance of $1000
2.	○ $25,000	OR	○ 50% chance of $50,000, and 50% chance of $1000
3.	○ $25,000	OR	○ 50% chance of $52,000, and 50% chance of $1000
4.	○ $25,000	OR	○ 50% chance of $54,000, and 50% chance of $1000
5.	○ $25,000	OR	○ 50% chance of $56,000, and 50% chance of $1000
6.	○ $25,000	OR	○ 50% chance of $58,000, and 50% chance of $1000

About you

This final section asks about you and your operation.

22. Approximately what percentage of your household income came from agriculture in 2019? *(Please choose only **one** option.)*

- ○ 0-19%
- ○ 20-39%
- ○ 40-59%
- ○ 60-79%
- ○ 80-100%

23. In what year were you born? ____________

24. Which best describes your gender? *(Please choose only **one** option.)*

- ○ Male
- ○ Female
- ○ Other

About you *(continued)*

25. What is the highest level of school you have completed? *(Please choose only **one** option.)*

- ◯ Grade school
- ◯ High school / GED
- ◯ Some college or vocational training
- ◯ 2-yr college
- ◯ 4-yr college
- ◯ Postgraduate

26. What was your total household income before taxes in 2019? *(Please choose only **one** option.)*

- ◯ Less than $25,000
- ◯ $25,000 - $49,999
- ◯ $50,000 - $99,999
- ◯ $100,000 - $149,999
- ◯ $150,000 - $249,999
- ◯ Greater than $250,000

Thank you for taking this survey. If you have any comments, please let us know here:

Please use the postage-paid envelope to mail the completed survey back to us.

Return address:

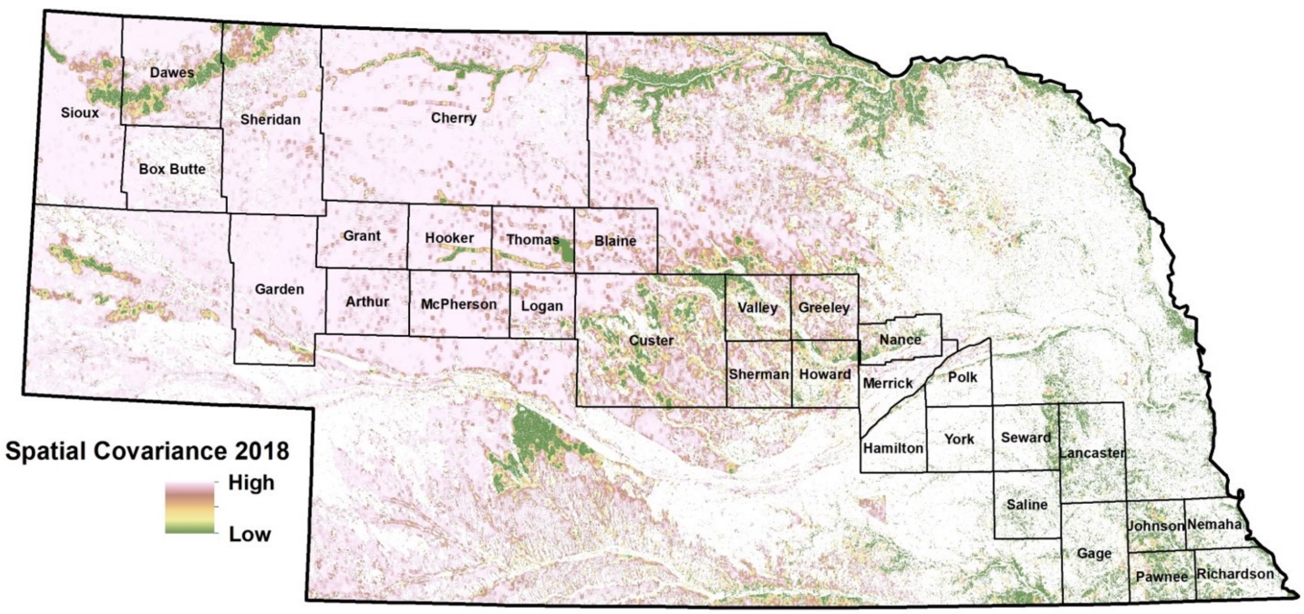
Center for Resilience in Agricultural Working Landscapes
203 Keim Hall
University of Nebraska-Lincoln - East Campus
Lincoln, NE 68583

Appendix 3B: Nebraska rangeland survey 2021 – Summary statistics of general data

Nebraska Rangeland Survey 2021 - Summary Statistics of General Data

About the sample

We surveyed a cross-section of Nebraska counties from the NW corner to the SE corner of the state because these counties were representative of the vegetation transition gradient.



We bought names and addresses from FarmMarketID. The purchased list constitutes the entire population of people who responded to the National Agricultural Survey in the counties we requested who self-identified as having >20 acres of pasture/rangeland (6546 people). Of this population, 3448 people had emails. We took a simple random sample of 4500 from the population of 6546 individuals.

Response rates

Initial sample size = 4500
Sample size after duplicates were removed = 4494

Number of responses = 573
Number of refusals = 176

Response rate = 13%

Note: We did not receive any "return to sender" envelopes and the post office did not track this for us. Because the addresses were purchased, it's possible that all the mailings were deliverable, but we don't know for certain.

Responses by prompt

We administered the paper survey in three waves. The first wave was a letter introducing the survey, which included a TinyURL. The second and third waves included a letter and paper survey.

First mailing - 4494 people, 103 responses; June 4, 2021
Second mailing - 4385 people, 253 responses, 43 refusals; June 23, 2021
Third mailing - 3932 people, 211 responses, 71 refusals; July 23, 2021

In addition to the paper surveys, we sent out three waves of emails.

First email - 2409 people, 98 emails bounced, 30 responses, 42 refusals; May 26, 2021
Second email - 2314 people, 101 emails bounced, 12 responses, 12 refusals; June 11, 2021
Third email - 2302 people, 100 emails bounced, 12 responses, 8 refusals; June 24, 2021

After duplicates and completely empty responses were removed, the final number of responses for each prompt is shown below.

prompt	n
email	33
paper	456
tinyurl	84

q1 - Type of agricultural production

Which of these options makes up the largest proportion of your operation?

question	variable	n	mode
q1	production type	545	3

answer	n	percent
1. Cattle ranching	236	41.19%
2. Other livestock	10	1.75%
3. Farming	244	42.58%
4. Specialty farm products	5	0.87%
5. Other	50	8.73%
NA	28	4.89%

q1b Other livestock, please specify Note: If the respondent selected “2. Other livestock,” they were prompted to specify with a fill in the blank.

answer	n	percent
BISON	1	0.17%
CATTLE & BOER GOATS	1	0.17%
CATTLE & SHEEP	1	0.17%
DAIRY	1	0.17%
HORSES	3	0.52%
PIGS	1	0.17%
POULTRY	1	0.17%
SHEEP	1	0.17%
SHEEP & GOAT	1	0.17%

answer	n	percent
NA	562	98.08%

q1d Specialty farm products, please specify Note: If the respondent selected "4. Specialty farm products," they were prompted to specify with a fill in the blank.

answer	n	percent
BEES & FRUIT	1	0%
CORN & BEANS	1	0%
LOCAL ECOTYPE WILDFOWER SEED PRODUCTION	1	0%
NATIVE GRASS SEED PRODUCTION	1	0%
NATIVE PRAIRIE FORBSEED POLLINATOR	1	0%
NA	568	99%

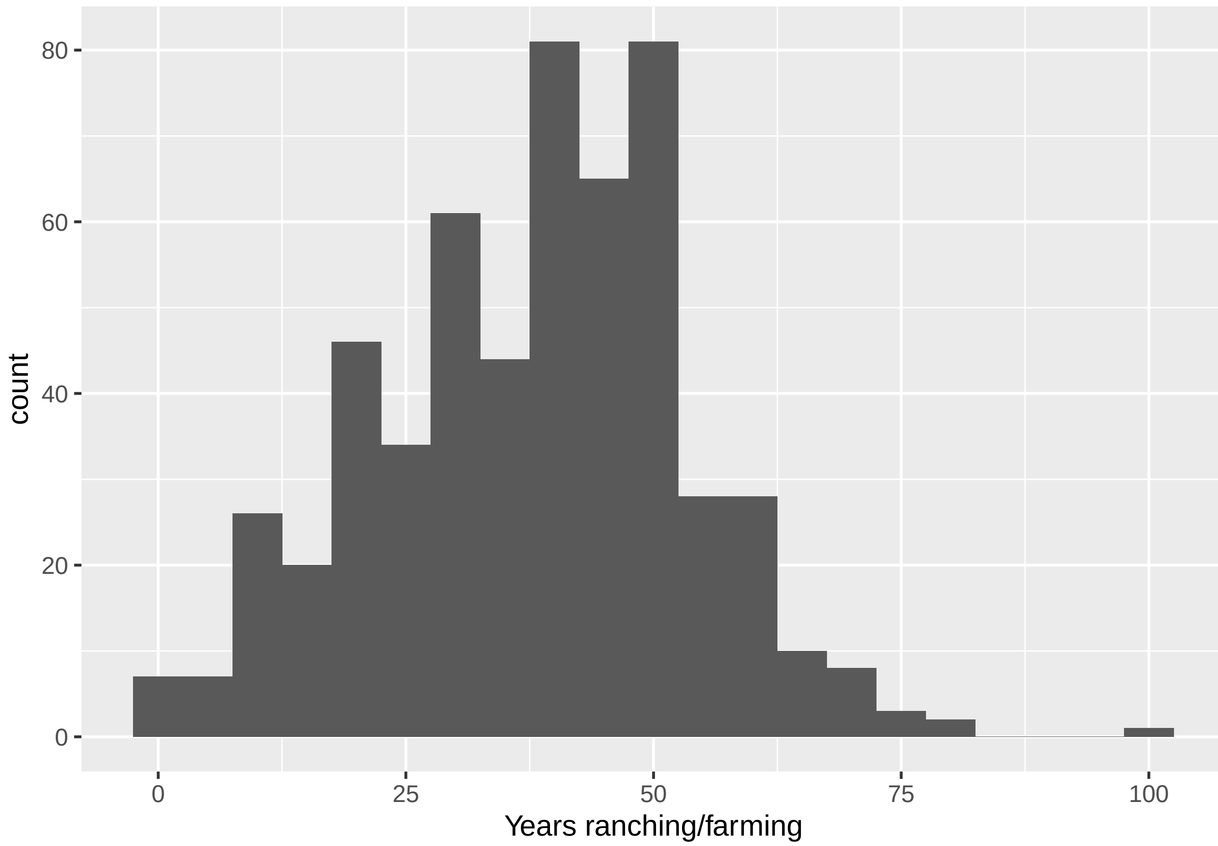
q1e Other, please specify Note: If the respondent selected "5. Other," they were prompted to specify with a fill in the blank.

answer	n	percent
ALFALFA & PRAIRIE	1	0.17%
CATTLE & FARM	4	0.70%
CATTLE & OFFFARM RUN	1	0.17%
CORN, BEANS, ALFALFA	1	0.17%
CROP	1	0.17%
CRP	11	1.92%
CRP & HABITAT RESTORATION	1	0.17%
CRP & PRAIRE HAY	1	0.17%
CRP & ROW CROPS	1	0.17%
CUSTOM HIRE & PASTURE RENTAL	1	0.17%
HAY	8	1.40%
HAY & PASTURE	1	0.17%
HORSES, HAY GROUND, FARMLAND LEASE	1	0.17%
MULTI SPECIES GRAZING	1	0.17%
NATIVE GRASS	1	0.17%
PASTURE & CPR LAND	1	0.17%
RENT/LEASE OUT	11	1.92%
RETIRED	2	0.35%
WILDLIFE ENHANCEMNET	1	0.17%
WORKED DAY TIME JOB	1	0.17%
NA	522	91.10%

q2 - Years in agricultural production

How many years have you personally been ranching or farming?

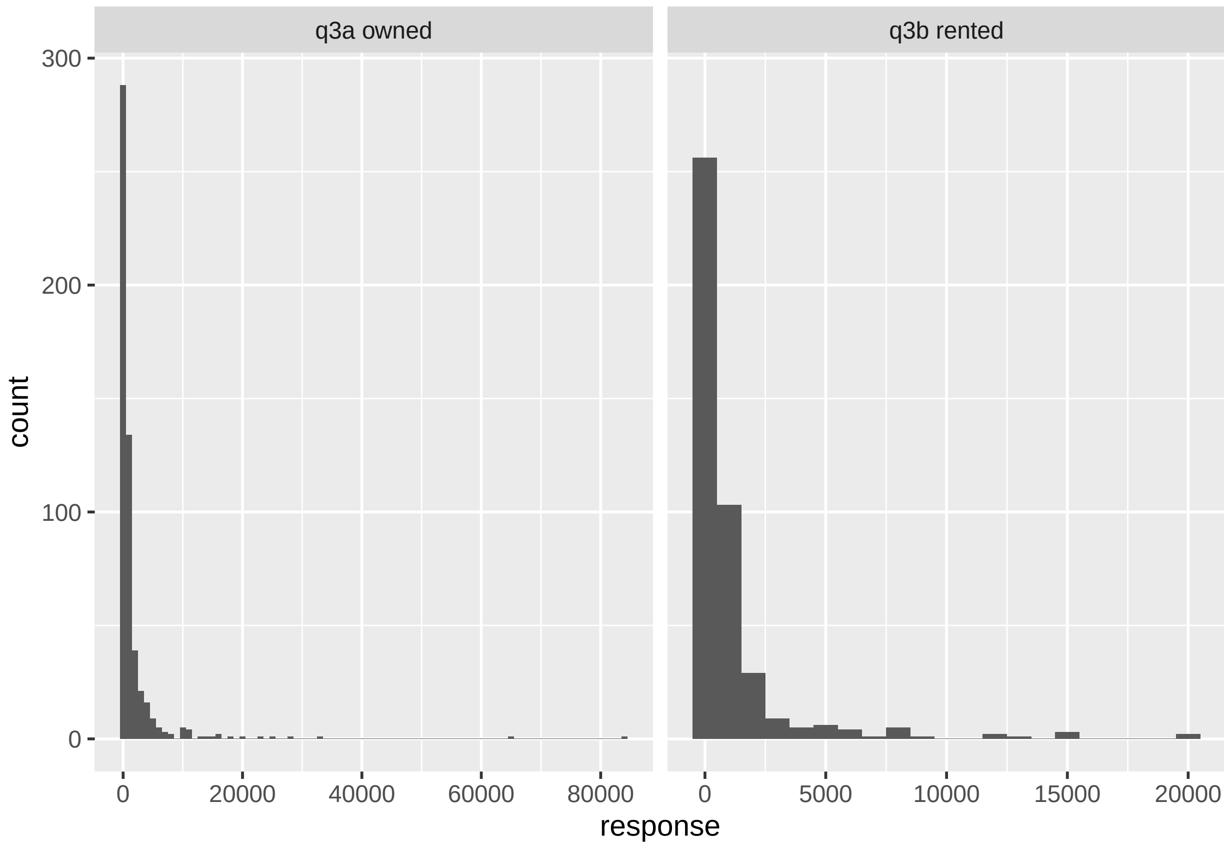
question	variable	n	mean	sd	min	median	max
q2	years ranching/farming	552	37.9	15.65	0	40	98



q3 - Acres owned/rented

Please estimate the acreage of your operation in 2020.

