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The Greater the Risk, The Greater the Reward: How Environmental Risk Shapes Policy Response

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The Greater the Risk, The Greater the Reward: How Environmental Risk Shapes Policy Response

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ABSTRACT

How best to address so-called wicked problems that threaten the social and physical environment is a ubiquitous question in environmental governance scholarship. Lacking clear boundaries and straight-forward solutions, the sources and impacts of wicked problems are heterogeneously distributed across the landscape. Existing literature emphasizes the importance of myriad factors like knowledge, financial resources, and time, in catalyzing decision-maker response to these impacts. However, given the uneven distribution of impacts across the landscape, society translates their own experiences into valued environmental risks. It is up to decision-makers to assess these environmental risk valuations and determine how and when to respond and with whom to respond. To date, research into how environmental risk shapes decision-maker response is nascent. To fill this knowledge gap, this dissertation explores the role of environmental risk in shaping policy response across three cases: drinking water quality management and climate extremes in California, unconventional oil and gas drilling in Ohio, Pennsylvania, and West Virginia, and harmful algal bloom governance in Lake Erie.

Each chapter in this dissertation relies on a different data set and case study to assess how science supply aligns with perceived environmental risk (Chapter 1), whether and how actual environmental risk shapes policy response (Chapter 2), and how environmental risk shapes planned collaborative approaches to addressing wicked problems (Chapter 3). Data types employed in this dissertation include survey instruments (Chapters 1 and 2), literature reviews (Chapters 1 and 2), and planning document analysis (Chapter 3). Utilizing quadratic assignment procedure (Chapter 1), logistic regressions (Chapter 2), and social-ecological network analysis (Chapter 3), results suggest that environmental risk does play a role in catalyzing and shaping policy response to wicked problems.

OVERVIEW

This dissertation is formatted so that the three chapters operate as standalone manuscripts. Each chapter has its own abstract, set of references, and supplemental materials. Each chapter's abstract is included below.

Chapter 1: Does risk perception align with scientific information? The case of California climate extremes and drinking water quality management

Managing drinking water quality under a changing climate will become more complex as climate change projections indicate increases in the frequency and severity of climate extremes like droughts and heavy precipitation. These extremes already impact water quality in a variety of ways but will become more challenging to manage with climate change. Previous literature points to the need for more information on how climate extremes influence water quality. But what kind of information is needed? This paper assesses whether and what kind of gaps exist in the science around water quality and climate extremes. To aid in this assessment, we develop and present a Perceived Risk–Science Supply tool that compares managers perceived risks with available scientific information. We use this tool to examine the case of California drinking water management. Our analyses indicate an overall undersupply of science with variation in the degree of alignment, both topically and regionally, across California. Dominant water quality concerns include eutrophication (surface water) and salinity (surface and groundwater), with drought being the driving climate extreme trigger. This work benefits researchers and managers by 1) identifying gaps in research based on water quality and climate extreme concerns among California drinking water managers and 2) offering a tool to identify gaps in scientific research for other resource management issues.

Chapter 2: Fracked if you do, fracked if you don't: how does environmental risk shape local policy response to fracking?

Unconventional oil and gas drilling, or fracking, is touted as a solution to domestic energy security. However, all stages of the fracking process can negatively impact the environment and public health, particularly at the local

scale. Drawing on literature that measures distances from fracking wells at which environmental impacts are measurable, we conceptualize an environmental risk gradient. Environmental risk is greatest proximate to fracking wells and decreases as the distance from fracking wells to jurisdictional boundaries increases. Using a series of distances (0.5km, 1km, 2km, 3km, 5km, and 20km) and an original survey of local government officials across Ohio, West Virginia, and Pennsylvania, we evaluate whether environmental risk influences the likelihood of a sub-state jurisdiction adopting local policies in response to fracking. Overall, we find that environmental risk does shape policy adoption, though the influence of risk varies across policy type. We argue that going forward, local environmental policy adoption scholarship needs to consider how environmental risk shapes local policy adoption and that in doing so, scholars should consider more nuanced policy types when evaluating determinants of policy adoption. This research contributes to literature on local policy adoption and the nascent scholarship on how environmental risk shapes environmental policy adoption.

Chapter 3: (HAB)itual challenges: how does environmental risk shape Lake Erie harmful algal bloom governance?

Research in environmental governance shows that misalignment between management boundaries and ecological systems can be addressed through collaboration. Existing research shows that the types of collaborative approaches pursued as well as with whom governance actors pursue them is shaped by perceived transaction costs of searching, bargaining, and negotiating, as well as by underlying ecological processes. Wicked problems, like nonpoint source pollution, may be best addressed through a variety of collaborative management approaches. Given that nonpoint source pollution loading is heterogeneously distributed across the landscape, we raise the question of how environmental risk, measured as the pollutant loading contribution, shapes the broader social-ecological governance network. Using the case of Lake Erie harmful algal bloom (HABs) management, we employ exponential random graph modeling and multilevel motif analysis to understand how environmental risk influences the social-ecological governance system of Lake Erie HABs. HABs have been a

policy challenge in the Lake Erie region for more than 40 years despite widespread international to local efforts to reduce them. We analyzed a set of planning documents written between 2012 and 2017 and found: 1) activity is highest in regions of higher environmental risk, 2) within the governance network, social actors show a preference for forming bonding relationships (closed network motifs) in the high environmental risk region (Western Basin) and within the higher transaction cost (e.g., institution building) relationship networks, and 3) within the social-ecological network, social actors show a preference for forming social-ecologically aligned relationships in the higher environmental risk region (Western Basin). This research builds on environmental governance and social-ecological network scholarship by explicitly considering the role of environmental risk in influencing network structure.

INTRODUCTION

A ubiquitous question in environmental governance scholarship is how best to address *wicked* problems that lack clear structure, are scientifically, socially, and politically complex and divisive, and at best, have only temporary solutions (Mason and Mitroff 1973, Rittel and Webber 1973, Roberts 2000, Hatch and Ehrlich 2002, Weber 2003, van Bueren et al. 2003, Kreuter et al. 2004, Durant and Legge 2006, Weber and Khademian 2008, Wexler 2009, Wasson and Gluesing 2015, Newman and Head 2017). Some scholars argue that all environmental problems fall along a gradient of wickedness and that the wickedness of any one problem is a function of stakeholder disagreement over that problem and its risk (Brown 2010, Balint et al. 2011, Galaz 2014). The impacts of wicked problems are often unequally distributed among society and as a result, wicked problems likely require a combination of traditional command-and-control and bottom-up collaborative approaches (Agranoff and McGuire 1998, 2003, Feldman and Khademian 2002, Kamensky and Burlin 2004, Homsy and Warner 2013, Patterson et al. 2013, Kettl 2015, Krauz 2016, Walton et al. 2016). There is a rich literature investigating how decisions are made about what approaches to pursue, with whom to pursue them, and when to pursue them. Scholarship identifies key determining factors of policy response as timely and salient knowledge (Lemos and Morehouse 2005, Adger et al. 2005, McNie 2007, Sarewitz and Pielke 2007, Dilling and Lemos 2011, Ekstrom et al. 2017), financial and other capacity (Dye 1966, Gray 1973, Ringquist 1994, Betsill 2001, Sapat 2004, Chapin and Connerly 2004, Shipan and Volden 2008, Lubell et al. 2009, Krause 2012, Opp et al. 2014, Loh and Osland 2016, Arnold and Long 2019), stakeholder sociodemographics and advocacy (Jones and Dunlap 1992, Portney and Berry 2010, Davis 2012, Opp et al. 2014), ideology (Jones and Dunlap 1992, Ringquist 1994, Heath and Gifford 2006, Daley 2008, Walsh et al. 2015, Dokshin 2016, Arnold and Neupane 2017, Davis 2017), trust (Renn and Levine 1991, Ostrom 1998, Jenkins-Smith and Kunreuther 2001, Ostrom and Walker 2003, Burt and Burt 2005, Emerson et al. 2012, Blair et al. 2013), transaction costs like searching, bargaining, and negotiating with potential collaborators (Kreuter et al. 2004, King 2007, Lubell et al. 2017, Hileman and Bodin 2019, Klasic and Lubell 2020), and ecological connectedness (Bodin and Crona 2009, Bodin and Tengö 2012, Bergsten et al. 2014, Guerrero et al. 2015, Bodin et al. 2016). Given the heterogenous distribution of the impacts of wicked problems, the risk to any one person or community likely varies spatially and temporally. Therefore, this dissertation adds to existing scholarship by:

How does environmental risk shape policy response?

To explore the role of environmental risk in shaping policy response, I use three wicked problem cases: 1) drinking water management and climate extremes in California, 2) unconventional oil and gas drilling in Ohio, Pennsylvania, and West Virginia, and 3) harmful algal bloom management in Lake Erie (United States and Canada). These three cases allow me to analyze how environmental risk influences policy response across topics and geographies. Below I present the conceptual framework guiding this dissertation and briefly review the literature on environmental risk, before providing an overview of the dissertation chapters that follow.

Conceptual Framework

In Figure 1, I present the conceptual framework that drives the inquiries made in this dissertation. The inner circle represents the decision-making entity, which may be an individual, an organization, a government, or some other unit with the authority to act to address a particular problem. Key determinants that influence a decision-makers' choice of what action to take, when to take it, and with whom to take it are represented around the outer circle. In any given environmental challenge, these determinants may exert more or less influence on the decision-making entity, as represented by the two-way arrows. The accumulation of these weighted determinants eventually leads to a decision to act. This dissertation contributes to the existing literature by theorizing and empirically testing how environmental risk influences policy response. Specifically, I consider three theorizations of environmental risk: *uncertainty, proximity,* and *severity.* For any given environmental governance challenge, several decision-making entities may be interacting and exerting pressures on one another. While this dissertation focuses on the decision-making processes of single challenges, one could surmise a situation in which several challenges are simultaneously occurring, leading to additional positive and negative feedback between and among the challenges and decision-makers (Lubell 2013). In this dissertation, I use the conceptual framework as a guide to empirically test how environmental risk (among other factors) influences policy response. I will now turn to a discussion of environmental risk.

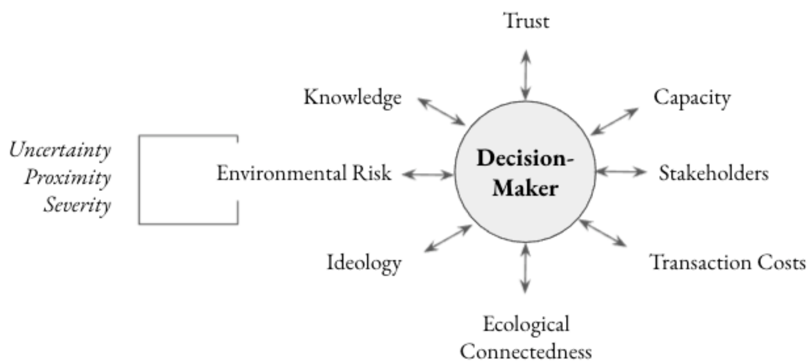

Figure 1. Conceptual framework for the dissertation (developed based on ideas by Ringquist 1994, Jenkins-Smith and Sabatier 1994, Ostrom and Walker 2003, Sapat 2004, Lemos and Morehouse 2005, Adger et al. 2005, King 2007, Bodin and Crona 2009, Dilling and Lemos 2011, Guerrero et al. 2015, Walsh et al. 2015, Bodin et al. 2016, Loh and Osland 2016, Arnold and Neupane 2017, Barnes et al. 2017, Lubell et al. 2017, Arnold and Long 2019, Hileman and Bodin 2019).

Environmental Risk

Environmental risk can be conceptualized in several ways, but generally refers to the probability and consequences of undesirable harm (Whyte and Burton 1980, Ellis et al. 2009, Kasperson and Kasperson 2013, Raue et al. 2018). Environmental risks are by definition socially attributed, meaning that they only exist if decision-makers recognize that they exist (Hurlbert and Gupta 2016). Understanding the mechanisms that structure environmental risk is therefore important in theorizing how environmental risk may influence policy response. The mechanisms of environmental risk that I analyze are *uncertainty, proximity*, and *severity*.

In evaluating environmental risk, decision-makers may use a combination of magnitude, spatial scale, duration, intensity of impacts, and probability of impacts (Whyte and Burton 1980). Decision-maker risk valuation correlates with estimations of actual probable impacts (Brody et al. 2008), therefore requires knowledge to reduce *uncertainty* around the environmental problem. Risk may be valuated at a higher level when decision-makers are more knowledgeable about the environmental problem or hazard, particularly when the knowledge is concrete (Evans and Durant 1995). For example, research shows that society assigns a higher level of risk to climate change when exposed to evidence quantifying carbon dioxide leakage from carbon capture and storage when compared with exposure to general science claiming that the earth is warming (Tobler et al. 2012, Kahan et al. 2012, L'Orange Seigo et al. 2014, Shi et al. 2015). Along a similar vein, risk levels are elevated for anthropogenically driven challenges (e.g., oil and gas drilling) when compared to natural disasters like earthquakes (Baum et al. 1983, Schwartz 1992, Shi et al. 2015). Knowledge or scientific information that informs that knowledge must be salient to the issue (Cash et al. 2006, Buizer et al. 2016). Decision-makers, however, do not necessarily have access to all available information or they may not use it if they do not trust the information or the information does not align with their current cognitive structure of decision-making (Ezrahi 1980, Callahan et al. 1999, Patt and Gwata 2002, Rayner et al. 2005, Lowrey et al. 2009, Ronen et al. 2012, Lemos et al. 2012). In Chapter 1, utilizing the idea of environmental risk as *uncertainty*, I develop and present a perceived risk–science supply diagnostic tool to assess the (mis)alignment between decision-maker perceived environmental risk and available information on similar topics. I then empirically test this diagnostic tool on the case of California drinking water management and climate extremes to ascertain how perceived environmental risk shapes decision-maker knowledge.

Decision-makers may also valuate environmental risk based on *proximity* to the issue at hand. Proximity may consist of actual and psychological distance (e.g., if an individual feels they will be impacted by a hazard). Proximity therefore can be broadly categorized in terms of time, space, social distance, and hypotheticality (probability versus certainty) (Trope and Liberman 2000, 2010, Wakslak et al. 2006, Fujita et al. 2006, Hughes et al. 2018). When proximity decreases (e.g., shorter time, closer space, shorter distance, and high hypotheticality), hazards may be more mentally concrete, resulting in a higher cognitive valuation of risk (Trope and Liberman 2000, 2003, 2010). Additionally, when environmental impacts threaten moral values like human health and livelihood, proximity may be cognitively closer (Evans and Durant 1995). Closer proximity, in turn, may catalyze policy response. For example, Hughes et al. (2018) study three environmental challenges (local, regional, and global) and find that action is more likely for local challenges when problem severity and consequences are higher. Drawing on the mechanism of environmental risk as *proximity*, in Chapter 2, I consider the proximity, in terms of geographic distance, of sub-state jurisdictions (e.g., counties, cities, boroughs, towns, and villages) to unconventional oil and gas wells. The distances I select for analysis are based on scientific studies that identify critical distances from oil and gas wells at which environmental impacts are measurable. I then analyze how proximity-based environmental risk influences local policy adoption to address these impacts. Relatedly, scientific studies find that more proximate distances from oil and gas wells have higher problem severity.

Decision-makers are tasked with prioritizing and solving problems. In selecting which problems to prioritize and how to allocate limited time and resources, decision-makers may consider problem severity (Ruhil et al. 1999, Mullin 2008). Problem severity may be an even stronger influence on elected decision-makers as they seek to ensure their priorities align with their constituents' opinions and priorities (Page and Shapiro 1983, Kingdon 1989, Wlezien 2004). Research shows constituent prioritization of policy issues likely reflects actual problem severity (Arnold 1993, Wlezien 2005, Kalesnikaite and Neshkova 2021) and when problem severity is sufficiently high, policy response is more likely (Ringquist 1993, O'Connor et al. 1999, Sharp et al. 2011, Kettle and Dow 2016, Page and Dilling 2020). For example, Kalesnikaite and Neshkova (2021) show that cities with higher problem severity (measured as sea-level rise vulnerability) are more likely to adopt higher levels of collaborative action than cities with lower problem severity. Utilizing environmental risk as *severity*, in Chapter 3, I measure environmental risk using contributions of phosphorus loading towards Lake Erie harmful algal bloom occurrence. I then evaluate how collaborative policy response varies between regions with low and high problem severity. Specifically, I consider how environmental risk shapes the social and social-ecological network structures across three policy responses: information sharing, collaboration, and institution building.

In sum, reflecting the existing literature about how environmental risk is estimated in terms of *uncertainty, proximity,* and *problem severity*, I *hypothesize that environmental risk catalyzes policy response*. Put another way, higher levels of environmental risk result in an increased likelihood of action.

In the chapters that follow, I empirically test environmental risk as a catalyst to policy response using mixed methods across three different cases: drinking water quality and climate extremes in California (Chapter 1), unconventional oil and gas drilling in Ohio, Pennsylvania, and West Virginia (Chapter 2), and harmful algal bloom governance in Lake Erie (Chapter 3). Each chapter utilizes different methods and scholarship to investigate the role of environmental risk is shaping policy response. In Chapter 1, I first present a tool to diagnose the potential causes of environmental risk and scientific information. Then, combining a survey of drinking water managers and a literature review of scholarship on water quality and climate extremes, I apply the diagnostic tool utilizing the quadratic assignment procedure. In Chapter 2, combining a survey of local decision-makers with a literature review on actual measured environmental risk from unconventional oil and gas drilling, I run a series of logit models to evaluate whether and how measure risk influences policy response. Finally, in Chapter 3, based on coding of Lake Erie planning documents, I construct social-ecological networks of planned harmful algal bloom policy, and analyze how and in what ways environmental risk shapes decision-makers' choice of how to collaborate and with whom.

Decision-makers continue to be plagued by wicked problems that are complex and lack clear boundaries and solutions. Given the heterogenous distribution of impacts across the landscape, this dissertation theorizes and empirically tests to role of environmental risk in shaping policy response. In doing so, it contributes to our understanding of how best to address wicked environmental governance challenges.

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1. Does risk perception align with scientific information? The case of California climate extremes and drinking water quality management

INTRODUCTION

A key tenet of effective water quality management lies on decision-makers' access to information about the impact of climate extremes (Michalak 2016). Information about expected vulnerabilities and impacts must be timely and reliable (Adger et al. 2005; Füssel 2007; Harrison et al. 2013; van Stigt et al. 2015; Boholm and Prutzer 2017; Lorenz et al. 2017; Hayes et al. 2018). However, the information demands and needs of managers may not always *align* with the available supply of scientific information (Lemos and Morehouse 2005; McNie 2007; Sarewitz and Pielke 2007). This management-science *(mis)alignment* depends on factors related to the information users as well as the knowledge systems generating or supplying the information. On the management side, a misalignment may occur if managers do not perceive a need for information or lack the capacity to acquire and incorporate information into their decisions. On the supply side, scientists and their embedded knowledge systems may not create the *right kinds* of knowledge or may fail to effectively distribute and communicate the information. The potential misalignment between decision-making and science production is a ubiquitous barrier to water quality management (Huang and Xia 2001), climate adaptation (Bolson et al. 2013; Berrang-Ford et al. 2015; Ekstrom et al. 2017), and other environmental topics.

At its core, demand for information can drive decisions on what science researchers prioritize. An absence of demand from managers and decision-makers may signal to researchers that knowledge is not needed. This is not to say that science for the sake of science is not useful. In some cases, science production may *precede* science need. For example, there is often a time lag discrepancy, sometimes several years, between users demanding information and science production and publication being completed (Rayner et al. 2005). Managers demand information on priorities that are in part formed by their beliefs, experiences, and perceptions (used as heuristics). These heuristics reflect managers' evaluations of the seriousness of different competing challenges (Kahneman et al. 1982; Jenkins-Smith and Sabatier 1994) resulting in decisions based on their *best available knowledge* (Jones et al. 2017). We posit that *perceived risk* can be a useful proxy for measuring managers' priority scientific needs because it drives institutional and policy change (Jones et al. 2017). Low levels of perceived risk may contribute to inaction or otherwise influence prioritization of management responsibilities (Jones et al. 2017).