question	variable	n	mean	sd	min	median	max
q3a	owned	539	1800.52	5596.59	0	450	84000
q3b	rented	427	1073.72	2432.92	0	320	20000



Acres owned

owned_interval	n	percent
a. 0	8	1.40%
b. 0<acres<640	310	54.10%
c. 640-1279	87	15.18%
d. 1280-1919	25	4.36%
e. 1920-2559	31	5.41%
f. 2560-3199	15	2.62%
g. 3200-3839	9	1.57%
h. 3840-4479	11	1.92%
i. 4480-5119	5	0.87%
j. >5120	38	6.63%
NA	34	5.93%

Acres rented

rented_interval	n	percent
a. 0	116	20.24%
b. 0<acres<640	153	26.70%
c. 640-1279	80	13.96%
d. 1280-1919	22	3.84%
e. 1920-2559	17	2.97%
f. 2560-3199	6	1.05%
g. 3200-3839	5	0.87%

rented_interval	n	percent
h. 3840-4479	2	0.35%
i. 4480-5119	7	1.22%
j. >5120	19	3.32%
NA	146	25.48%

q4 - Main county of operation

In what county in Nebraska is the largest proportion of your operation located?

question	variable	n	mode
q4	main county of operation	573	CUSTER

answer	n	percent
ARTHUR	3	0.52%
BLAINE	2	0.35%
BOONE	1	0.17%
BOX BUTTE	15	2.62%
BOX BUTTE/SIOUX	1	0.17%
BUTLER	3	0.52%
CASS	1	0.17%
CHERRY	19	3.32%
CHERRY/THOMAS	1	0.17%
CHEYENNE	1	0.17%
CLAY	1	0.17%
CUSTER	46	8.03%
CUSTER/GOSPER	1	0.17%
DAWES	25	4.36%
DAWSON	1	0.17%
DUNDY	1	0.17%
FILLMORE	2	0.35%
GAGE	37	6.46%
GAGE/LANCASTER	1	0.17%
GAGE/SALINE	1	0.17%
GARDEN	8	1.40%
GARFIELD	2	0.35%
GRANT	4	0.70%
GRANT/CUSTER	1	0.17%
GREELEY	13	2.27%
HALL	1	0.17%
HAMILTON	16	2.79%
HOOKER	3	0.52%
HOWARD	24	4.19%
JEFFERSON	2	0.35%
JOHNSON	20	3.49%
KEYA PAHA	1	0.17%
KIMBALL	1	0.17%
KNOX	1	0.17%
LANCASTER	34	5.93%
LOGAN	3	0.52%
LOUP	3	0.52%

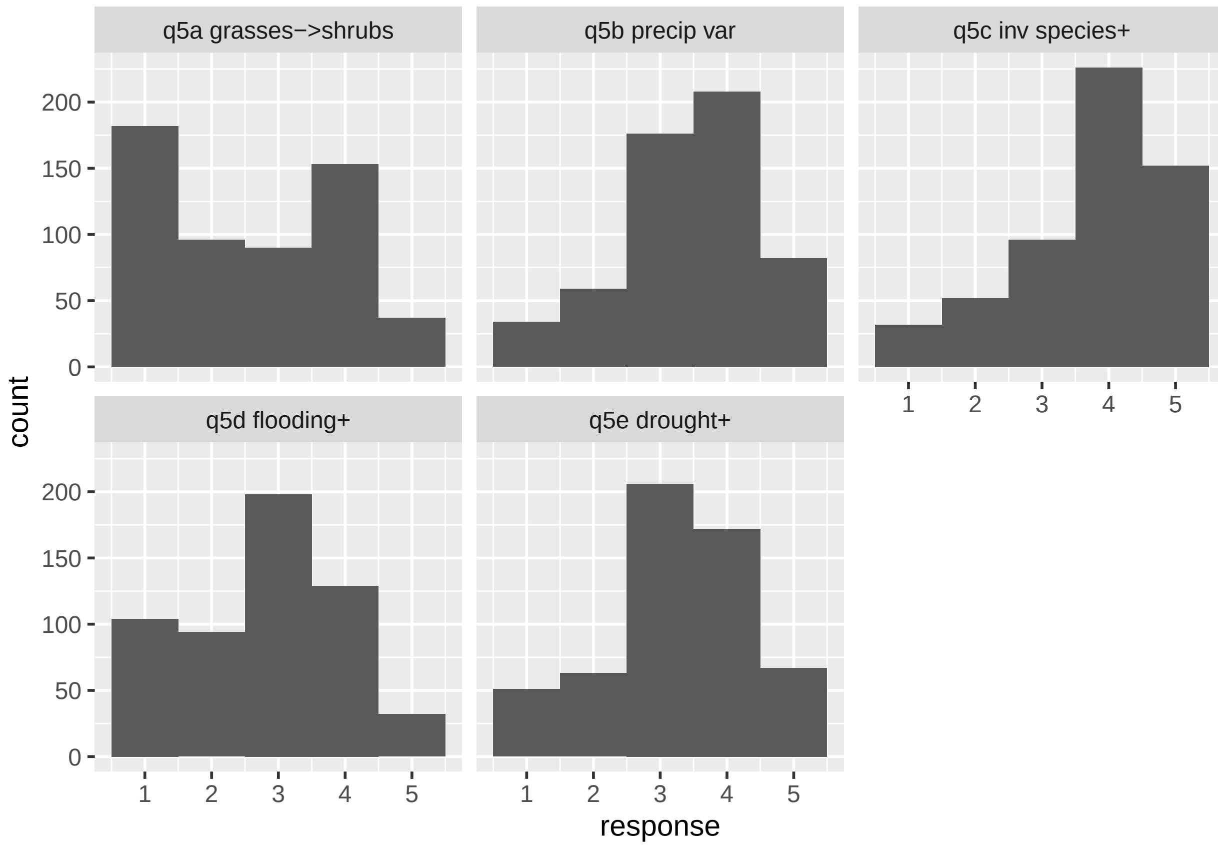
answer	n	percent
MADISON	1	0.17%
MCPHERSON	5	0.87%
MERRICK	11	1.92%
MORRILL	1	0.17%
NANCE	7	1.22%
NANCE/BOONE	1	0.17%
NEMAHA	14	2.44%
NUCKOLLS	1	0.17%
OTOE	1	0.17%
PAWNEE	20	3.49%
PIERCE	1	0.17%
PLATTE	1	0.17%
POLK	17	2.97%
RICHARDSON	17	2.97%
SALINE	29	5.06%
SAUNDERS	2	0.35%
SCOTTS BLUFF	1	0.17%
SEWARD	27	4.71%
SHERIDAN	27	4.71%
SHERMAN	17	2.97%
SIOUX	12	2.09%
THOMAS	1	0.17%
VALLEY	19	3.32%
WEBSTER	1	0.17%
WHEELER	2	0.35%
YORK	13	2.27%
NA	24	4.19%

q5 - Notice environmental changes

Please indicate how strongly you agree or disagree with the following statements about landscape changes in your area. In my time managing my operation, I have noticed. . .

(1=strongly disagree, 2=somewhat disagree, 3=neither, 4=somewhat agree, 5=strongly agree)

question	variable	n	mean	sd	min	median	max
q5a	grasses->shrubs	558	2.58	1.36	1	3	5
q5b	precip var	559	3.44	1.06	1	4	5
q5c	inv species+	558	3.74	1.13	1	4	5
q5d	flooding+	557	2.80	1.16	1	3	5
q5e	drought+	559	3.25	1.10	1	3	5

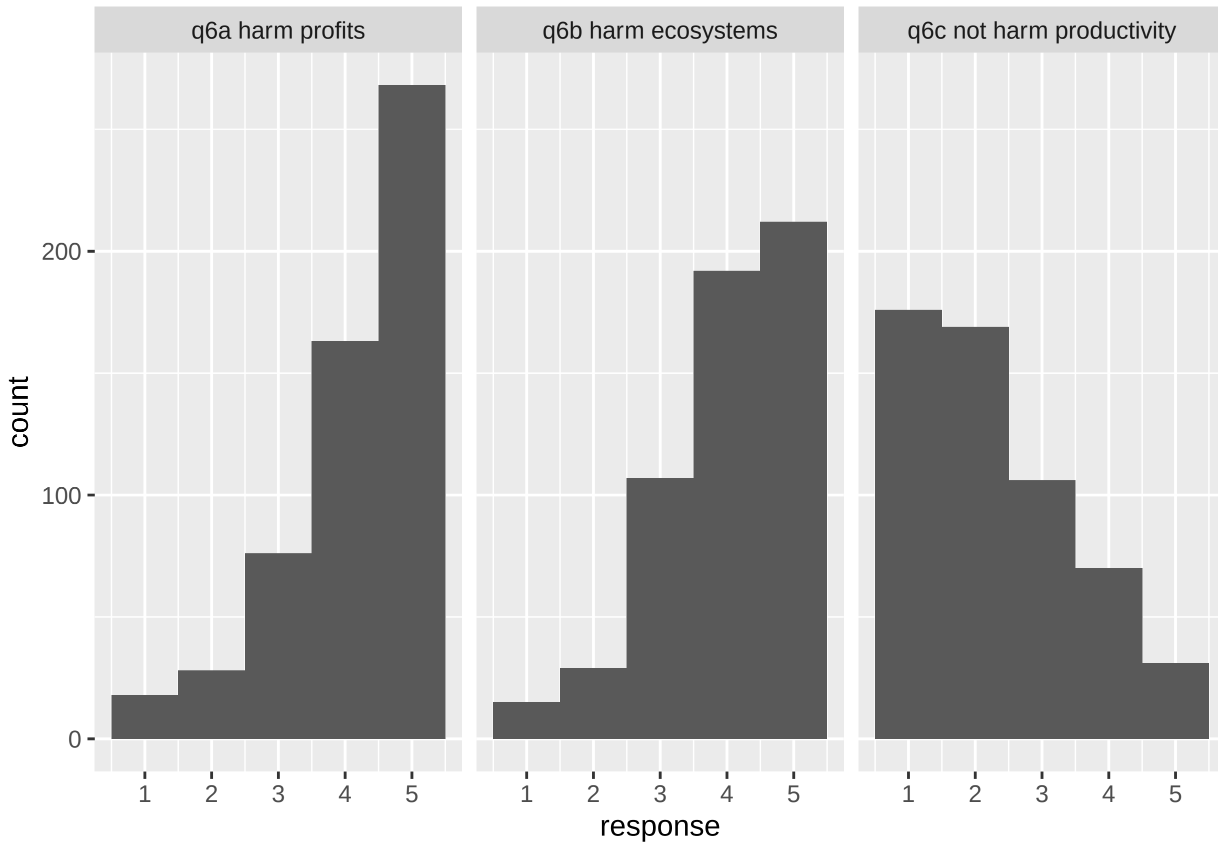


q6 - Effects of vegetation transitions

Please indicate how strongly you agree or disagree with the following statements about the general effects of vegetation transitions from mostly grasses to mostly shrubs/trees.

(1=strongly disagree, 2=somewhat disagree, 3=neither, 4=somewhat agree, 5=strongly agree)

question	variable	n	mean	sd	min	median	max
q6a	harm profits	553	4.15	1.05	1	4	5
q6b	harm ecosystems	555	4.00	1.01	1	4	5
q6c	not harm productivity	552	2.30	1.20	1	2	5

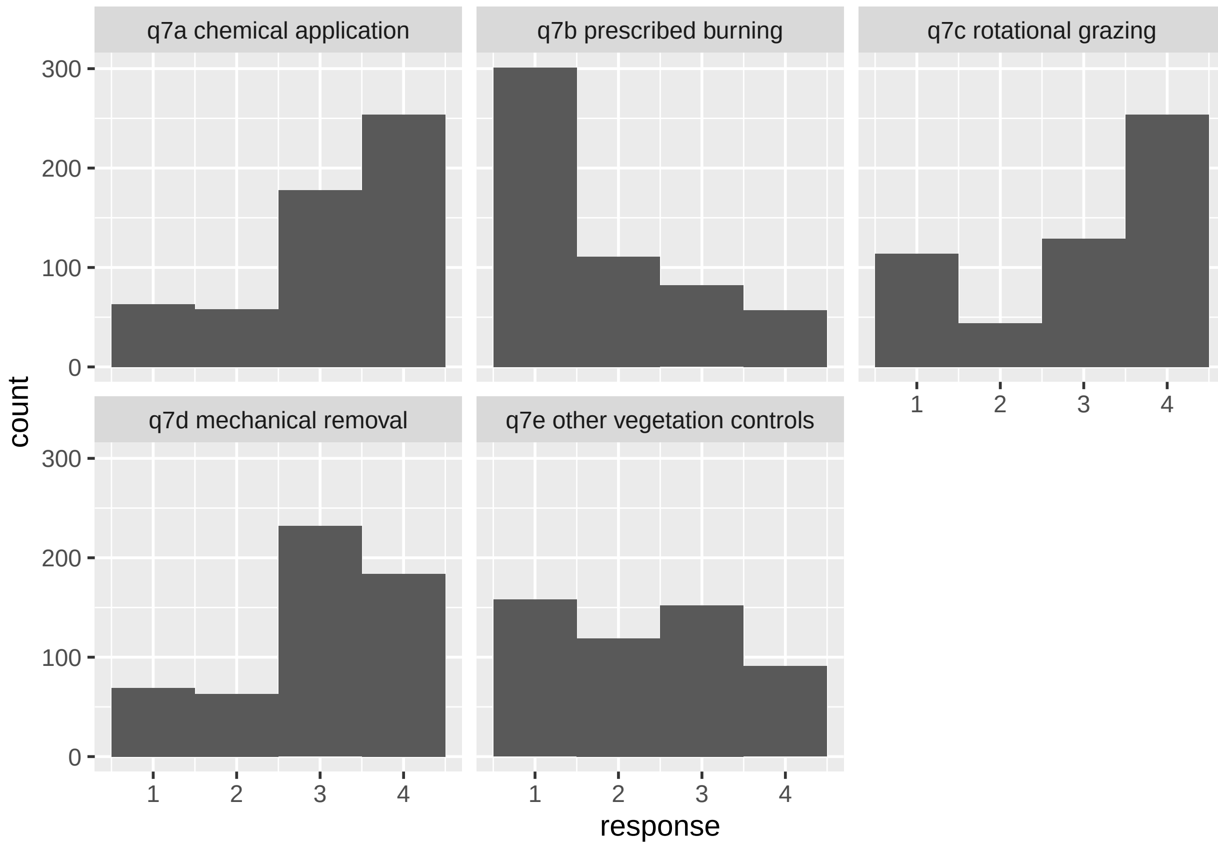


q7 - Adaptive behaviors

Please rate how often you have taken the following actions to manage vegetation transitions on your operation in the past three years.