Existing scholarly work largely focuses on explaining types of misalignment between science produced and managerial decision-making, and potential approaches for overcoming each driver of misalignment. There is no panacea for resolving management-science misalignment; instead, each specific case and its context must be considered to develop a potential solution to the misalignment. Identifying *the type* of misalignment can be a helpful first step in determining which approach to pursue. To our knowledge, no one has yet provided a framework or tool for diagnosing management-science (mis)alignment. To address this gap, we develop and present a perceived risk–science supply diagnostic tool (PRSS) that can be used to identify the potential driver of management-science (mis)alignment (hereinafter referred to as management-science alignment). We then use the PRSS tool to analyze and identify the drivers of management-science alignment in the case of California drinking water quality perceived risk and science supply on the same topics.

While initial research on climate change and water focused primarily on *quantity* and *supply* rather than *quality* (Whitehead et al. 2009; Delpla et al. 2009; Kiem and Austin 2013), recent research emphasizes the importance of understanding how climate change will affect water quality, especially in the case of climate extremes (Michalak et al. 2013; Michalak 2016; Sinha et al. 2017). Floods and drought events can influence the concentration of dissolved constituents (Evans et al. 2005), while extended warm periods without flushing can lead to an increased production of disinfection byproducts in drinking water storage (Mosley 2015). The combination of climate extremes creates even more complex water quality challenges. Warm dry periods followed by a heavy precipitation event, for example, are linked to increased prevalence and severity of harmful algal blooms in reservoirs and lakes (Michalak et al. 2013; Khan et al. 2015; Sinha et al. 2017).

This article takes a multi-phase approach to diagnose water quality management-science alignment. First, we present our PRSS tool and ground it in existing theory on management-science alignment. Next, we measure perceived risk of climate extremes to water quality by analyzing survey data fielded to California drinking water managers. Then, we measure available scientific information linking California water quality and climate extremes, using content analysis of available peer-reviewed information. Finally, we combine data collected from the survey and content analysis with our PRSS tool to identify the types of management-science misalignment in California drinking water quality management, before suggesting potential priority areas of research investment.

BACKGROUND AND THEORY

Evaluating the alignment of perceived risk and science supply

Drawing on policy research that evaluates the links and potential misalignment between science and managerial decision-making (Lemos and Morehouse 2005; McNie 2007; Sarewitz and Pielke 2007), we developed a perceived risk–science supply (PRSS) diagnostic tool (Figure 2). The PRSS tool maps perceived risk on the horizontal x-axis and supply of scientific information on the vertical y-axis. The tool assesses alignment of decision-makers' perceptions of risk to the available supply of scientific information. The color gradient represents three categories of alignment between perceived risk and science supply: (A) *potential undersupply* (*misalignment)* where there is a *lesser emphasis* on a climate extreme and water quality issue in the scientific literature than what decision-makers perceive; (B) *alignment*, where the supply potentially meets the relative perceived risk; and (C) *potential oversupply* (*misalignment*) where there is a *greater emphasis* on the climate extreme and water quality issue in the scientific literature than what decision-makers perceive. For example, in the case of drinking water management, if a high proportion of water managers perceive their water quality as impacted by extreme storm events, we would characterize the perceived risk as high (further along the x-axis). Similarly, if we found a high number of scientific articles documenting how extreme storm events degrade water quality, we would characterize the scientific information supply as high (further along the y-axis). In this scenario, the alignment of perceived risk and science supply on extreme storms would be plotted somewhere in the white colored region, indicating potential alignment (Figure 2). Inherent in the terminology (alignment and misalignment), our normative presumption is that alignment increases the likelihood of effective environmental management (Lemos and Morehouse 2005; van Kerkhoff and Pilbeam 2017). We recognize, however, that effective decision-making often requires blending scientific knowledge with traditional and local knowledge (Berkes et al. 2000).

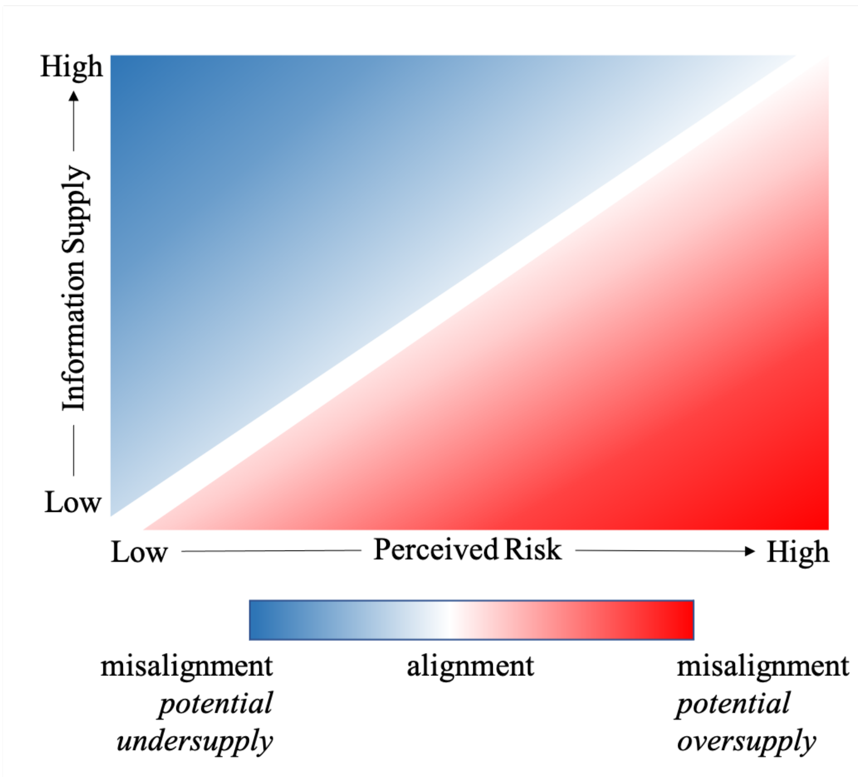

Figure 2. Conceptualization of three types of perceived risk – science supply alignment: A. *potential undersupply (misalignment)*; B. *alignment*; C. *potential undersupply (misalignment)*. This tool is based on ideas from (Cash et al. 2003; Lemos and Morehouse 2005; McNie 2007; Sarewitz and Pielke 2007; Jasanoff 2010; Kirchhoff et al. 2013; Wachinger et al. 2013; Archie et al. 2014; Janmaimool and Watanabe 2014; Treml et al. 2015; van Kerkhoff and Pilbeam 2017).

Potential undersupply is the most commonly identified management-science misalignment and is traditionally blamed on a failure of scientific researchers to appreciate the needs of managers and other decision makers (Cash et al. 2003). The typical response to this problem is to increase science production, especially tailored studies of specific issues or local areas (Dessai and Hulme 2004; Carbone and Dow 2005; Meyer et al. 2011; Kirchhoff et al. 2013; Weaver et al. 2013; Buizer et al. 2016). At times, this process may lead to a loading dock approach which assumes that available information will be used by managers (Rayner et al. 2005; Cash et al. 2006). The loading dock approach fails to consider that scientific information may not be accessible or trusted by managers (Patt and Gwata 2002), a benefit of co-produced knowledge by scientists and users. In other cases, potential undersupply may occur because of disparate timing. For example, a recent catastrophe or climate extreme event may drive an immediate increase in perceived risk, while the production of scientific knowledge may lag years behind due to the slow process of creating the administrative infrastructure for science and the long-term nature of research itself.

In contrast, there are three possible explanations for potential oversupply. First, science production may be driven by regulatory and funding mechanisms that are not linked to heterogeneous local perceived risk. Agenda-setting events like flash flooding and regulatory programs under the 1972 Clean Water Act catalyzed an environmental research infrastructure in which grant program priorities and funding emphasize particular aspects of water quality and climate change, which in turn shape the research activities of academic and government scientists. For example, USEPA policy related to municipal stormwater runoff (MS4) drives science supply relative to heavy precipitation and point and nonpoint source pollution. Second, science may be produced for management issues that are outside of the geographic scope of the perceived risk. Science produced to examine the link between extreme storms and water quality in the Gulf of Mexico and the eastern coast of the United States may not be relevant to places like California that experience extreme drought. Third, managers and other decision-makers may be unaware or unwilling to accept new scientific knowledge about the drivers and responses of environmental change. For instance, individuals are less likely to take action to combat climate change if they are unaware of the actions they could take, do not perceive threat from climate change, or do not feel responsible for causing climate change (O'Connor et al. 2005; Lorenzoni et al. 2006; Whitmarsh 2009; Flagg and Kirchhoff 2018). In California, despite experiencing intensified drought, some agricultural interests expressed doubts about the link between climate change and drought (Niles et al. 2013). This is associated with a tendency to downplay scientific research demonstrating how climate change and drought affect water quality.

CASE STUDY: CALIFORNIA DRINKING WATER QUALITY MANAGEMENT

This article uses the PRSS tool to understand the alignment of drinking water managers' perceived risks to water quality from climate extremes and the supply of scientific information on the same issue. In doing this analysis, we leverage multiple data sources, including survey data and content analysis from peer-reviewed scientific literature. With the integration of perceived risks and available scientific information, we analyzed the extent to which they align, both geographically and topically, and suggest potential investment opportunities that could help overcome misalignment. California makes an ideal study location because it is comprised of climatologically varied regions that depend on either (or both) groundwater and surface water sources. This allows for an examination of the scientific gaps across regions and water source types. Furthermore, California is constantly experiencing a number of climate extremes (e.g., drought, wildfire, etc.) and projections indicate that they will grow in frequency and severity (Mastrandrea et al. 2010; Diffenbaugh et al. 2015), increasing the salience of water quality concerns.

HYPOTHESES

Based on the *drivers* of potential undersupply and potential oversupply discussed in the previous section, we offer the following hypotheses about the level of *alignment* surrounding climate extremes and water quality in California:

A. *H1:* There is a better alignment for surface water than groundwater. Because of its visibility and accessibility, surface water is often the predominant focus of research, indicating a potentially higher supply of surface water science than groundwater science (Knapp and Vaux 1982; Green et al. 2011). Likewise, groundwater has only recently been incorporated into California water quality policies, like the Irrigated Lands Program in 2012 (CAEPA and CVRWQCB 2018).