(1=never, 2=rarely, 3=occasionally, 4=always as appropriate)

question	variable	n	mean	sd	min	median	max
q7a	chemical application	553	3.13	1.00	1	3	4
q7b	prescribed burning	551	1.81	1.04	1	1	4
q7c	rotational grazing	541	2.97	1.18	1	3	4
q7d	mechanical removal	548	2.97	0.98	1	3	4
q7e	other vegetation controls	520	2.34	1.09	1	2	4

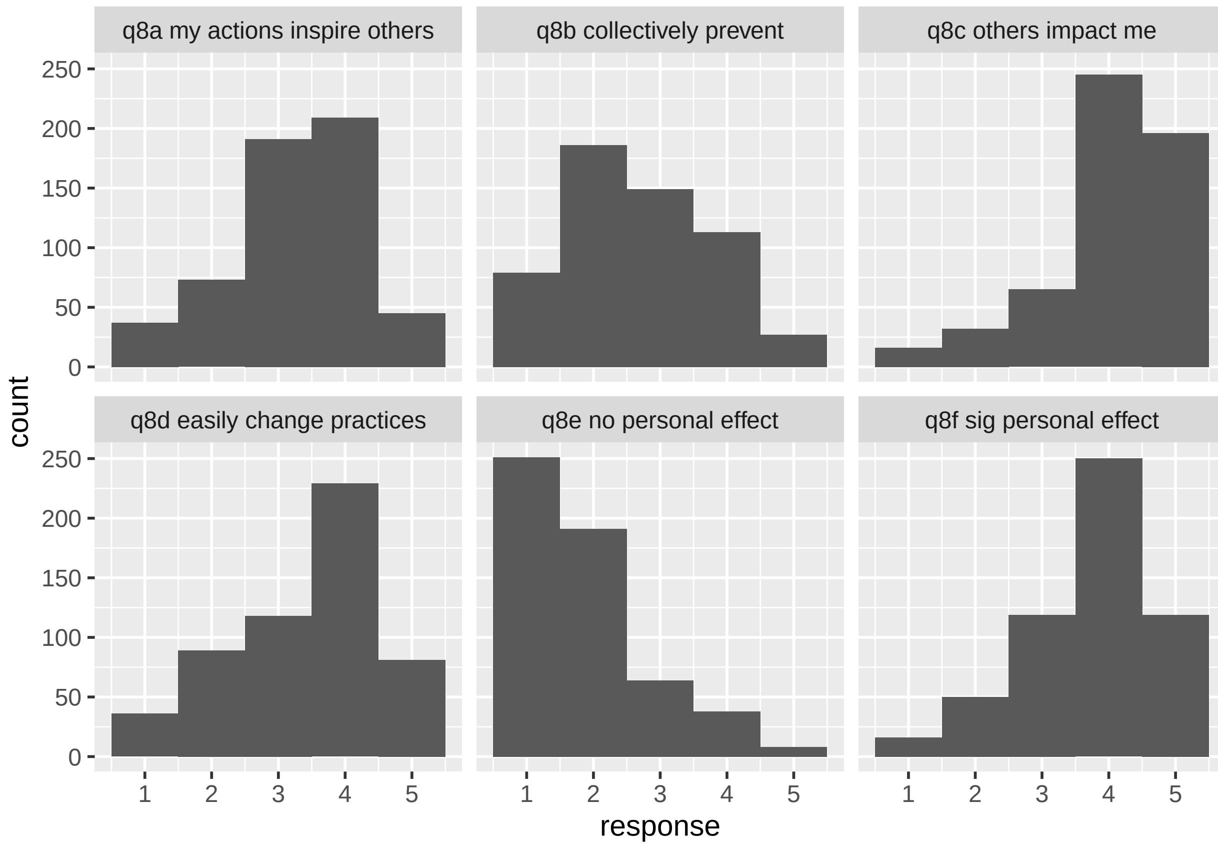


q8 - Group & self-efficacy

Please indicate how strongly you agree or disagree with the following statements about managing vegetation transitions from mostly grasses to mostly shrubs/trees on your operation.

(1=strongly disagree, 2=somewhat disagree, 3=neither, 4=somewhat agree, 5=strongly agree)

question	variable	n	mean	sd	min	median	max
q8a	my actions inspire others	555	3.27	1.01	1	3	5
q8b	collectively prevent	554	2.68	1.10	1	3	5
q8c	others impact me	554	4.03	0.98	1	4	5
q8d	easily change practices	553	3.42	1.12	1	4	5
q8e	no personal effect	552	1.84	0.98	1	2	5
q8f	sig personal effect	554	3.73	0.99	1	4	5

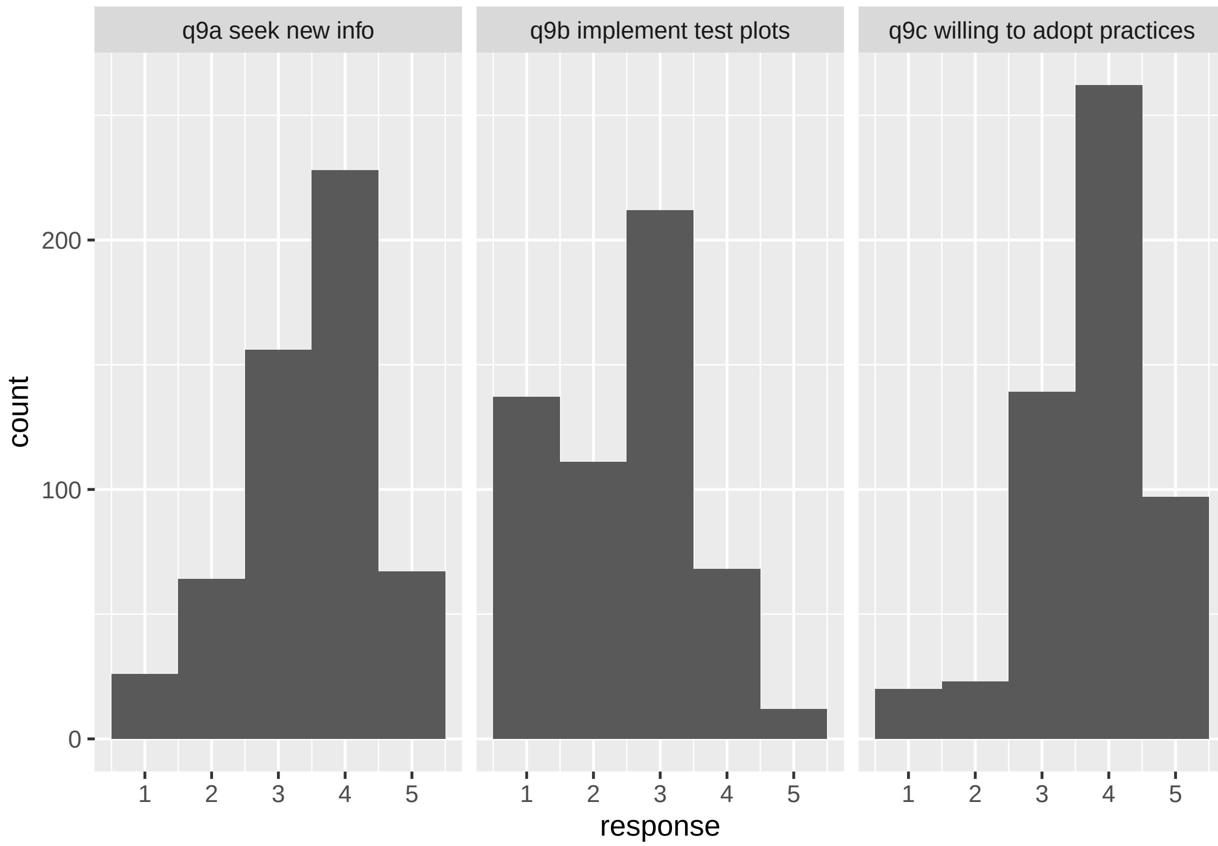


q9 - Innovation adoption

Please indicate how strongly you agree or disagree with the following statements about trying different ranching/farming practices on your operation to prevent vegetation transitions from mostly grasses to mostly shrubs/trees.

(1=strongly disagree, 2=somewhat disagree, 3=neither, 4=somewhat agree, 5=strongly agree)

question	variable	n	mean	sd	min	median	max
q9a	seek new info	541	3.45	1.01	1	4	5
q9b	implement test plots	540	2.46	1.07	1	3	5
q9c	willing to adopt practices	541	3.73	0.93	1	4	5

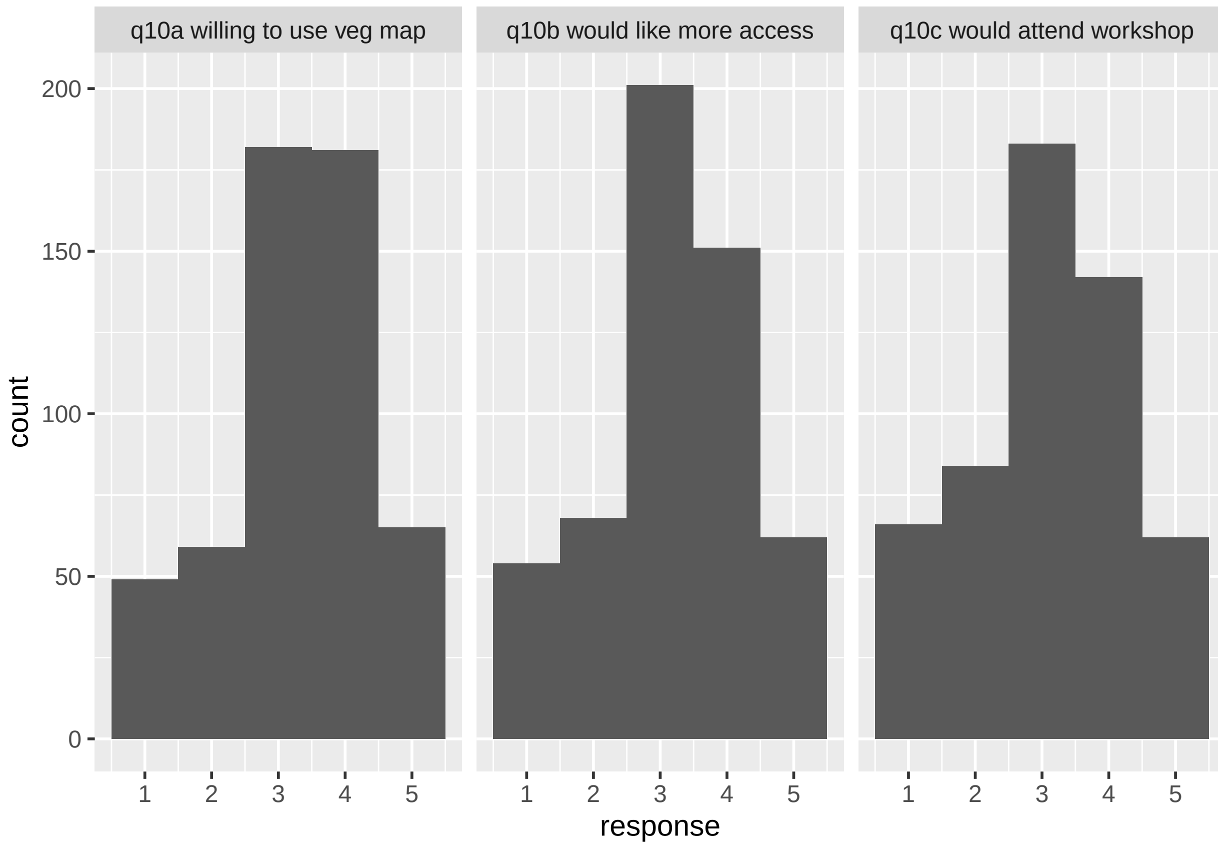


q10 - Vegetation mapping

Please indicate how strongly you agree or disagree with the following statements about information provided by technology.