B. *H2:* There are topical differences in the degree of alignment among pairings of climate extremes and water quality issues, specifically a potential undersupply of drought science and a potential oversupply of extreme storm information. We expect that California's 2012-2016 drought and related policies like Governor Brown's State of Emergency Declaration in California (Brown Jr. 2014), created an immediate increased feeling of risk among drinking water managers (Wachinger et al. 2013). We expect science supply lagged behind this risk because of delays in developing and publishing research. Additionally, we hypothesize that the absence of experiencing extreme precipitation, combined with the long-standing call for research on storm and flood-related activities in the Clean Water Act, like the National Pollution Elimination System (NRC 2008), will result in a potential oversupply (misalignment) of extreme storm science relative to perceived risk of extreme storms to water quality.

C. *H3:* There are regional differences in the degree of alignment between science supply and perceived risk within California. Climate change impacts are projected to vary across California due to governance and ecological characteristics of the regions (CEMA and CNRA 2012). We hypothesize that this creates a variation in perceived risk across California regions. In contrast, science supply production may be driven by regional or national water quality laws or policies and will not reflect finer-level regional variation.

RESEARCH METHODS

We take a four-step approach to evaluating perceived risk and science supply. First, we measure perceived risk using drinking water managers' experiences with water quality issues and climate extremes.

Second, we measure science supply using content analysis of peer-reviewed literature. Third, we evaluate the alignment of perceived risk and science supply using the presented PRSS tool (Figure 2). Finally, we consider where and how future investments could help resolve pervasive management-science misalignment.

Survey

Data used in this study come from a survey of California drinking water managers that was distributed during July and August 2015 by the University of California – Policy Institute for Energy, Environment, and the Economy. The survey was distributed to 756 drinking water managers, each representing one drinking water system. Managers that received the survey were listed as the point of contact on the Electronic Annual Report, a state-required summary of system activities. Collectively, the surveyed systems distribute drinking water through more than 8 million potable connections. Managers were selected based on criteria related to their system's number of service connections and/or acre-feet of water their utility provides annually. The survey asked managers about existing water quality issues and climate extreme triggers, climate change perceptions, climate adaptation activities, and sources of climate information. We received 259 full and partial responses, yielding a 34% response rate. The respondents collectively represented about 11% of California public water systems with 200 or more service connections. Responses were also categorized into California Climate Impact Regions (CEMA and CNRA 2012) to evaluate perceived threats across California regions (for survey details see Ekstrom et al. 2017).

Perceived risk

We developed a *perceived risk metric* using drinking water manager survey responses to two questions about current water quality issues and climate extreme triggers (Figure 3). Based on the source type of the drinking water system (groundwater and/or surface water), managers were asked which of a set of water quality issues threaten their system operations. For each water quality issue that a manager reported as some type of threat to their system (*slightly serious* or higher), they were then asked to *select all* climate extremes that trigger or worsen (hereinafter referred to as triggering) that water quality issue. Respondents could report that a single water quality issue was triggered by more than one type of climate extreme. We calculated the perceived risk metric as the proportion of respondents that reported each climate extreme as triggering each water quality issue. For example, if 67 respondents reported that eutrophication is a water quality issue for their system and that it is triggered by at least one type of climate extreme (denominator) and 40 of those 67 respondents reported that it is triggered by drought specifically (numerator), the *perceived risk score* for eutrophication and drought is 0.60 (Supplementary Information). This created a perceived risk metric ranging from zero to one for each water quality issue (e.g., eutrophication) and climate extreme trigger (e.g., drought) combination, where *one* meant all respondents perceived the water quality issue to be triggered by that climate extreme and *zero* meant no respondents perceived that water quality issue to be triggered by that climate extreme. Because respondents could report more than one climate extreme as triggering a specific water quality issue, perceived risk scores for any water quality issue (across *all climate extremes)* may sum to more than 1.00.

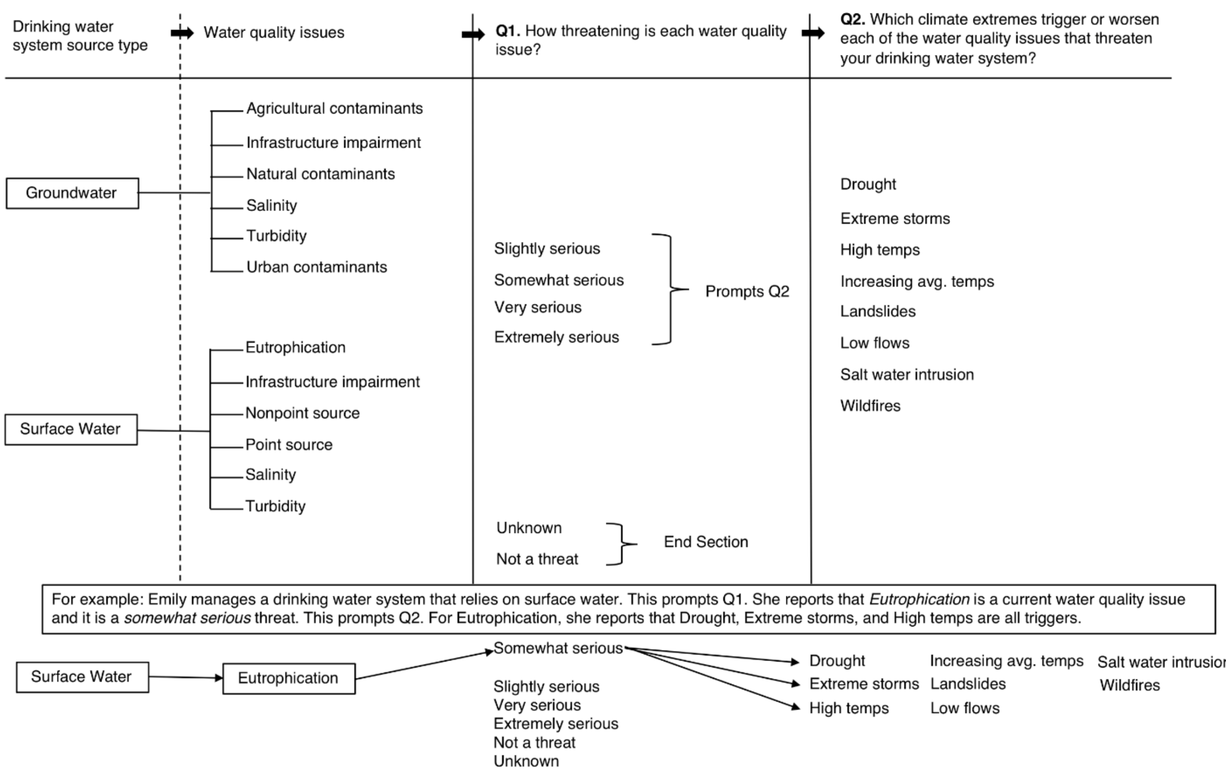

Figure 3. The perceived risk metric was developed using two survey questions about: 1) current water quality issues (tied to the drinking water system source type, surface water and/or groundwater) and 2) climate extreme

triggers (See Supplementary Information for full survey questions). For each water quality issue reported as a threat (Q1), respondents were shown Q2 and asked to *select all* climate extremes that trigger or worsen those water quality issues.

Science supply

To measure science supply in an accessible and repeatable method, we compiled peer-reviewed journal articles, book chapters, and conference proceedings published between 2006 – 2016 from Scopus©, an online abstract and citation database. This approach of using formal research reported in scientific literature is similar to Kiparsky et al. (2006). Compiled literature contained tittles or abstracts with terms related to the study's focal topics (

Table 1). Search topics were categorized by water characteristics, system shocks, and geographical regions. We selected the 2006 – 2016 timeframe to represent recent literature, assuming that local level managers were likely to use recent best available science (Dessai et al. 2009). Moreover, the Intergovernmental Panel on Climate Change Fourth Climate Change Assessment (IPCC 2007) triggered an increase in climate change research over this decade (Hulme et al. 2018).

We recognize that peer-reviewed literature only represents a portion of available information. While resource managers and consultants may rely on scientific information in the form of technical reports and grey literature (Koontz and Thomas 2018), both are strongly influenced by peer-reviewed literature even when they involve primary data collection and analysis. Peer-reviewed scientific journal articles and the peer-review process are central to the scientific enterprise (Scott 2007; Hulme et al. 2018), therefore, this study uses peer-reviewed journal articles to represent scientific information supply.

Table 1. Search terms used to compile journal articles, book chapters, and conference proceedings in Scopus© for 2006 – 2016.

	Topic	Search Terms
Water Characteristics	water quantity	water quantity, water supply, water availability, water volume
	water quality	water quality, water chemistry
System Shocks	climate extremes	extreme event*, extreme weather, hydroclimate* extreme*, storm, flood, high flow, extreme precipitation, heavy precipitation, heavy rain, extreme rain, high temperature, heat event, extreme heat, drought, increase* temperature, low flow, landslide, saltwater/salt water intrusion, saline intrusion, wildfire, fire
	climate change	climat* chang*, global warming
Geographic Region	all literature	N/A (all regions)
	California-specific literature	California

To calculate a supply metric, we subset our Scopus© search results to those containing *California* and terms comprising water quality and climate change or climate extreme terms (

Table 1). Next, we read and coded the unique publications for water quality issues and climate extreme triggers (Supplementary Information). Lastly, we calculated the supply metric as the proportion of publications that discussed each water quality issue and climate extreme trigger combination. For example, if 17 publications discussed eutrophication (denominator) and two of those 17 publications discussed eutrophication being triggered by drought (numerator), the supply score for eutrophication and drought would be 0.12 (Supplementary Information, Eq S4). This created a supply metric ranging from zero to one for each combination of water quality issue and climate extreme trigger, where one meant all articles discussed the water quality issue as triggered by that climate extreme and zero meant none of the articles discussed that water quality issue as triggered by that climate extreme. Publications that discussed multiple water quality issues were treated as unique publications in the calculation of the science supply metric. For example, if one of the 17 eutrophication documents also discussed salinity and drought, it would be included in the calculation of the salinity and drought supply metric as well.