(1=strongly disagree, 2=somewhat disagree, 3=neither, 4=somewhat agree, 5=strongly agree)

question	variable	n	mean	sd	min	median	max
q10a	willing to use veg map	536	3.29	1.10	1	3	5
q10b	would like more access	536	3.18	1.11	1	3	5
q10c	would attend workshop	537	3.09	1.17	1	3	5

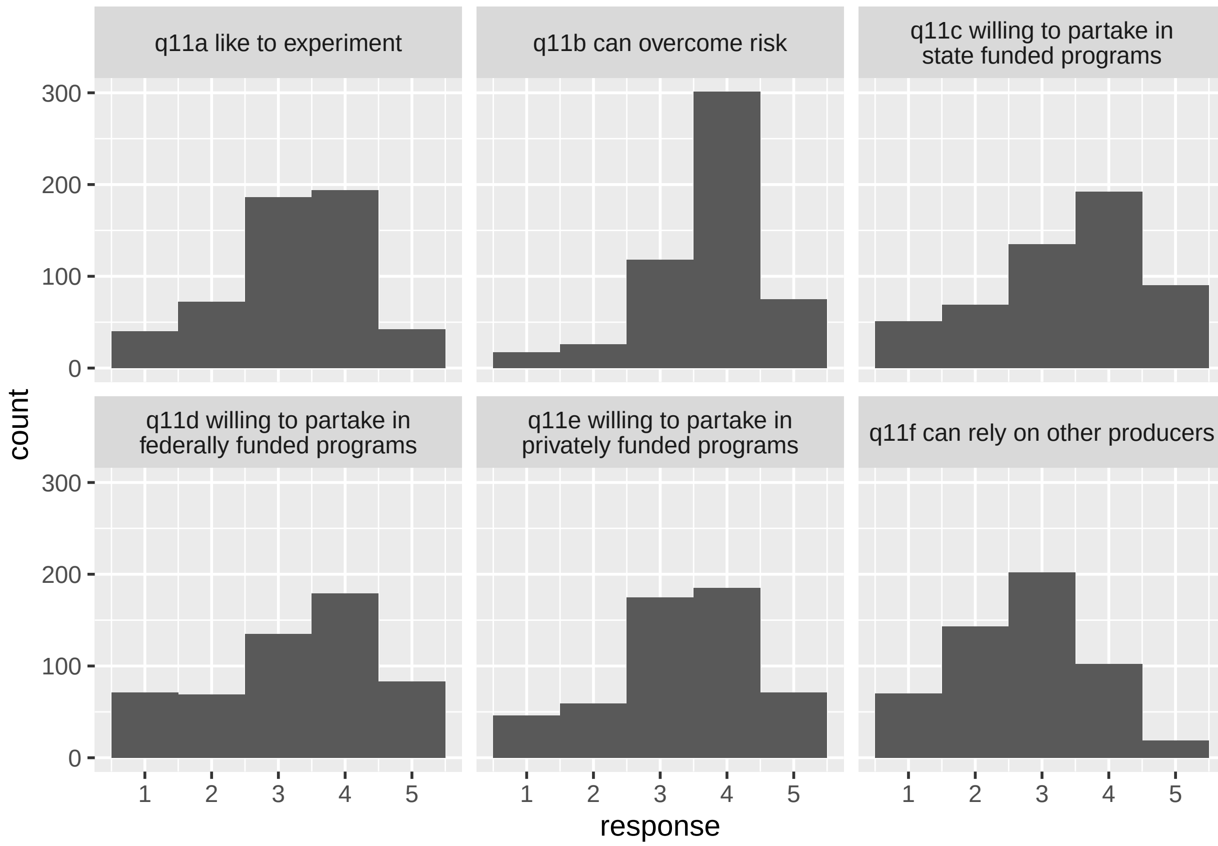


q11 - Risks, program participation, innovation

Please indicate how strongly you agree or disagree with the following statements about managing risk on your operation related to vegetation transitions from mostly grasses to mostly shrubs/trees.

(1=strongly disagree, 2=somewhat disagree, 3=neither, 4=somewhat agree, 5=strongly agree)

question	variable	n	mean	sd	min	median	max
q11a	like to experiment	534	3.24	1.03	1	3	5
q11b	can overcome risk	537	3.73	0.87	1	4	5
q11c	willing to partake i nstate funded programs	537	3.37	1.18	1	4	5
q11d	willing to partake in federally funded programs	537	3.25	1.24	1	3	5
q11e	willing to partake in privately funded programs	536	3.33	1.11	1	3	5
q11f	can rely on other producers	536	2.73	1.03	1	3	5
q11g	risks outweigh benefits of new tech	536	2.80	0.99	1	3	5

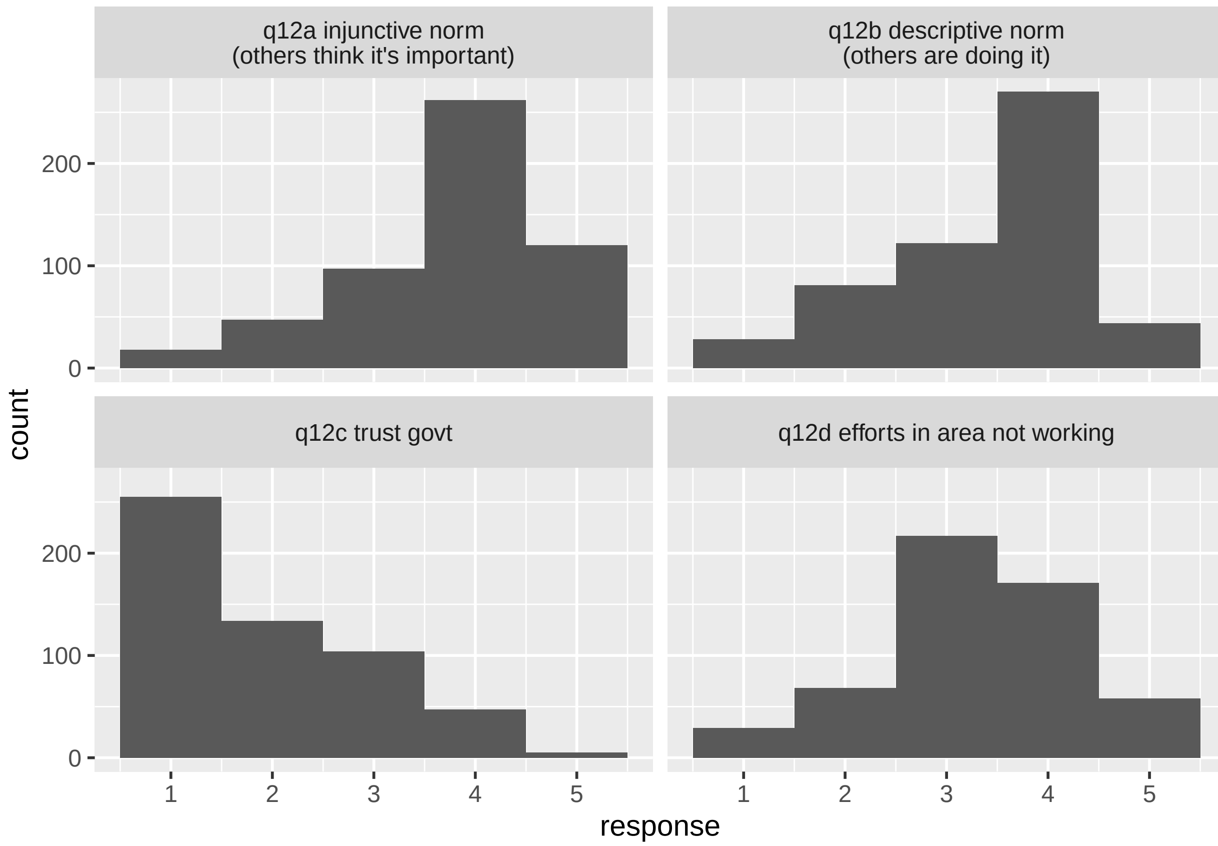


q12 - Norms, trust, satisfaction

Please indicate how strongly you agree or disagree with the following statements about other people's efforts to manage vegetation transitions from mostly grasses to mostly shrubs/trees.

(1=strongly disagree, 2=somewhat disagree, 3=neither, 4=somewhat agree, 5=strongly agree)

question	variable	n	mean	sd	min	median	max
q12a	injunctive norm	544	3.77	1.00	1	4	5
q12b	descriptive norm	545	3.41	1.00	1	4	5
q12c	trust govt	545	1.92	1.04	1	2	5
q12d	efforts in area not working	543	3.30	1.00	1	3	5



q19 - COVID-19

Due to COVID-19, communication with the people I listed above has been...

Note: This question is referring back to the people that the respondent listed in the social network section, which is not included here.

question	variable	n	mean	sd	min	median	max
q19	effects of COVID-19	371	2.71	0.71	0	3	5

answer	n	percent
1. very negatively affected	21	3.66%
2. somewhat negatively affected	84	14.66%
3. unaffected	252	43.98%
4. somewhat positively affected	4	0.70%
5. very positively affected	9	1.57%
NA	203	35.43%

q20 - Collaborative groups

Skip logic: q20) If no, skip to q21; if yes, continue to q20b. q20b) If not involved, skip to q21; if involved, continue to q20c.

question	variable	n	mean	sd	min	median	max
q20a	collaborative group(s) in area	410	0.12	0.32	0	0.0	1
q20b	involved in group(s)	65	1.83	1.17	0	1.0	4
q20c	years of involvement	40	3.08	1.56	0	3.5	5

a) Are there groups of people in your area that regularly meet to discuss rangeland management?

answer	n	percent
0. no	362	63%
1. yes	48	8%
NA	163	28%

b) What's the extent of your involvement with these groups?

Note: If you are using this question, you may want to recode it as the order is wonky.

answer	n	percent
1. not involved	37	6.46%
2. heavily involved	9	1.57%
3. moderately involved	8	1.40%
4. minimally involved	10	1.75%
NA	509	88.83%

c) What's the longest amount of time you have been involved in any of these groups?

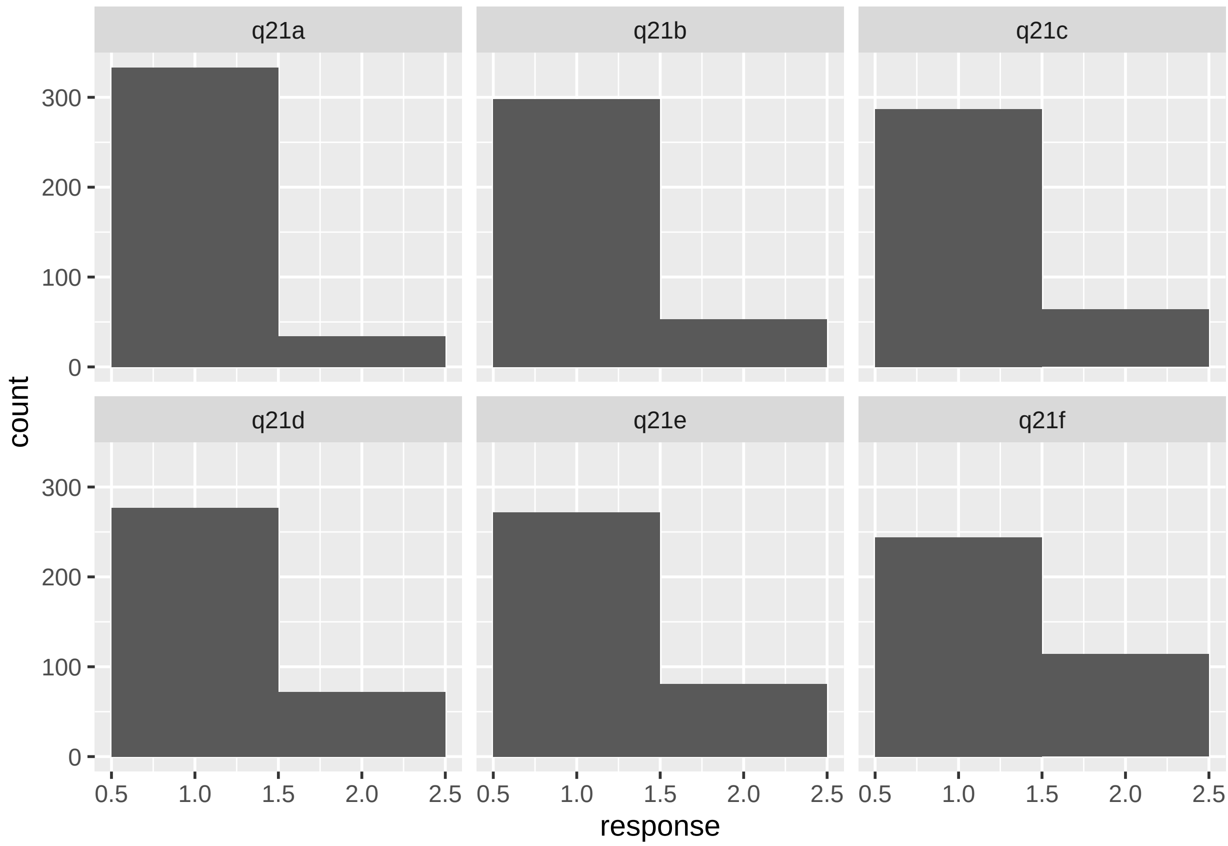
answer	n	percent
1. <1 year	10	1.75%
2. 1-3 years	2	0.35%
3. 4-10 years	7	1.22%
4. 11-20	12	2.09%
5. >20 years	8	1.40%
NA	534	93.19%

q21 - Risk preferences

Option A guarantees a payment of $25,000, while option B there is a 50-50 chance of winning a certain amount. Which option would you choose for each question?

(1=$25,000 in each question; 2=50-50 chance of $48K-$1K(a), $50K-$1K(b), $52K-$1K(c), $54K-$1K(d), $56K-$1K(e), $58K-$1K(f))

question	variable	n	mean	sd	min	median	max
q21a	50/50 $48K	367	1.09	0.29	1	1	2
q21b	50/50 $50K	351	1.15	0.36	1	1	2
q21c	50/50 $52K	351	1.18	0.39	1	1	2
q21d	50/50 $54K	349	1.21	0.41	1	1	2
q21e	50/50 $56K	353	1.23	0.42	1	1	2
q21f	50/50 $58K	358	1.32	0.47	1	1	2



q22 - Income from agricultural production

Approximately what percentage of your household income came from agriculture in 2019?

question	variable	n	mean	sd	min	median	max
q22	income from agricultural production	460	3.46	1.56	1	4	5

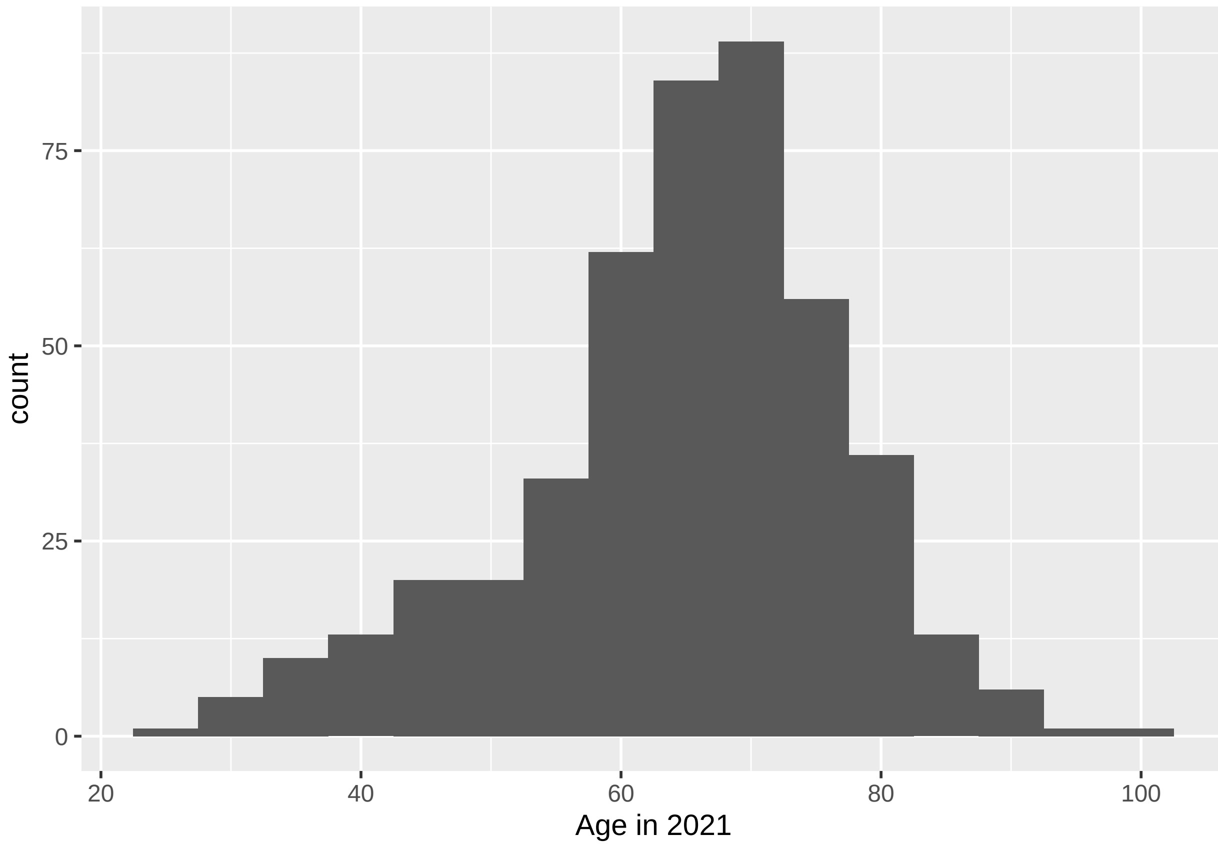
answer	n	percent
1. <20%	84	14.66%
2. 20-39%	59	10.30%
3. 40-59%	64	11.17%
4. 60-79%	66	11.52%
5. >80%	187	32.64%
NA	113	19.72%

q23 - Age

In what year were you born?

Note: This variable was converted to age in 2021 for this output.

question	variable	n	mean	sd	min	median	max
q1	age	450	64.81	12.35	23	67	98



q24 - Gender

Which best describes your gender?

question	variable	n	mode
q24	gender	463	1

answer	n	percent
1. male	419	73.1%
2. female	42	7.3%
3. other	2	0.3%
NA	110	19.2%

q25 - Education

What is the highest level of school you have completed?

question	variable	n	mean	sd	min	median	max
q25	education	516	3.7	1.39	1	3	6

answer	n	percent
1. grade school	4	0.70%
2. high school / GED	129	22.51%
3. some college or vocational training	126	21.99%
4. 2-yr college	74	12.91%
5. 4-yr college	125	21.82%
6. postgraduate	58	10.12%
NA	57	9.95%

q26 - Income

What was your total household income before taxes in 2019?

question	variable	n	mean	sd	min	median	max
q26	income	471	3.5	1.3	1	3	6

answer	n	percent
1. <$25k	20	3.5%
2. $25k-$49,999	79	13.8%
3. $50k-$99,999	170	29.7%
4. $100k-$149,999	95	16.6%
5. $150k-$249,999	62	10.8%
6. >$250k	45	7.9%
NA	102	17.8%

Descriptive statistics summary tables

question	variable	n	mean	sd	min	median	max
q2	years ranching/farming	552	37.90	15.65	0	40.0	98
q3a	acres owned	539	1800.52	5596.59	0	450.0	84000
q3b	acres rented	427	1073.72	2432.92	0	320.0	20000
q5a	grasses->shrubs	558	2.58	1.36	1	3.0	5
q5b	precip var	559	3.44	1.06	1	4.0	5
q5c	inv species+	558	3.74	1.13	1	4.0	5
q5d	flooding+	557	2.80	1.16	1	3.0	5
q5e	drought+	559	3.25	1.10	1	3.0	5
q6a	harm profits	553	4.15	1.05	1	4.0	5
q6b	harm ecosystems	555	4.00	1.01	1	4.0	5
q6c	not harm productivity	552	2.30	1.20	1	2.0	5
q7a	chemical application	553	3.13	1.00	1	3.0	4
q7b	prescribed burning	551	1.81	1.04	1	1.0	4
q7c	rotational grazing	541	2.97	1.18	1	3.0	4
q7d	mechanical removal	548	2.97	0.98	1	3.0	4
q7e	other vegetation controls	520	2.34	1.09	1	2.0	4

question	variable	n	mean	sd	min	median	max
q8a	my actions inspire others	555	3.27	1.01	1	3.0	5
q8b	collectively prevent	554	2.68	1.10	1	3.0	5
q8c	others impact me	554	4.03	0.98	1	4.0	5
q8d	easily change practices	553	3.42	1.12	1	4.0	5
q8e	no personal effect	552	1.84	0.98	1	2.0	5
q8f	sig personal effect	554	3.73	0.99	1	4.0	5
q9a	seek new info	541	3.45	1.01	1	4.0	5
q9b	implement test plots	540	2.46	1.07	1	3.0	5
q9c	willing to adopt practices	541	3.73	0.93	1	4.0	5
q10a	willing to use veg map	536	3.29	1.10	1	3.0	5
q10b	would like more access	536	3.18	1.11	1	3.0	5
q10c	would attend workshop	537	3.09	1.17	1	3.0	5
q11a	like to experiment	534	3.24	1.03	1	3.0	5
q11b	can overcome risk	537	3.73	0.87	1	4.0	5
q11c	willing to partake i nstate funded programs	537	3.37	1.18	1	4.0	5
q11d	willing to partake in federally funded programs	537	3.25	1.24	1	3.0	5
q11e	willing to partake in privately funded programs	536	3.33	1.11	1	3.0	5
q11f	can rely on other producers	536	2.73	1.03	1	3.0	5
q11g	risks outweigh benefits of new tech	536	2.80	0.99	1	3.0	5
q12a	injunctive norm	544	3.77	1.00	1	4.0	5
q12b	descriptive norm	545	3.41	1.00	1	4.0	5
q12c	trust govt	545	1.92	1.04	1	2.0	5
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q21b	50/50 $50K	351	1.15	0.36	1	1.0	2
q21c	50/50 $52K	351	1.18	0.39	1	1.0	2
q21d	50/50 $54K	349	1.21	0.41	1	1.0	2
q21e	50/50 $56K	353	1.23	0.42	1	1.0	2
q21f	50/50 $58K	358	1.32	0.47	1	1.0	2
q22	income from agricultural production	460	3.46	1.56	1	4.0	5
q23	year born	450	1956.19	12.35	1923	1954.0	1998
q25	education	516	3.70	1.39	1	3.0	6
q26	income	471	3.50	1.30	1	3.0	6

question	variable	n	mode
q1	production type	545	Farming
q4	main county of operation	549	Custer
q24	gender	463	Male

Appendix 3C: Nebraska rangeland survey 2021 – Summary statistics of network data

Nebraska Rangeland Survey 2021 - Summary Statistics of Network Data

About the network part of the survey

Respondents (aka egos) were asked to name up to 15 people (aka alters) involved in rangeland management and the operations of their ranch or farm, including people with whom they work, people with whom they communicate, and people from which they seek advice. After ego named alters, we asked a series of questions about each alter, numbered 1-15.

q13 - Size (aka degree)

The number of people each respondent listed

variable	n	mean	sd	min	median	max
Size	338	4.72	3	1	4	15

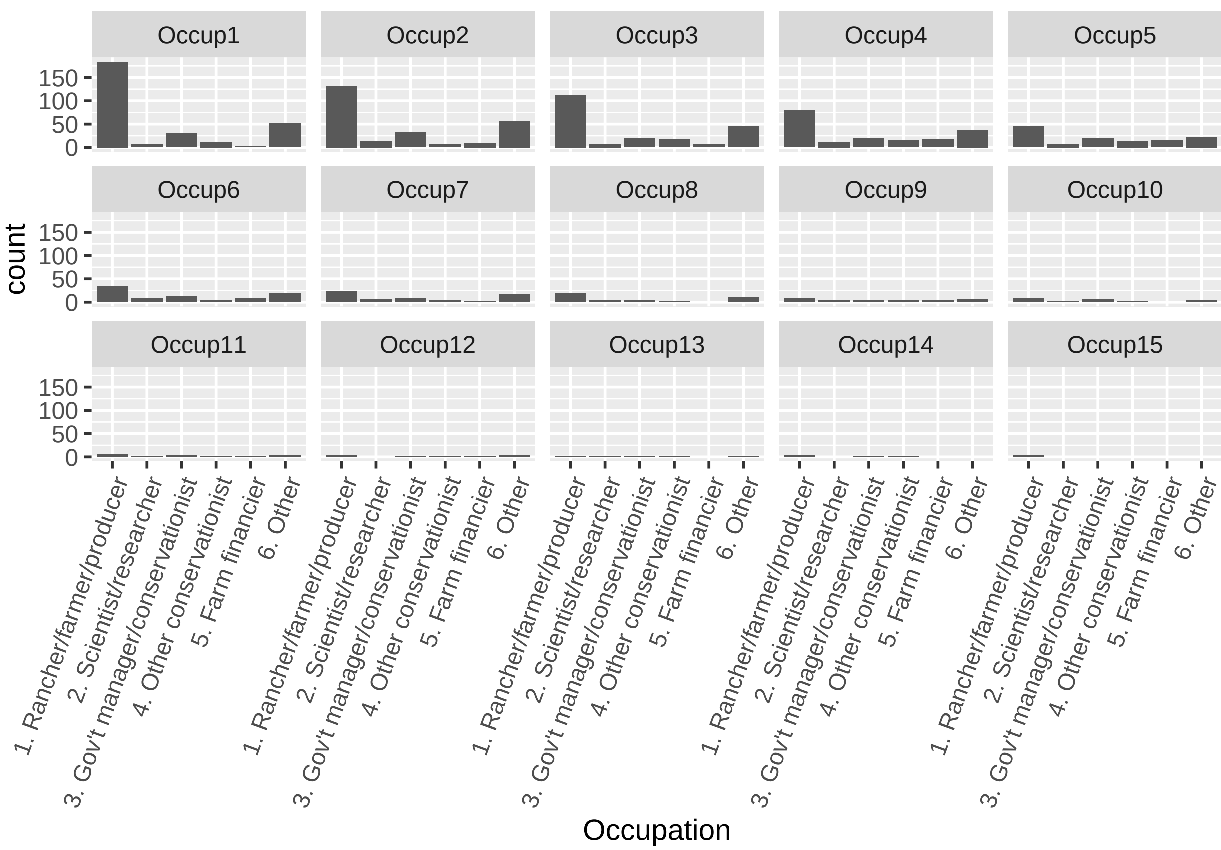
Size	n	percent
1	41	12.13%
2	48	14.20%
3	28	8.28%
4	77	22.78%
5	37	10.95%
6	32	9.47%
7	24	7.10%
8	15	4.44%
9	10	2.96%
10	6	1.78%
11	6	1.78%
12	7	2.07%
14	3	0.89%
15	4	1.18%

q14 - Primary occupation

What is each person's primary occupation?

OccupX corresponds to the occupation of alter X. Each ego was able to list up to 15 alters, thus there is the possiblity of Occup1 to Occup15 for each ego.
(1 = rancher/farmer/producer, 2 = scientist/researcher, 3 = government agency manager/conservationist, 4 = other conservation professional, 5 = farm financier, 6 = other)

variable	n	mode
Occup1	287	1
Occup2	250	1
Occup3	210	1
Occup4	183	1
Occup5	123	1
Occup6	89	1
Occup7	62	1
Occup8	41	1
Occup9	33	1
Occup10	24	1
Occup11	17	1
Occup12	10	1
Occup13	8	1
Occup14	7	1
Occup15	4	1

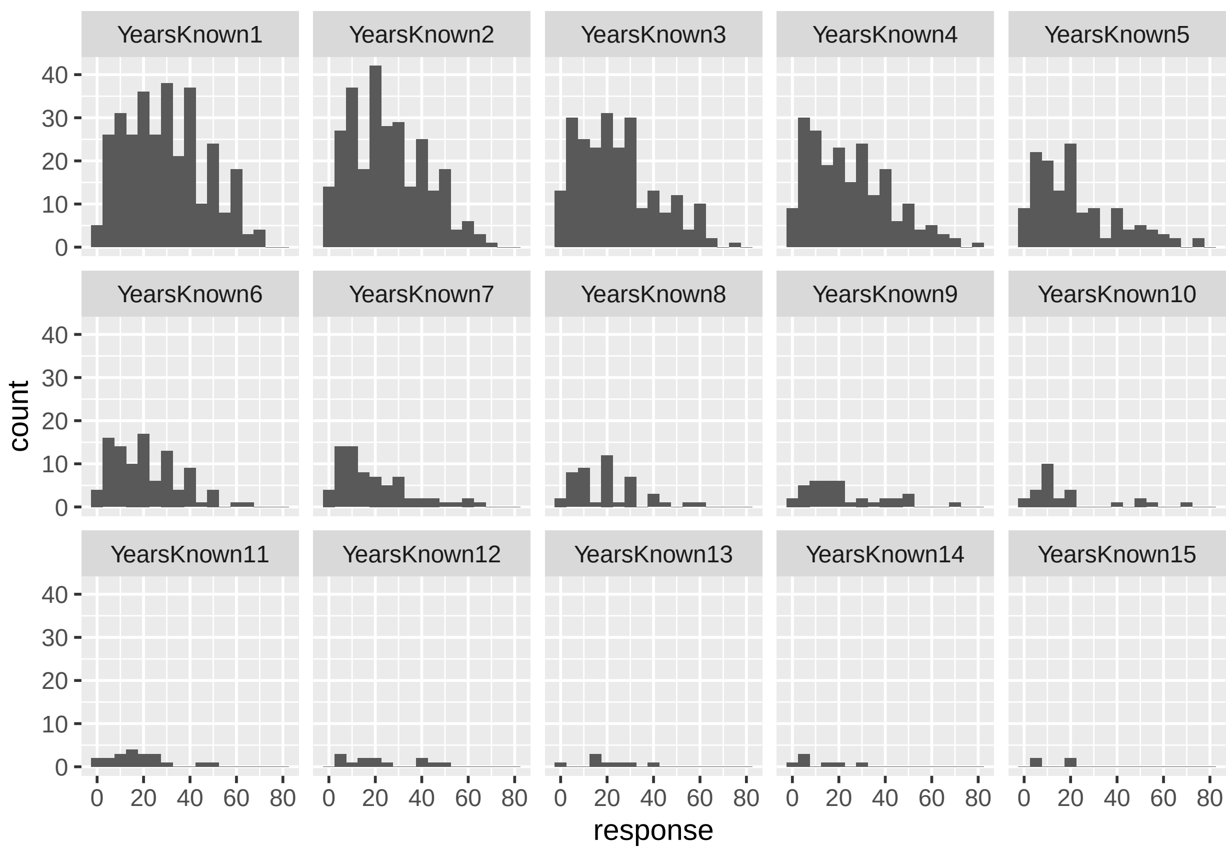


q15 - Years known

How many years have you known each person?