Evaluating perceived risk and supply alignment

To evaluate the perceived risk – science supply alignment we used the quadratic assignment procedure (QAP), alignment scores, and our PRSS tool. The QAP is a standard method of calculating matrix correlations and involves a simulation-based approach that uses permutations of the dataset to adjust standard errors to account for observation correlation (Simpson 2001). First, we assembled two data matrices where rows specified water quality issues and the columns specified climate extreme triggers. In the perceived risk matrix, the cell entries for each water quality and climate extreme ranged between [0,1] based on the perceived risk survey metric. In the science supply matrix, the cell entries ranged between [0,1] based on the content analysis of scientific articles. Tables 2 and 3 in the results section are the basis of these matrices. Second, we calculated QAP scores at statewide and regional scales. The QAP evaluates the slope representing the relationship between x (in our case, perceived risk) and y (in our case, science supply). In our paper, a high QAP (maximum value = 1) shows that perceived risk and supply matrices are similar (potential alignment). In other words, a larger perceived risk score is generally correlated with a larger supply score (or a lower perceived risk score is generally correlated with lower supply score). Likewise, a low QAP (minimum value = 0) shows that perceived risk and supply matrices are less similar (poorer alignment). In other words, a larger perceived risk score is generally correlated with a smaller supply score (or a smaller perceived risk score is generally correlated with a larger supply score).

We then plotted each water quality and climate extreme's perceived risk and science supply scores onto our PRSS tool. For example, if eutrophication and drought had a perceived risk score of 0.60 and a science supply score of 0.12, the point (0.60, 0.12) was added to the PRSS tool. This allowed for a visual explanation of the type and size of alignment across groundwater and surface water quality issues and climate extremes. To explore these relationships further, we calculated an *alignment score* for each water quality issue and climate extreme combination by subtracting the science supply score from the perceived risk score. In the example given above, eutrophication and drought would have an alignment score of 0.48 (Supplementary Information, Eq S5). Alignment scores ranged from -1 to 1, where a score of 0 represented a relative alignment of perceived risk and supply (potential alignment), while a score of -1 or 1 indicated a potential oversupply or undersupply of science, respectively (misalignment). Alignment scores were calculated at statewide and regional scales and then plotted as heat maps.

Investment prioritization

Finally, we calculated investment prioritization scores (IPS) for each water quality and climate extreme combination by taking the absolute value of the alignment scores and summing them by i) water quality issue and ii) climate extreme trigger (Supplementary Information, Eq S6 – Eq S7). IPS ranged from 0 to 8 for water quality issues and 0 to 6 for climate extreme triggers, with 0 representing potential alignment and scores above 0 increasingly indicating misalignment. The higher the IPS, the larger the misalignment. IPS methodology should not be conflated with QAP analyses described in Section 4.4. While QAP is calculated using the relative relationship between perceived risk and science supply, the IPS calculates the difference between raw perceived risk and supply scores. In this way, a smaller QAP (lower correlation) could be presented as having a larger IPS and a larger QAP (higher correlation) could be presented as having a lower IPS. Calculating IPS based on the overall size of misalignment regardless of whether it was driven by oversupply or undersupply allowed us to identify where investment could be most effective in creating better alignment between perceived risk and supply. Investment could take various forms including managerial training on available science; investing in boundary organizations to facilitate science co-production (Vogel et al. 2016); or increasing the production of science on specific topics.

RESULTS

In this section, we present the results of the application of the perceived risk–science supply (PRSS) tool to the case of California drinking water quality management. This section first presents risk and supply analyses, followed by the alignment of supply and perceived risk, and finally, the investment prioritization opportunities.

Perceived risk

Among systems with some groundwater, drought was the most important trigger for all the groundwater quality issues, especially natural contaminants (0.52 of the 130 water managers who mentioned natural contaminants as a threat to water quality indicated drought as a trigger) and turbidity (0.54). Drinking water managers with some surface water reported a much broader range of climate extreme triggers across multiple water quality issues. For example, eutrophication triggered by high temperatures (0.72), low flows (0.58), and increasing average temperatures (0.52), were the highest perceived risks (

Table 2). Traditional water quality issues such as point source and non-point source pollution were also perceived to be triggered by diversity of climate extremes, especially drought (0.47 for nonpoint, 0.46 for point), low flows (0.50 and 0.36), extreme storms (0.48 for both) and wildfires (0.35 and 0.37). The most concentrated risk was for drought as a trigger for salinity (0.77).

Table 2 Perceived risk scores. Each cell represents the proportion of survey respondents that reported the water quality issue as triggered by the climate extreme labeled in the column headings. Because respondents could report more than one climate extreme as triggering each water quality issue, total row sums may be greater than one. The *n* in parentheses represents the number of survey respondents that reported the water quality issue as being triggered by any climate extreme.

		Climate extremes							
		Drought	**Low flows**	**Extreme storms**	**Landslides**	**Salt water intrusion**	**Increasing avg. temps**	**High temps.**	**Wildfire**
Groundwater	Agricultural contaminants (n = 95)	0.21	0.13	0.24	0.12	0.01	0.06	0.09	0.16
	Infrastructure impairment (n = 118)	0.40	0.13	0.25	0.02	0.00	0.02	0.01	0.04
	Natural contaminants (n = 130)	0.52	0.13	0.05	0.00	0.29	0.11	0.09	0.02

	Salinity (n = 56)	0.30	0.13	0.30	0.06	0.00	0.02	0.02	0.09
	Turbidity (n = 47)	0.54	0.14	0.11	0.01	0.07	0.05	0.08	0.05
	Urban contaminants (n = 85)	0.42	0.15	0.17	0.03	0.01	0.05	0.03	0.05
Surface water quality issues	Eutrophication (n = 67)	0.60	0.58	0.06	0.03	0.00	0.52	0.72	0.07
	Infrastructure impairment (n = 77)	0.25	0.17	0.38	0.36	0.01	0.05	0.06	0.30
	Nonpoint source pollution (n = 60)	0.47	0.50	0.48	0.17	0.07	0.15	0.18	0.35
	Point source pollution (n = 67)	0.46	0.36	0.48	0.25	0.09	0.09	0.13	0.37
	Salinity (n = 30)	0.77	0.37	0.03	0.03	0.40	0.10	0.07	0.03
	Turbidity (n = 65)	0.28	0.18	0.75	0.37	0.00	0.05	0.09	0.35

Science supply

Regardless of geographic scale, we found less emphasis on climate change and climate extreme impacts on water quality than water availability (Supplementary Information, Table S2). This trend is consistent with current qualitative experienced-based assessments (Michalak 2016), however our study derives this from an objective systematic analysis. Within the subset of California-related literature on climate extremes and water quality, we found a larger focus on surface water than groundwater. Within 115 California-related publications, 111 (97%) were related to surface water and 9 (8%) were related to groundwater. Subsequently, most groundwater supply scores were 0.00, a reflection of the lack of relevant publications (

Table 3). Current research on groundwater quality and climate change notes the uncertainty around the science as one explanation for its general lag in production (Green et al. 2011). Our finding combined with current research highlights a major disconnect in the management-science interface that will expand as extreme weather becomes more frequent and severe (GAO 2007).

Overall, there was an imbalance in the number of publications on water quality and climate extreme topics. Supply scores were highest among extreme storms and certain surface water-related quality issues (eutrophication, infrastructure, nonpoint and point source pollution). Among water quality issues, nonpoint source pollution had the highest number publications (58), with turbidity a close second (46). Saltwater intrusion and high temperatures were not associated with water quality in any publications. Additionally, very few publications discussed landslides, wildfire, and drought, the latter two of which are persistent problems across California.

Table 3. Science supply scores. Each cell represents the proportion of California-centric publications that discussed a water quality issue triggered by the climate extreme. Because publications could discuss more than one climate extreme or water quality issue, total row sums and/or column sums may be greater than one. The *n* in parentheses represents the number of publications that discussed that water quality issue as being triggered by a climate extreme.

		Climate extremes							
		Drought	**Low flows**	**Extreme storms**	**Landslides**	**Salt water intrusion**	**Increasing avg. temps**	**High temps.**	**Wildfire**
Groundw	Agricultural contaminants (n = 5)	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00
	Infrastructure impairment (n = 0)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

	Natural contaminants (n = 0)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Salinity (n = 4)	0.00	0.25	0.25	0.00	0.00	0.00	0.00	0.00
	Turbidity (n = 1)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Urban contaminants (n = 2)	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
Surface water quality issues	Eutrophication (n = 17)	0.12	0.35	0.47	0.00	0.00	0.35	0.00	0.00
	Infrastructure impairment (n = 9)	0.11	0.22	0.89	0.11	0.00	0.00	0.00	0.11
	Nonpoint source pollution (n = 58)	0.03	0.19	0.84	0.00	0.00	0.05	0.00	0.03
	Point source pollution (n = 15)	0.00	0.40	0.80	0.00	0.00	0.00	0.00	0.00
	Salinity (n = 26)	0.12	0.15	0.65	0.00	0.00	0.00	0.00	0.04
	Turbidity (n = 46)	0.02	0.15	0.83	0.00	0.00	0.04	0.00	0.04

Comparing perceived risk and science supply alignment by water source type

Consistent with H1, Our QAP results at the statewide level (Table 4) showed that surface water had a better overall alignment (0.514**) than groundwater (0.287*). This trend is consistent in both statewide and regional comparisons. While other studies found that information supply is not a major barrier to climate adaptation, our findings suggest it might be a hindering factor in the water quality and climate extreme domain.

Table 4. QAP correlation scores between statewide perceived risk, regional perceived risk, and statewide supply of science for groundwater (left) and surface water (right). Cells with less than five survey respondents for that region were deemed insufficient to run QAP analysis and are denoted by *insufficient data*. Symbols (* and ** respectively) indicate correlations that are significant to the p<0.10 and p<0.05 values.