YearsKnownX corresponds to the number of years ego has known alter X. Each ego was able to list up to 15 alters, thus there is the possiblity of YearsKnown1 to YearsKnown15 for each ego.

variable	n	mean	sd	min	median	max
YearsKnown1	313	29.51	16.96	1	30.0	71
YearsKnown2	279	25.20	16.15	1	23.0	70
YearsKnown3	234	24.11	16.70	1	20.0	75
YearsKnown4	208	24.42	17.21	1	21.0	78
YearsKnown5	136	22.00	17.53	1	20.0	75
YearsKnown6	100	21.22	14.20	1	20.0	66
YearsKnown7	70	19.13	15.70	2	15.0	65
YearsKnown8	46	19.48	13.84	2	20.0	60
YearsKnown9	37	22.00	16.77	2	15.0	70
YearsKnown10	27	18.44	17.88	2	12.0	70
YearsKnown11	20	18.10	12.48	1	15.0	48
YearsKnown12	13	22.62	16.01	3	20.0	49
YearsKnown13	8	19.75	11.16	2	17.5	40
YearsKnown14	7	12.43	10.66	2	7.0	32
YearsKnown15	4	12.50	8.81	3	13.5	20



q16 - Information types

What kinds of information do you receive from each person?

Each ego was able to check all options (out of 5) that apply. The data are organized as dummy variables, such that there is a 0/1 variable for each information type and each alter, leading to 5*15=75 variables. Here, we summarized the data to show the number of alters that provide each information type overall.

Type	sum
Ranch or farm operations	914
Ranch or farm technology	509
Conservation practices (prescribed burning, weed control, etc.	589
Financial or insurance programs (CRP, EQIP, etc.)	327
Non-operations	273

In addition, we created summary information variables for each alter (InfoX). InfoX corresponds to the amount of information types that ego received from alter X. For example, if ego received information about ranch operations and conservation practices from alter 1, Info1 would equal 2. These variables can be thought of as a measure of multiplexity (typically multiplexity is used to describe multiple kinds of relationships with an alter).

variable	n	mean	sd	min	median	max
Info1	307	1.92	1.22	1	1.0	5
Info2	270	1.75	1.05	1	1.0	5
Info3	228	1.67	1.04	1	1.0	5
Info4	208	1.75	1.13	1	1.0	5
Info5	133	1.65	0.95	1	1.0	5
Info6	99	1.80	1.07	1	1.0	5
Info7	70	1.73	1.02	1	1.0	5
Info8	46	1.87	1.07	1	1.5	5
Info9	37	1.73	1.02	1	1.0	5
Info10	26	1.85	1.19	1	1.0	5
Info11	20	1.50	0.76	1	1.0	3
Info12	12	1.42	0.67	1	1.0	3
Info13	9	2.22	1.72	1	1.0	5
Info14	7	1.86	1.07	1	2.0	4
Info15	4	2.25	0.96	1	2.5	3

Overall, the average amount of information types is shown below.

n	mean	sd	min	median	max
1476	1.77	1.09	1	1	5

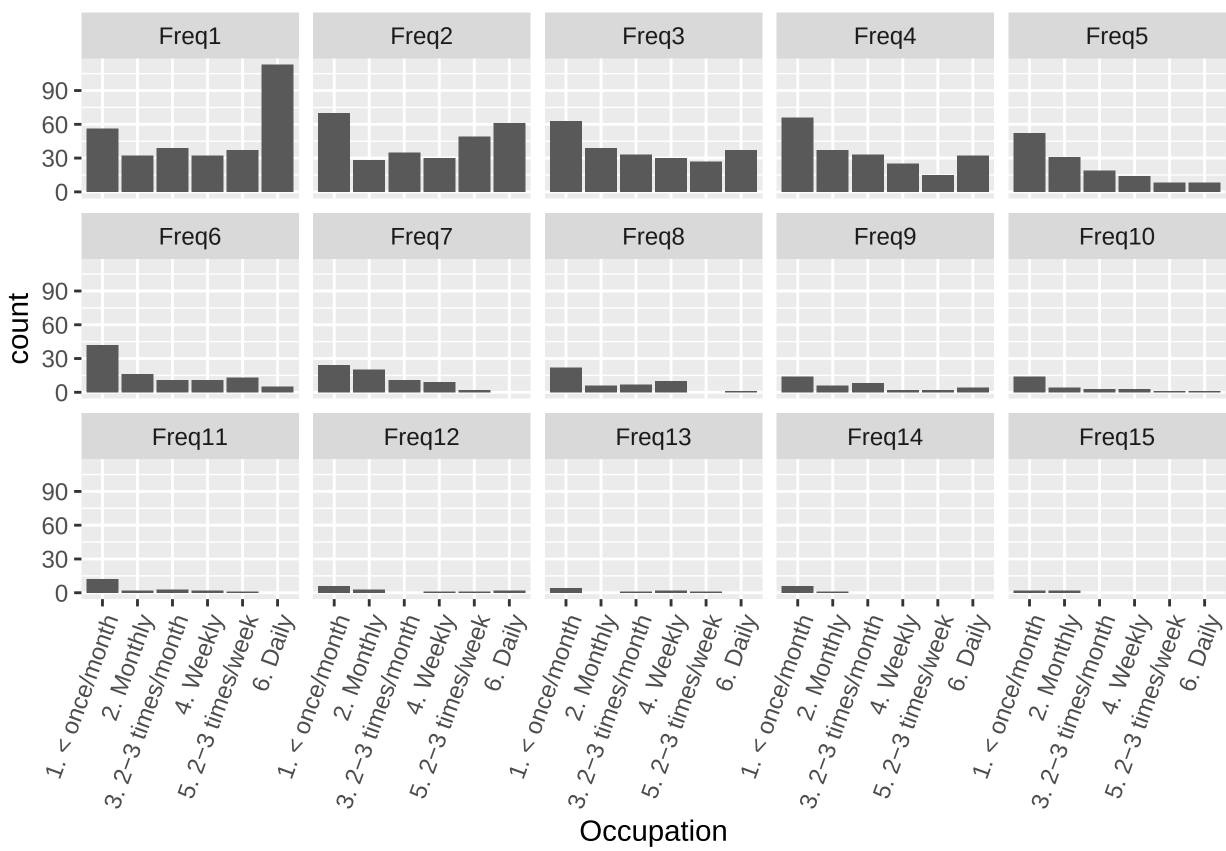
q17 - Frequency

How frequently do you interact with each person?

FreqX corresponds to the how often ego interacts with alter X. Each ego was able to list up to 15 alters, thus there is the possiblity of Freq1 to Freq15 for each ego.

(1 = < once/month, 2 = monthly, 3 = 2-3 times/month, 4 = weekly, 5 = 2-3 times/week, 6 = daily)
Note: These codes were entered differently in the original dataset. We recoded them so that frequency increases in magnitude.

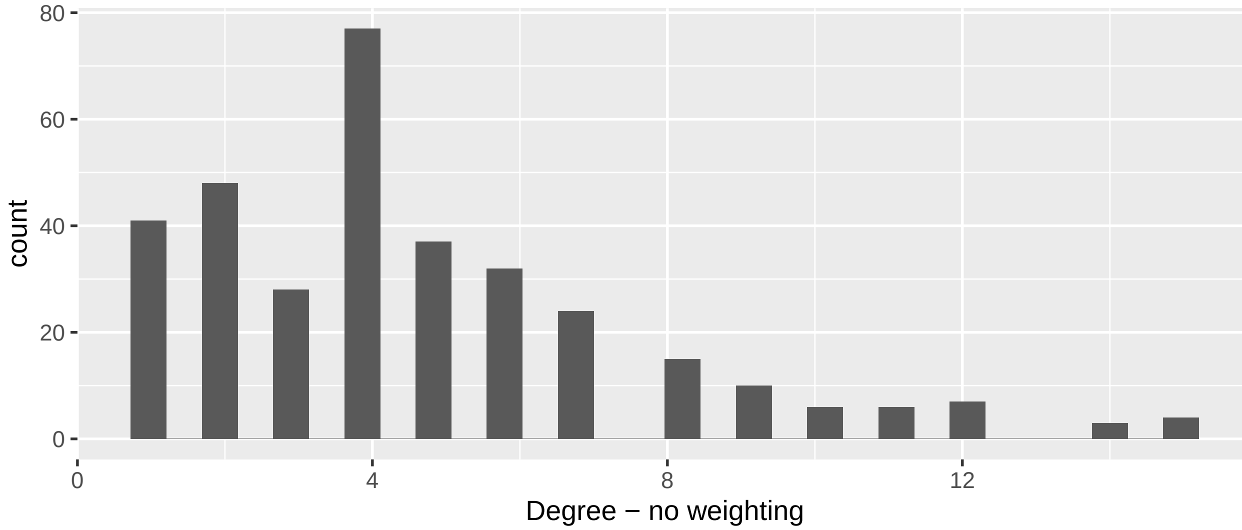
variable	n	mean	sd	min	median	max
Freq1	309	3.97	1.94	1	4.0	6
Freq2	273	3.52	1.93	1	4.0	6
Freq3	229	3.13	1.82	1	3.0	6
Freq4	208	2.91	1.80	1	3.0	6
Freq5	132	2.39	1.53	1	2.0	6
Freq6	98	2.51	1.66	1	2.0	6
Freq7	66	2.17	1.16	1	2.0	5
Freq8	46	2.20	1.36	1	2.0	6
Freq9	36	2.56	1.70	1	2.0	6
Freq10	26	2.08	1.47	1	1.0	6
Freq11	20	1.90	1.29	1	1.0	5
Freq12	13	2.54	1.98	1	2.0	6
Freq13	8	2.50	1.69	1	2.0	5
Freq14	7	1.14	0.38	1	1.0	2
Freq15	4	1.50	0.58	1	1.5	2



Degree (aka size)

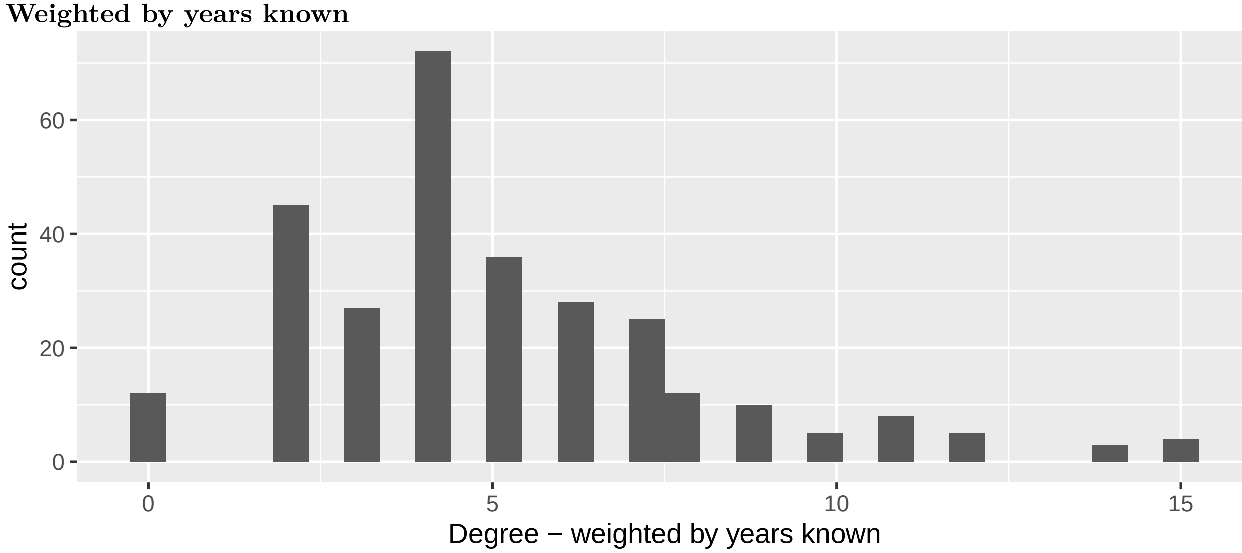
Note: Some egos listed alters but then did not fill out the rest of the network questions. In those cases, we recorded the number of alters (degree) per ego but we are unable to weight the degree based on other network questions for these egos. Thus, you'll see below that the sample size diminishes for weighted degree compared to unweighted degree and the minimum drops to 0.

No weighting



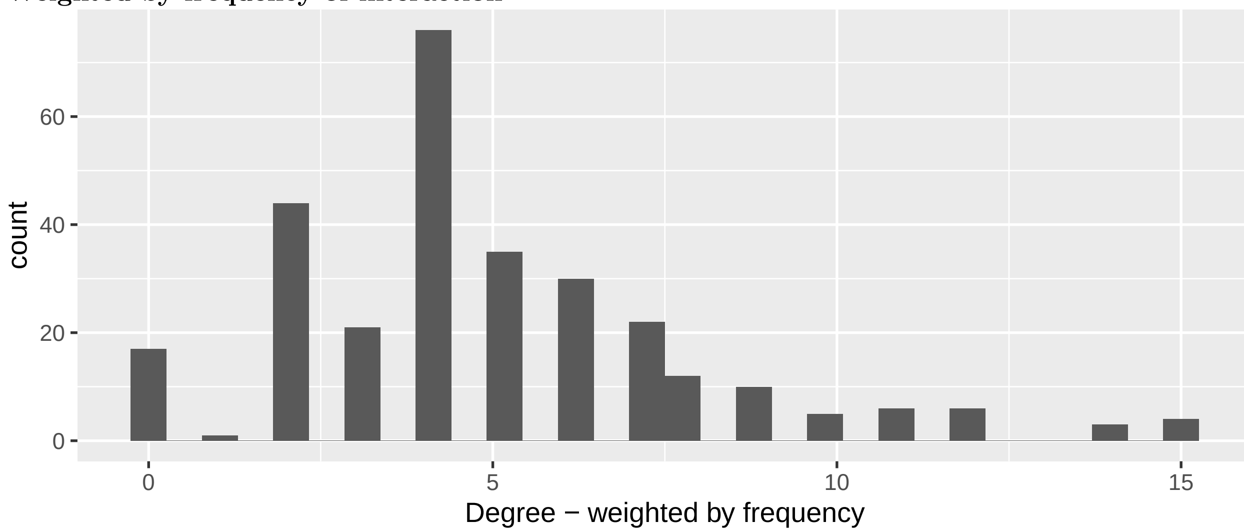
n	mean	sd	min	median	max
338	4.72	3	1	4	15

Weighted by years known



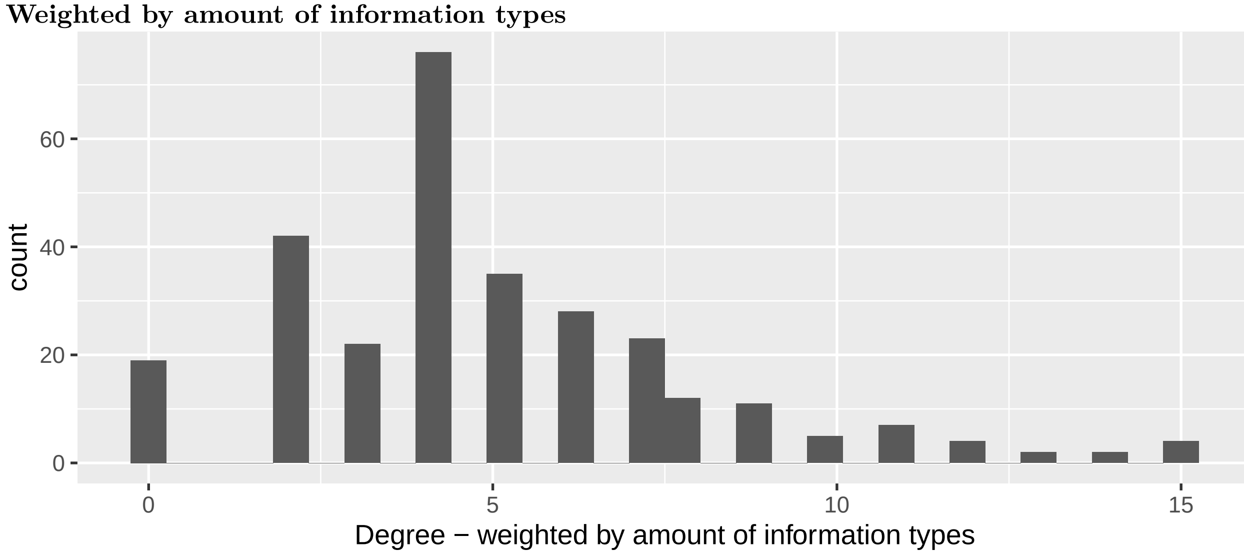
n	mean	sd	min	median	max
292	5.03	2.98	0	4	15

Weighted by frequency of interaction



n	mean	sd	min	median	max
292	4.93	3.02	0	4	15

Weighted by amount of information types



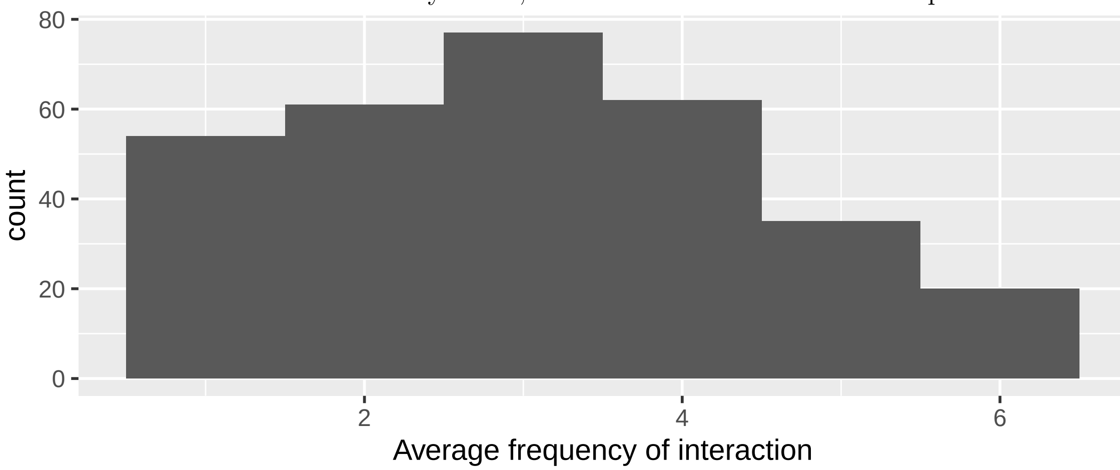
n	mean	sd	min	median	max
292	4.94	3.04	0	4	15

Strength of ties

Average tie strength - Frequency of interaction

(1 = < once/month, 2 = monthly, 3 = 2-3 times/month, 4 = weekly, 5 = 2-3 times/week, 6 = daily)
Note: These codes were entered differently in the original dataset. We recoded them so that frequency increases in magnitude.

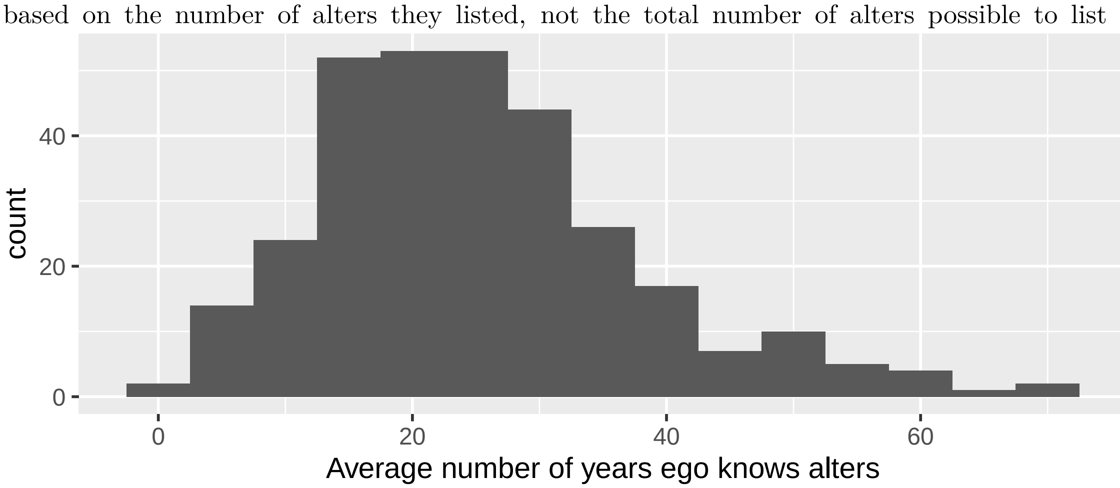
For each ego, we averaged the frequency that they engage with their alters. The average was calculated based on the number of alters they listed, not the total number of alters possible to list (up to 15).



n	mean	sd	min	median	max
309	3.13	1.44	1	3	6

Average tie strength - Years known

For each ego, we averaged the number of years they've known their alters. The average was calculated based on the number of alters they listed, not the total number of alters possible to list (up to 15).



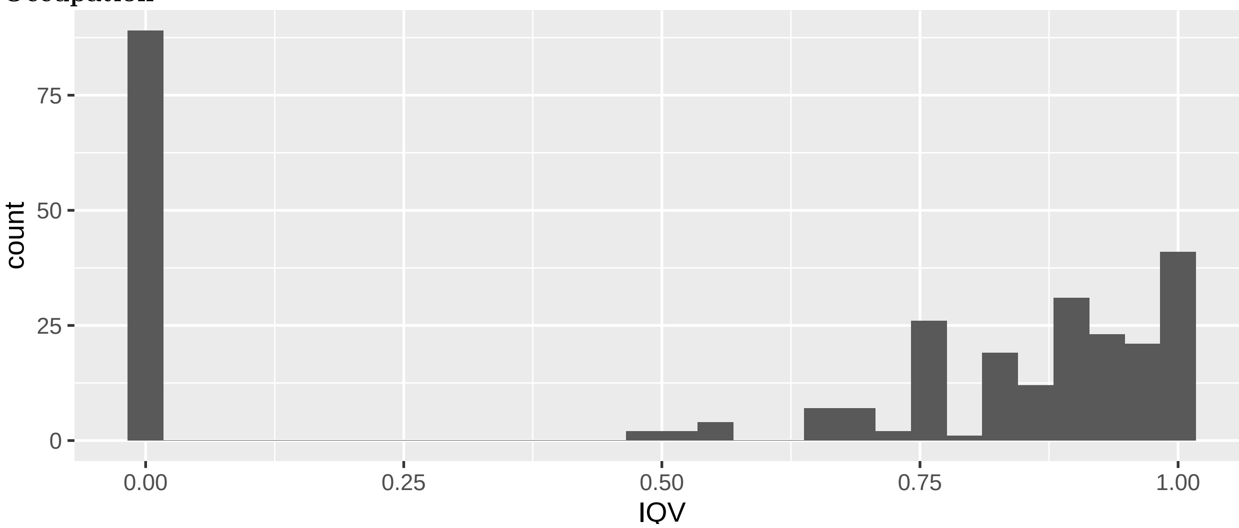
n	mean	sd	min	median	max
314	25.32	12.69	1.5	23.75	71

Alter analysis

Heterogeneity - categorical variables

Index of qualitative variation (IQV) varies from 0 to 1. When all cases are in one category, there is no variation and IQV = 0. When cases are evenly dispersed across categories, variation is at its highest and IQV = 1.

Occupation

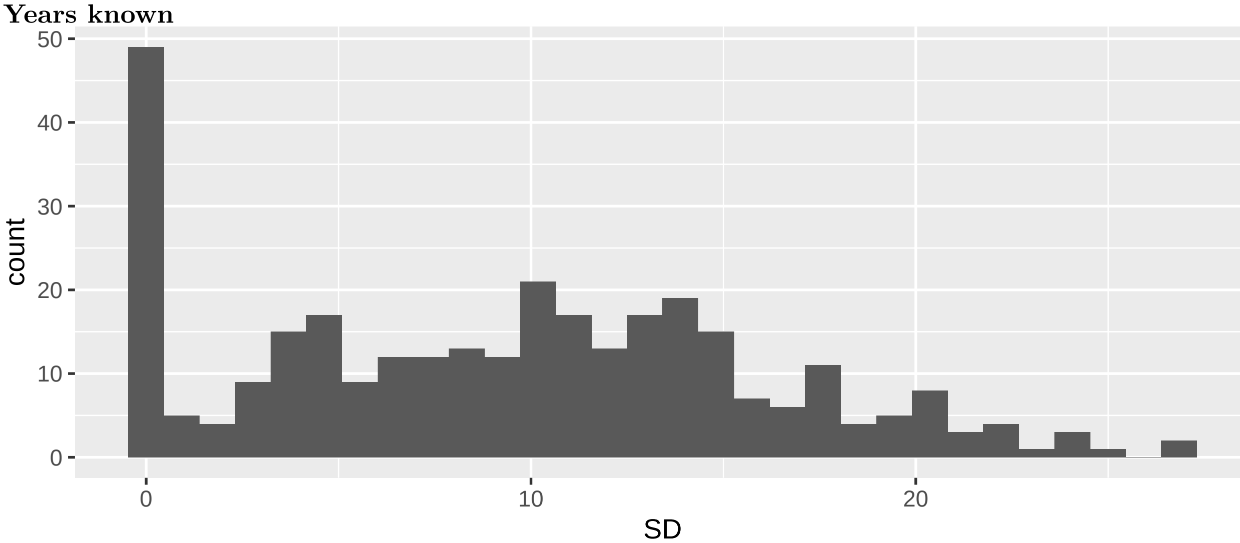


n	mean	sd	min	median	max
287	0.6	0.41	0	0.82	1

Heterogeneity - continuous and ordinal variables

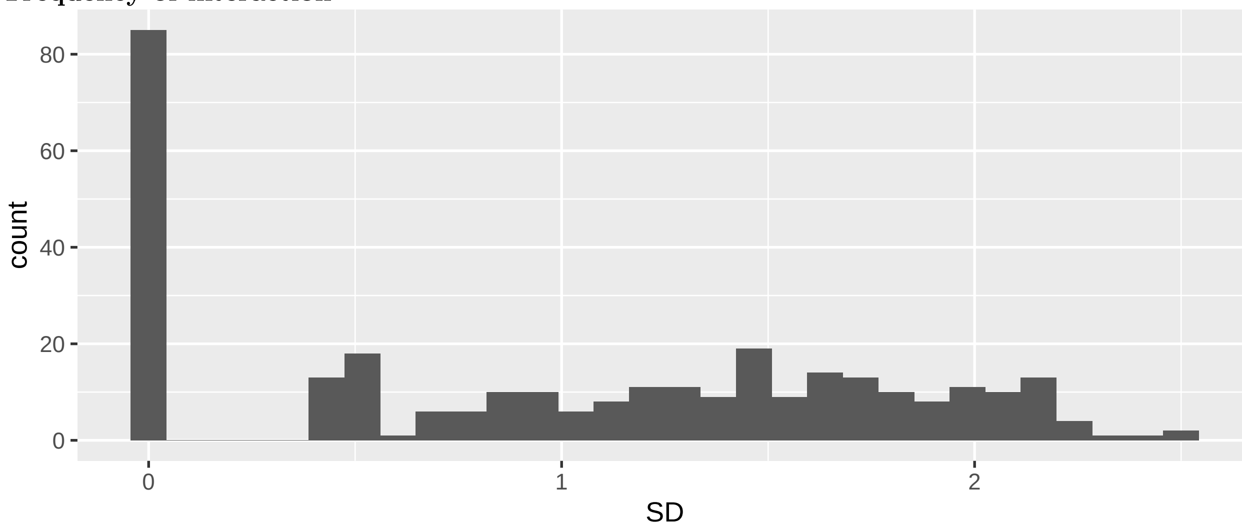
We used standard deviation to measure heterogeneity for continuous and ordinal variables.