Statewide and Climate Impact Region Perceived Risk	**Statewide California Science Supply**	
	Groundwater QAP correlation	*Surface water QAP correlation*
Statewide	0.287*	0.514**
Bay Area	0.237*	0.584**
North Coast	*insufficient data*	0.322*
North	0.138	*insufficient data*

North Central Valley	0.020	0.369**
North Sierra	0.469*	0.498**
Central Coast	0.174	0.602**
Desert	0.336**	0.278*
South Central Valley	0.292*	*insufficient data*
South Coast	0.240*	0.390**
South Sierra	*insufficient data*	*insufficient data*

Comparing perceived risk – science supply alignment across topics

To explore the alignment of perceived risk and science supply across water quality and climate extreme topics, we used alignment score heat maps (Supplementary Information, Figure S1–Figure S9). Across all water quality issues, we found high perceived risk of drought and low perceived risk of extreme storms relative to the science supply on these topics (Supplementary Information, Figure S1). High temperatures and surface water eutrophication (0.72) and drought and surface water salinity (0.65) both showed high levels of perceived risk compared with supply (misalignment driven by potential undersupply). Comparatively, extreme storms triggering groundwater urban (-0.73) and agricultural contaminants (-0.56), indicated low levels of perceived risk relative to supply (misalignment driven by potential oversupply).

To visually explore the levels of alignment for each water quality and climate extreme combination, we plotted perceived risk scores (x-axis) against supply scores (y-axis), using the PRSS tool shown in Figure 2. This visualization showed that most of the perceived risk and science supply misalignment is driven by potential undersupply, with drought as the most disparate. Extreme storms generally appeared as potential oversupply (Figure 4), though less so for groundwater than surface water. Low flows measured as a relatively potential alignment, possibly driven in part by the State Water and Central Valley Projects, for which effective water supply relies on maintaining the balance of fresh and salt water in Sacramento and San Joaquin Delta, as well as federal regulations on nonpoint pollution, point source pollution, and endangered species flow and temperature requirements. Lastly, the results point to a major lack of literature on groundwater.

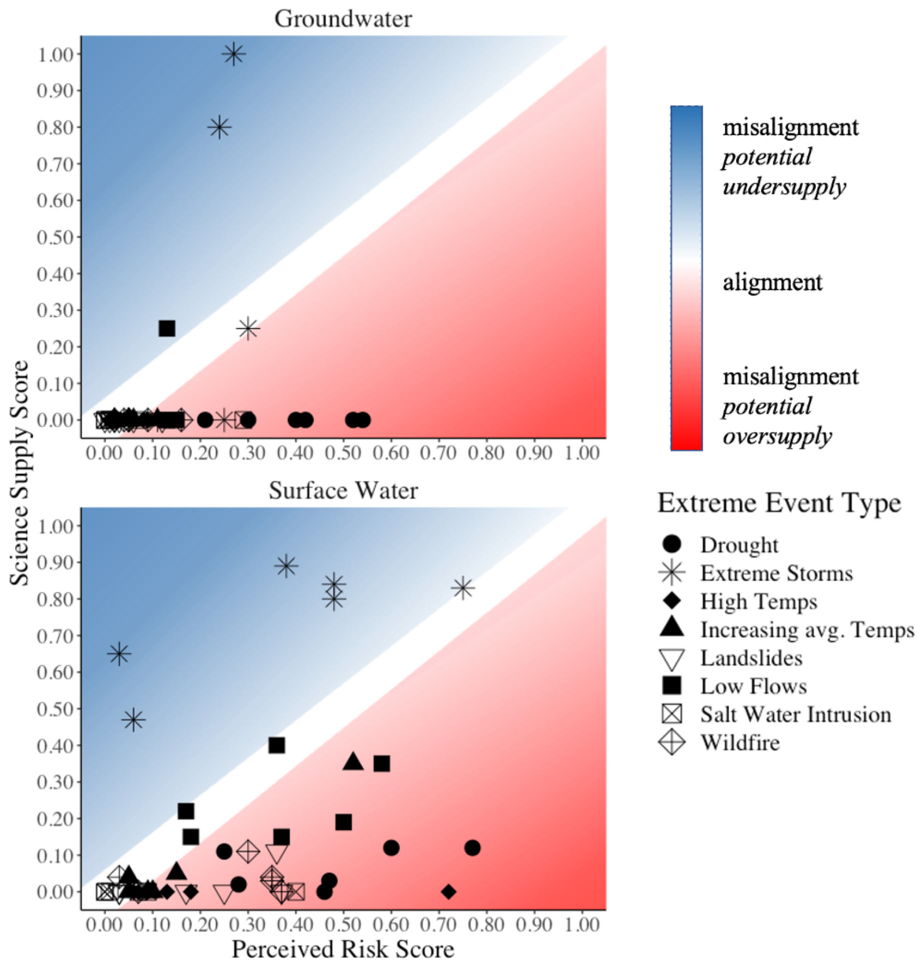

Figure 4. Statewide Perceived Risk – Science Supply maps of alignment of groundwater (top) and surface water (bottom). Points are comprised of the combination of the perceived risk score (x-axis) and science supply score (y-axis) for each water quality and climate extreme combination. Plots highlight two types of misalignment: potential oversupply (blue) and potential undersupply (red). The area along the diagonal (white) represents potential alignment. In this display, each symbol represents the relevant climate extreme of each point.

Comparing perceived risk – science supply alignment across California regions

To explore geographic variation, we compared the perceived risk scores for each California region with statewide science supply scores. The Central Coast (0.602**) and Bay Area (0.584**) regions had the strongest correlations with statewide supply for surface water, while the Desert region had the lowest correlation (0.278). The Central Coast and Bay Area regions are generally more impacted by extreme precipitation than drought-related concerns. This can partially explain the stronger correlation with statewide science supply, which focused primarily on extreme storm-related topics and less so on drought-related themes. In comparison, for groundwater systems, the North Sierra (0.469*) and Desert (0.336**) regions had the highest correlation with statewide science supply.

Alignment scores, although varying slightly across California regions, showed similar topical trends to the statewide analysis. For example, there was a high perceived risk of drought and a low perceived risk of extreme storms relative to science supply across water quality issues and source types. The exception to these general trends was groundwater turbidity and extreme storms in the Bay Area and North Sierra regions. In both regions, perceived risk was much higher than relative science supply (see Supplementary Information, Figure S1–Figure S9).

Investment prioritization

Lastly, we plotted the investment prioritization scores (IPS) across water quality issues and climate extreme triggers (Figure 5). Higher IPS represented larger gaps between perceived risk and supply scores, regardless of the type of misalignment. Drought and extreme storms had the highest IPS among climate extreme triggers, however, their drivers differed. While investment in more science supply is needed for drought, investment in translating existing science to decision-makers is needed for extreme storms. Among water quality issues, eutrophication (surface water, 2.11) and urban contaminants (groundwater, 1.47) scored the highest (Figure 5).

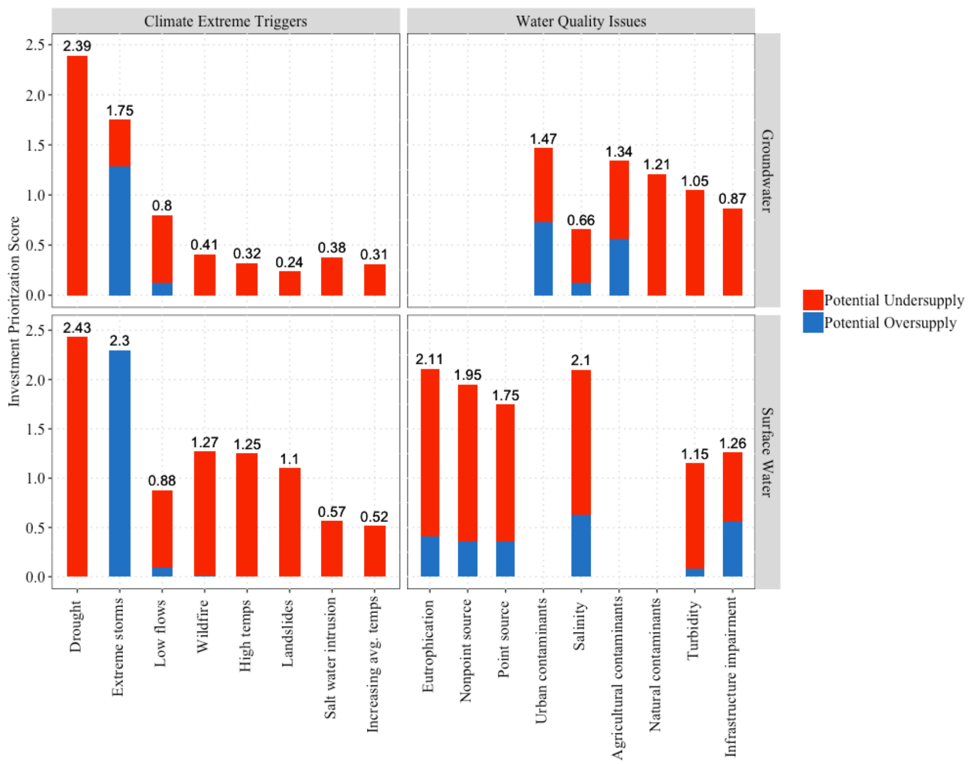

Figure 5. Investment prioritization scores plotted by water quality issue (bottom plots) and climate extreme trigger (top plots). Scores were calculated for groundwater (left column) and surface water (right column) separately. Data labels centered at the 0-line represent total investment prioritization scores, where larger scores represent higher investment potential (poorer alignment). Investment prioritization scores represent the sum of potential undersupply of science (red) and potential oversupply of science (blue) as described in Figure 2.

DISCUSSION

We developed and presented the PRSS tool to help understand the nuances of management-science disconnect. We sought to use this tool to empirically characterize the extent of water quality and climate extreme concerns among California drinking water managers and the production and use of science related to water quality, climate extremes, and climate change.