Years known



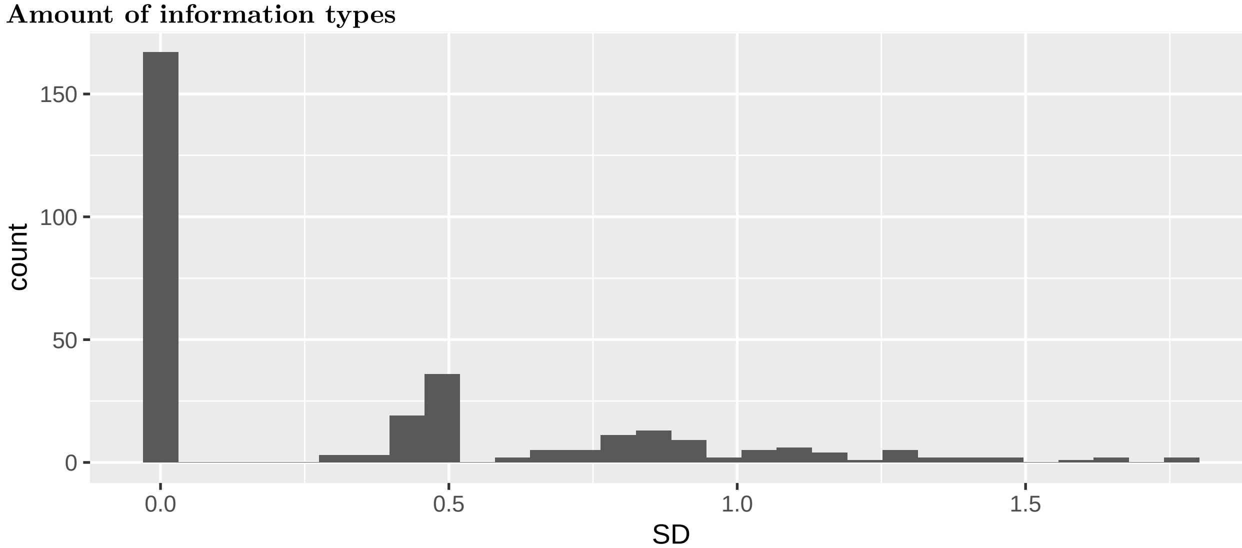
n	mean	sd	min	median	max
314	9.34	6.58	0	9.74	26.84

Frequency of interaction



n	mean	sd	min	median	max
309	0.99	0.77	0	1.07	2.5

Amount of information types

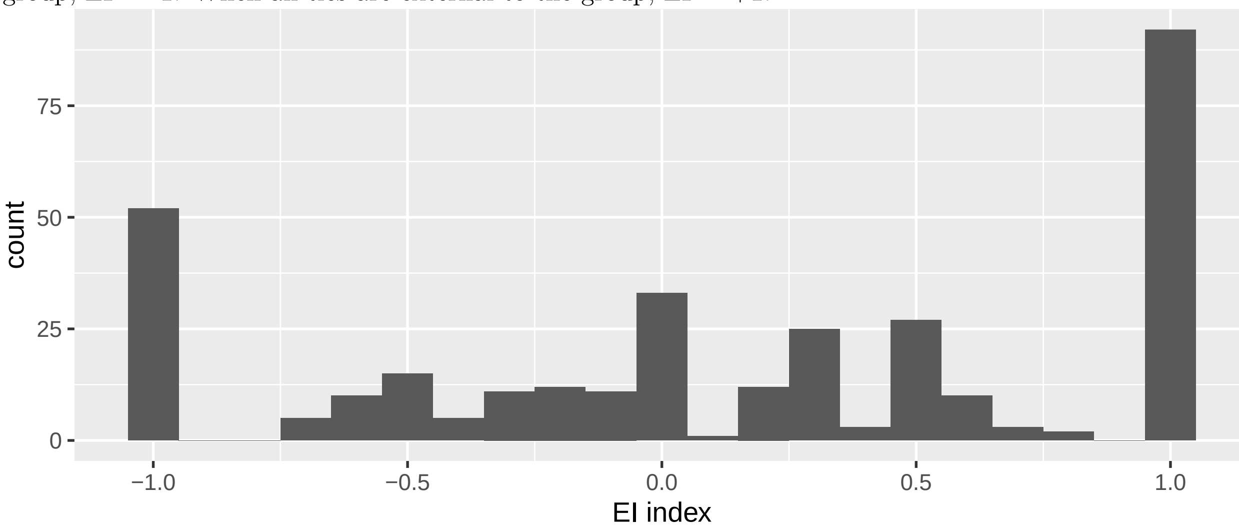


n	mean	sd	min	median	max
307	0.35	0.45	0	0	1.77

Ego-alter similarity (homophily)

Occupation

Assuming that all respondents are ranchers, farmers, or producers based on how we purchased the sample, we can determine how similar they are in terms of occupation with their alters. The external-internal (EI) index is one measure of homophily. The EI index ranges from -1 to +1. When all ties are internal to the group, EI = -1. When all ties are external to the group, EI = +1.

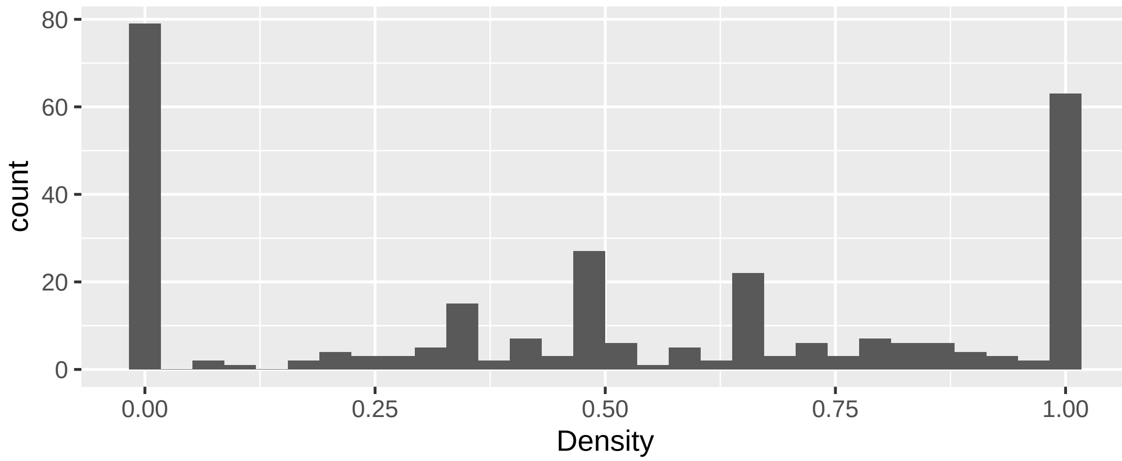


n	mean	sd	min	median	max
329	0.15	0.71	-1	0.2	1

Structure

Density

Density is the number of ties divided by the number of possible ties. It ranges from 0 to 1, where 0 is the lowest density possible (i.e., no ties between alters) and 1 is the highest density possible (i.e., all ties between alters).

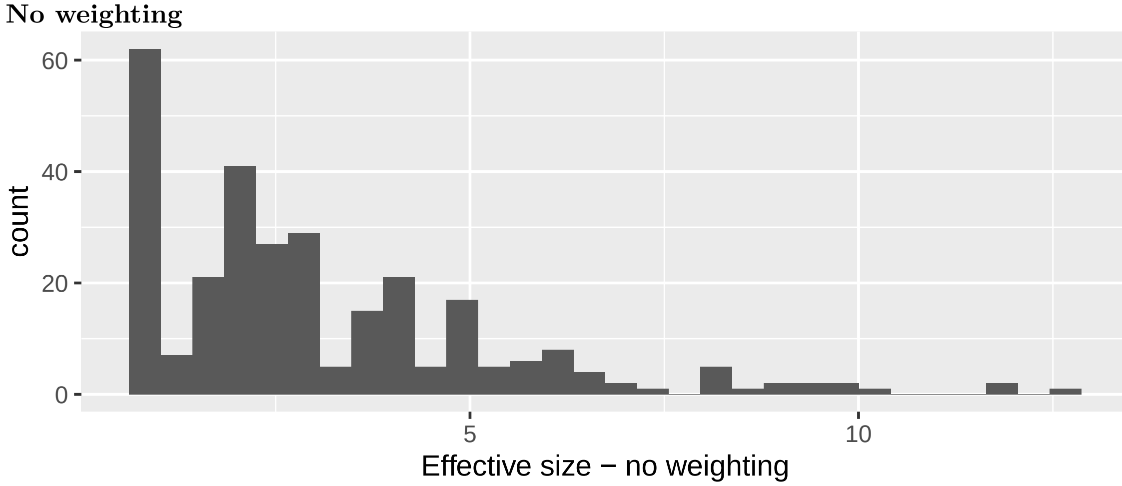


n	mean	sd	min	median	max
292	0.5	0.38	0	0.5	1

Effective size

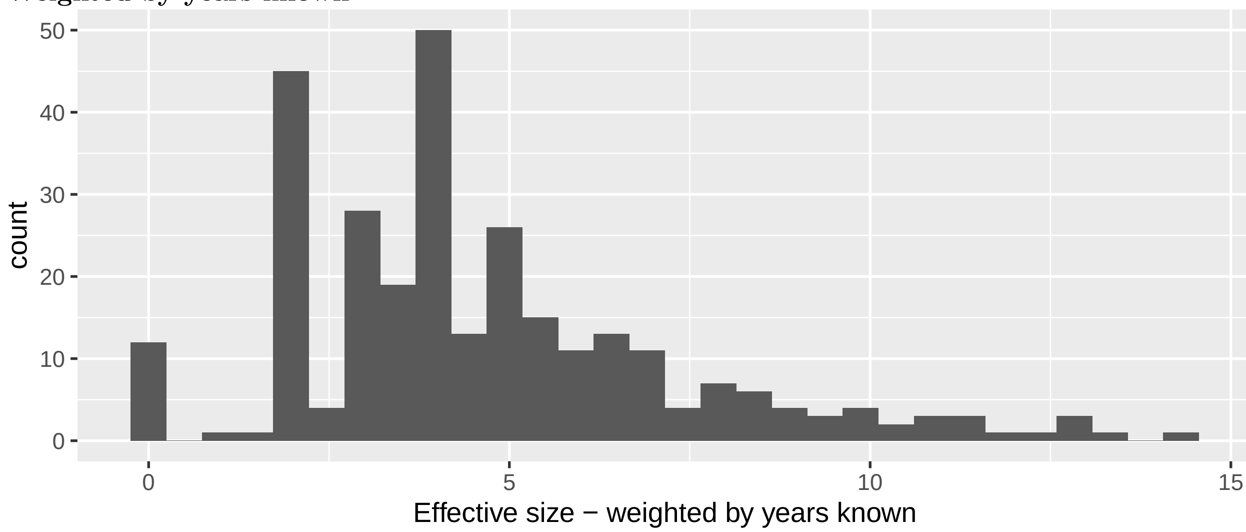
Effective size is the number of alters (i.e., degree) minus the average degree of alters (not including ties to ego). It ranges from 0 to whatever the degree is. Higher effective size is indicative of more structural holes

No weighting



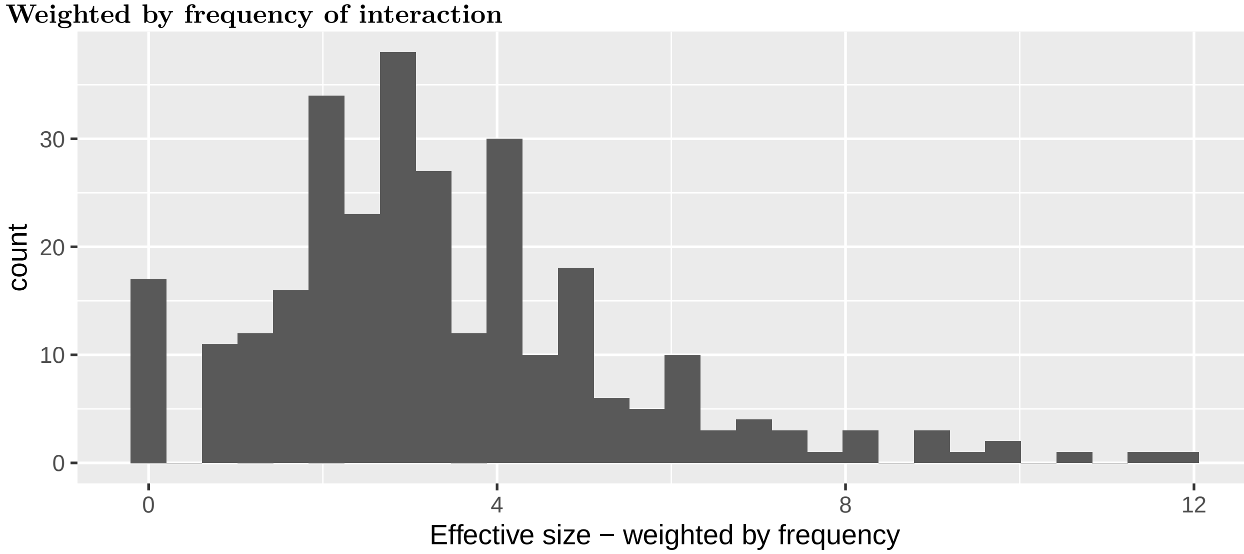
n	mean	sd	min	median	max
292	3.12	2.21	1	2.5	12.85

Weighted by years known



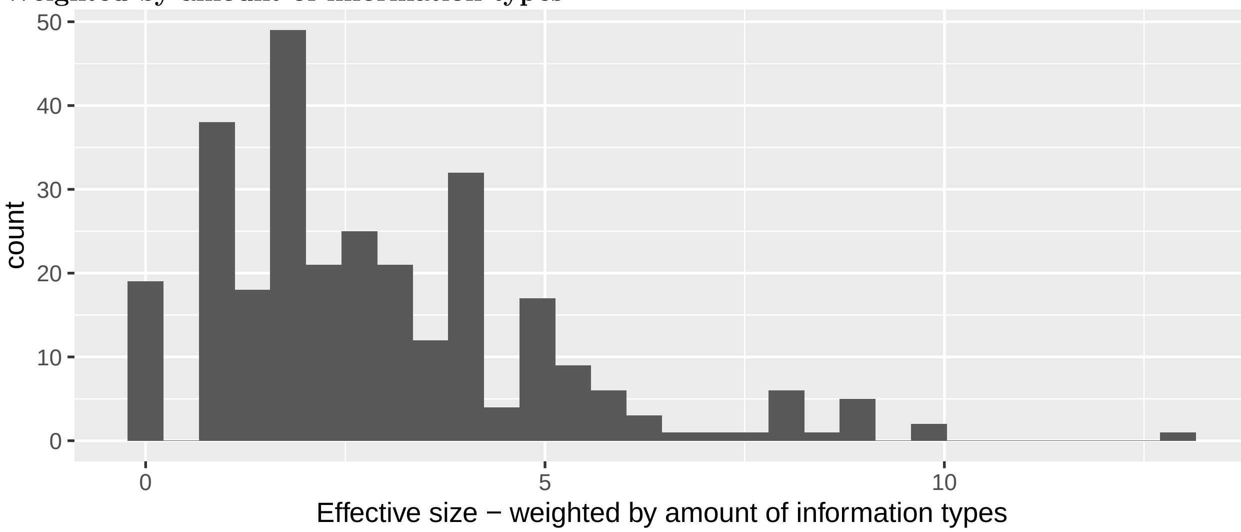
n	mean	sd	min	median	max
292	4.64	2.7	0	4	14.31

Weighted by frequency of interaction



n	mean	sd	min	median	max
292	3.37	2.09	0	3	11.85

Weighted by amount of information types



n	mean	sd	min	median	max
292	2.96	2.1	0	2.5	12.93