H1: Better PRSS alignment for surface water than groundwater

We found an overall undersupply of science discussing water quality and climate change and a better alignment of science and perceived risk for surface water than groundwater. Surface water has traditionally received more attention in California. Even with this, the consideration of how climate change impacts surface water quality and how management can address it didn't occur until recently. For example, climate change wasn't a required element of the Integrated Regional Water Management Planning process until 2010. The nascent scholarship on climate change and water quality, particularly for groundwater quality issues, may be explained by the historical lack of an overarching governance framework in California (Knapp and Vaux 1982; Sax 2002). This lack of direction, coupled with the physical barriers of groundwater (less visible, more cryptic) make it harder to observe and address the effects of climate extremes.

H2: Topical differences in PRSS alignment

Climate extremes variability

Across climate extremes in our study, drought showed the largest PRSS misalignment (high perceived risk, low science supply), and the highest investment prioritization score (low science supply). There are several possible explanations. Unlike other types of climate extremes like flooding or cyclones, drought is a creeping phenomenon (Tannehill 1947) and accumulates over time. Drought also lacks a definition with precise parameters that are universally accepted, potentially challenging managers who need to respond (Wilhite 2000). Drought impacts tend to occur over large geographical areas compared with other climate extremes; the 2012 – 2016 drought in California, for example, impacted most of the the state's communities. Further, research shows that experiencing natural hazards (like the drought) leads to higher risk perception in most cases (Wachinger et al. 2013) while managers shift efforts to address more structural and immediate challenges (Rayner et al. 2005). As this shift in attention occurs, the science supply lags. In the case of California, we are experiencing an increase in drought-related science following the 2012 – 2016 drought[1] as researchers analyze and publish drought data, and funders support more drought-related research.

Extreme storms showed the second largest PRSS misalignment (low perceived risk, high science supply), and the second highest investment prioritization score (high science supply). This finding may be in

[1] A search for peer-reviewed literature in Scopus© on June 10, 2021 found that of 2,363 articles published since 1934 that contain both "California" and "drought", 922 (~39%) were published from 2017 – 2021.

part driven by salience given that the survey was distributed during a drought and therefore managers may have conceptualized extreme storms as more distant. This could in turn decrease perceived risk of impact from extreme storms because the threat seemed less real or tangible (McDonald et al. 2015). Similarly, extreme storms may not be a challenge to California drinking water managers. However, Gao et al. (2016) indicate that there is a likelihood of more frequent *monster* storms in California in the future. The misalignment around extreme storms may also be driven by regulatory agendas. Our content analysis showed that most extreme storm science focused on construction runoff control. This emphasis may be policy driven by actions like the federal regulatory stormwater guidance that expanded the municipal separate storm sewer system (MS4) program to smaller urban centers and required construction runoff control (USEPA 2005).

Water quality issue variability

Our study also showed PRSS alignment variability across water quality issues. We found the largest PRSS misalignments for surface water salinity (from drought) and eutrophication (from drought and high temperatures). The 2012–16 California drought co-occurred with record high temperatures (Griffin and Anchukaitis 2014) and both drought and high temperatures are shown in research to exacerbate concentrations of salinity and eutrophication in water (Michalak 2016). Hydrologic changes in reservoirs and lakes, driven by external (decreased inflow, diversions for increased demand) and internal (diffusion, mineralization) factors can create a number of water quality challenges, including increased nutrient concentrations and salinization (Paerl and Huisman 2008; Wright et al. 2014). Both eutrophication and salinization can alter the taste and odor of drinking water and result in increased consumer complaints, potentially making these constituents more salient for drinking water managers. Finally, the PRSS misalignment for salinity and eutrophication was driven by a science undersupply, again raising the question of supply lag time mentioned previously.

Pertaining to broader drinking water management challenges, eutrophication may result in algal blooms, which create chemical and physical challenges for drinking water managers, necessitating costly financial and social decisions like issuing don't drink orders, shifting treatment technologies, and breaks in service due to clogged intakes (Chislock et al. 2013; Michalak 2016). When algal blooms are toxic (e.g. harmful algal blooms) they can cause health problems in both animals and humans (Chislock et al. 2013), making eutrophication management especially significant to the public. Experiences with algal blooms during the drought may have driven an increase in perceived risk (Wachinger et al. 2013; Janmaimool and Watanabe 2014). Eutrophication also had the highest investment prioritization score across all water quality issues, suggesting that further research into the specific drivers of the PRSS misalignment, information on managerial experiences with algal blooms, and support for scientific studies on how and why eutrophication is triggered by temperature and drought can inform discussions on why there is such a large misalignment between perceived risk and science supply.

H3: There are regional differences in the size of the alignment scores

The PRSS alignment varied across regions, suggesting that water quality and climate extreme impacts are influenced by ecological and social characteristics. This finding is parallel to a study that found climate extreme impacts vary based on location and operational conditions (Vogel et al. 2016). For example, California's desert region showed lower perceived risk to surface water quality from drought-related triggers than other regions. This lack of perceived risk may be explained by managerial familiarity with existing desert climate variations like dry weather and low annual precipitation (Rayner et al. 2005). Desert regions in southern California depend on imported water from other regions, so it is also possible that drinking water managers from the desert region are assigning drought management responsibilities to water wholesalers, seeing them as decision-makers. Comparatively, the North Sierra region showed high perceived risk to surface water quality from wildfire-related triggers. High perceived risk is likely a result of the North Sierra's ecological conditions, combined with research that shows positive feedback between drought and wildfire that may lead to more intense landscape impacts (Crockett and Westerling 2018).

We also found that Bay Area and Central Coast regions shared high correlations with statewide perceived risk and science supply. Both regions also showed similar trends in alignment scores for drought (high potential science undersupply) and extreme storms (high potential science oversupply). As political hubs with abundant resources there is a potential important role of social and economic power that may drive statewide trends in water quality and climate extreme science. The regional variability and trends that we found are consistent with the need for addressing climate change impacts to water quality at multiple levels of governance.

LIMITATIONS AND FUTURE RESEARCH

While the analytical method presented here contributes to literature on perceived risk and supply of scientific information, we recognize limitations consistent with any quantitative method. We suppose that perceived risk can be calculated using current water quality issues and climate extreme triggers when it may be more nuanced. For example, risk perception may be influenced by a feeling of inability to control risk (Janmaimool and Watanabe 2014). It may also be influenced by changes in priority over time, which we tried to mitigate by representing perceived risk using reported experiences with water quality and climate extremes. Additionally, our paper relies on a snapshot of reported experiences, rather than a dynamic assessment. A current water quality issue may not translate to a future issue, nor does it necessarily mean the water drinking manager needs information on it. However, a water quality issue that is not a current threat may become a threat.

Future research that considers how managers' needs change over time can be especially important for understanding the alignment of perceived risk and science supply in a more dynamic manner. Additionally, we encourage others to apply this framework to perceived risk and supply of grey literature. Though difficult to measure because there is no set database of grey literature, a quantitative assessment of grey literature could further illuminate how manager-science alignment differs between types of science supply. This type of analysis would add to our overall understanding and prioritization of research topics. Finally, beyond the focus of our project, the flexibility and design of our PRSS tool is useful in exploring other topic areas and geographic regions to understand the gaps between resource manager needs and the state of the science.

CONCLUSION

In this paper, we presented a Perceived Risk–Science Supply (PRSS) tool grounded in literature on management-science alignment. We used this PRSS tool to study the case of California drinking water management by comparing managers' perceived risk of climate extremes to water quality with peer-reviewed scientific information on the same topics. Then, we suggested potential research investment opportunities based on our findings. We found a general undersupply of science on how specific climate extremes will trigger different water quality issues. The overall nuanced misalignment of perceived risk and science supply underscores the need for understanding how climate impacts manifest at multiple levels of governance. Across California, for example, certain climate extremes (like drought) and certain water quality issues (like salinity and eutrophication) are a challenge for most drinking water systems. However, other water quality issues (urban contaminants) and climate extremes (sea level rise), vary significantly across California sub-regions, underscoring the importance of locally relevant research. The need to study climate extremes and water quality at multiple levels of governance to support climate adaptation will grow as climate extremes become more frequent and intense. This paper contributes to multi-level governance understanding by focusing on the local level and considering the important role of managerial experiences, needs, and perceptions in ascertaining research gaps.

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SUPPLEMENTAL INFORMATION

This supplemental information provides supplementary detail on methods development and examination of results to complement the main manuscript. Sections include addition information on: (1) perceived risk methodology, (2) science supply methodology, (3) quadratic assignment procedure (QAP) scores showing the correlation of perceived risk between sub-regions and statewide scales of California, (4) statewide and sub-region alignment score heat maps, and (5) investment prioritization score methodology.

METRIC DEVELOPMENT

To calculate the perceived risk metric for science related to water quality and climate extreme threats, we used four questions from a 2015 survey of California public drinking water system managers (Ekstrom et al. 2017). To minimize bias relative to *climate change* terminology, we used the phrases *extreme events*, *weather events,* and *environmental hazards* instead of *climate extremes* in the survey. Respondents saw 1 to 4 of the questions (Table S1 – Table S4) depending on: 1) whether they reported their system source as groundwater and/or surface water and 2) whether they reported any water quality issues as a threat to those sources.

Perceived risk metric

Table S1. [Question 21] In considering your district's groundwater sources (used for drinking water), indicate how threatening each issue is to water quality. Numbers in parentheses represent scores assigned to each level of threat. These scores were used to calculate the average water quality threat severity, as presented in *Water quality severity.*

	Extremely serious threat (4)	Very serious threat (3)	Somewhat serious threat (2)	Slightly serious threat (1)	Not a threat (0)	Unknown
Turbidity						
Contaminants present from urban or industrial land use						
Salinity						
Contaminants naturally present						
Contaminants present from agricultural land use						

Infrastructure impairment or failure						

Table S2. [Question 22] Please indicate which weather events or environmental hazards worsen or trigger groundwater quality issues. Select all that apply. These scores were used to calculate the perceived risk metric, as presented in *Perceived Risk* in the main manuscript.

	Drought	Low flows	Extreme storms, high flows	Landslides	Salt water intrusion	Increasing avg. temperatures	High temperatures	Wildfires
Turbidity								
Contaminants present from urban or industrial land use								
Salinity								
Contaminants naturally present								
Contaminants present from agricultural land use								
Infrastructure impairment or failure								

Table S3 [Question 18] In considering your district's surface water sources (used for drinking water), indicate how threatening each issue is to water quality. Numbers in parentheses represent scores assigned to each level of threat. These scores were used to calculate the average water quality threat severity, as presented in *Water quality severity.*

	Extremely serious threat (4)	Very serious threat (3)	Somewhat serious threat (2)	Slightly serious threat (1)	Not a threat (0)	Unknown
Point source pollution						
Nonpoint source pollution						
Turbidity						
Eutrophication, algal blooms or low dissolved oxygen						
Salinity						
Infrastructure impairment or failure						

Table S4 [Question 19] Please indicate which weather events or environmental hazards worsen or trigger surface water quality issues. Select all that apply. These scores were used to calculate the perceived risk metric, as presented in *Perceived Risk* in the manuscript.

	Drought	Low flows	Extreme storms, high flows	Landslides	Salt water intrusion	Increasing avg. temperatures	High temperatures	Wildfires
Point source pollution								
Nonpoint source pollution								
Turbidity								
Eutrophication, algal blooms or low dissolved oxygen								
Salinity								
Infrastructure impairment or failure								

Survey responses to water quality issue and climate extreme questions (Table S1 – Table S4) were combined (Question 18 and Question 19; Question 21 and Question 22) and respectively analyzed for systems with surface water and systems with groundwater. The survey question combinations were used to develop a perceived risk metric that represented the proportion of respondents that reported a climate extreme as triggering or worsening a water quality issue using the formula described below.

PR = perceived risk metric
R = number of respondents
WQI_i = specific water quality issue, for example: point source pollution
CE_j = specific climate extreme, for example: drought

$$\boldsymbol{PR} = \frac{R_{WQI_i,CE_j}}{\sum R_{WQI_i}} \quad \textbf{Eq S1}$$

In the case where WQT_i = point source pollution and CE_j = drought, R_{WQI_i,CE_j} is the number of respondents who marked point source pollution as a water quality issue and reported that it is triggered or worsened by drought. The denominator is the sum of all respondents who marked point source pollution as an issue that is triggered by a climate extreme despite whether they reported drought as a trigger.

Water quality severity

To better understand the perceived risk metric, we examined the survey responses from which the perceived risk metric was derived. This included the water quality threat severity that was expressed by respondents in Question 18 for systems with surface water (Table S1) and Question 21 for systems with groundwater (Table S3). An average severity of threat for each water quality issue was calculated using the equation described below.

P_R = proportion of respondents
R = number of respondents
$\overline{T}_{WQI_i}$ = average threat severity score for a water quality issue (i), for example: 1 (slightly serious threat)

$$\boldsymbol{P_R = \frac{\sum R_{WQI_i}}{\sum R_{WQI}}} \qquad \textbf{Eq S2}$$

$$\boldsymbol{\overline{T}_{WQI_i} = \frac{\sum R_{WQI_i} \times T_i}{\sum R_{WQI_i}}} \qquad \textbf{Eq S3}$$

Average threat severity scores for each water quality issue as well as the count (and percentage) of respondents that reported each issue as a threat to their utility are presented in Table S5.

Table S5. Summary table of water quality issues, the count of respondents that reported each issue as a threat to their system, and average threat severity score. Values of *n* represent the number of respondents that reported one or more groundwater (130) or surface water (115) quality issues as some level of threat to their system. Percentages in parentheses represent the number of total respondents by water source type (n = 115 or n = 130) that reported a water quality issue as some level of threat.

	Water quality issue	Count of respondents	Average threat severity score
Groundwater quality issues (n = 130)	Urban contaminants	85 (46%)	2.11
	Agricultural contaminants	95 (51%)	2.02
	Infrastructure impairment or failure	118 (64%)	1.96
	Naturally occurring contaminants	130 (70%)	1.93
	Salinity	56 (30%)	1.71
	Turbidity	47 (25%)	1.51
Surface water quality issues (n = 115)	Infrastructure impairment or failure	82 (71%)	2.21
	Point source pollution	70 (61%)	2.03
	Salinity	34 (30%)	2.03
	Nonpoint source pollution	67 (58%)	1.91
	Turbidity	67 (58%)	1.79
	Eutrophication	72 (63%)	1.78

Supply metric

contains the results of our initial publication search in Scopus©, conducted on September 21, 2016. Each cell in the table contains the number of publications that met the criteria indicated. Publications here were defined to include water characteristics (water quality, water quantity), system shocks (climate change, climate extremes), and geographic scope (global, California) as outlined in *Science Supply* in the main manuscript. For example, there were 34,428 publications that resulted from a search for *water quantity* and there were 3,342 publications that resulted from a search for *water quantity* and *climate change* (
S6). In conducting the literature search, we took three steps. In the first step, we identified publications containing the water characteristics, water quantity or water quality. Both global and California-scoped searches revealed more water quality results than water quantity. As a second step, we searched for publications containing a water characteristic and a system shock (climate extremes or climate change). We used the term *extreme events* for our publication searches to be consistent with survey terminology, rather than *climate extremes*. This kept the terminology consistent for calculating perceived risk and publications. We conducted a spot check using the terminology *climate extreme* in place of *extreme events*. Minor variation in the number of documents occurred, but overall, we pulled a larger number of documents when *extreme events* terminology was used. For both types of system shocks, the Scopus© query contained more water quantity publications than water quality, regardless of geographic scope. As a final step, we searched for publications containing a water characteristic and both system shocks. Again, the query results showed a greater number of water *quantity*-related publications than water *quality*, for both global and California-specific regions.

Table S6. Count of publications in Scopus© for 2006-2016 representing combinations of water characteristics, system shocks, and geographic regions. Shaded cells represent the subset of literature used to calculate science supply for California in this paper.

		Global (2006-2016)	**California (2006-2016)**
Climate change	water quantity	34,428	595
	water quality	49,730	692
	climate change	113,562	1,479
	+ water quantity	3,342	102
	+ water quality	1,604	30
Extreme events	extreme events	497,290	3,554
	+ water quantity	6,326	191
	++ climate change	1,262	47
	+ water quality	4,659	135
	++ climate change	450	13

Our search in Scopus© for California-related publications identified 165 results: 135 for water quality and climate extremes and 30 for water quality and climate change (grey cells in Table S6). These 165 results represented 143 unique publications. Of the 143 publications, one article was removed because its geographical scope was Baja, California (Mexico) and 27 articles were removed for being too vague or had purposes other than discussing water quality. This left 115 unique California, water quality-related publications.

These 115 peer-reviewed publications were manually reviewed for specific water quality issues triggered or worsened by any climate extreme. Some publications were tagged for more than one water quality issue and some were tagged for more than one climate extreme. In some cases, water quality issues were more specific than the categories used in this paper. In those cases, more specific terms were nested into broader water quality issues (Table S7) and climate extreme types (Table S8). Only terms that appeared in the articles are included in these table. Because some water quality issues are hard to categorize as one specific category (unless specifically addressed in the literature), some water quality terms were included in more than one water quality issue category. For example, stormwater may be classified as a point source pollutant or a nonpoint source pollutant, based on regulatory definitions. As a result, unless an article specified the classification, it was tagged as both point source pollution and nonpoint source pollution.

Table S7. Water quality issue terms identified through manual review of Scopus© literature (2006-present) on California, water quality, and climate extremes or climate change. Only those terms appearing in publications are included. A *blank cell* indicates that no additional terms appeared related to a water quality issue (e.g., natural contaminants).

	Water quality issue	**Topics covered**
Groundwater supplies	Urban Pollution	urban, industrial
	Agricultural Pollution	agriculture
	Turbidity	turbidity, total suspended solids
	Natural Contaminants	
	Salinity	TDS, conductivity
	Infrastructure Impairment/Failure	
Surface water supplies	Point Source Pollution	point source pollution, wastewater discharge, effluent, stormwater, industrial, urban runoff
	Nonpoint Source Pollution	nonpoint source pollution, runoff, stormwater, urban runoff
	Turbidity	turbidity, total suspended solids, sedimentation, sediment loading, erosion runoff
	Eutrophication	eutrophication, algal blooms, phytoplanktonic blooms, cyanotoxins, cyanobacteria, dissolved oxygen, biological oxygen demand
	Salinity	salinity, total dissolved solids, conductivity, bromide
	Infrastructure Impairment/Failure	infrastructure, treatment plants, equipment

Table S8 Climate extreme terms identified through manual review of Scopus© literature (2006-present) on California, water quality, and climate extremes or climate change. Only those terms appearing in publications are included.

Climate extreme type	Included terms
Drought	drought
Low flows	low flows, dry weather
Extreme storms	storms, heavy precipitation, wet weather, runoff, heavy rain
Landslides	landslide
Salt water intrusion	salt water intrusion, saline intrusion
Increasing average temperatures	increasing average temperatures, increased temperatures
High temperatures	high temperatures, high heat, extreme heat
Wildfire	wildfire, fire

Publication Search Limitations

We recognize that there are several ways in which publication searches can be done. We used Scopus©, an Elsevier database, because it contains more journals than other similar publication databases, such as Web of Science or PubMed (Falagas et al. 2008). However, because each database contains different sets of journals, it is possible that a similar publication search could present different results. Additionally, we chose to conduct an initial search using general terms, such as 'water quality' and 'water chemistry'. From there, our manual review tagged each representative article with appropriate water quality issues and climate extreme types. As an alternative, we could have used the specific water quality and climate extreme terms (presented in Table S7 and Table S8) to conduct another search in Scopus© for publications linking water quality and climate extremes. We did conduct spot checks using this alternative approach. While we found some variation in the number of publications addressing each water quality issue and climate extreme type, those combinations with zero results in our study (i.e., natural contaminants and any extreme event) remained consistent through this secondary approach. This shows that while different approaches may be taken to identify publications that discuss water quality issues and extreme events, overall trends remain the same.

Calculating the Supply metric

Using the manually reviewed and tagged publications identified through the publication search (

Supply metric in Supplemental Materials), we developed a supply metric. This metric calculated using Eq S4 (below) represented the proportion of publications that discussed each water quality issue as triggered by a climate extreme. We developed this metric as a proportion to evaluate the emphasis of each water quality-extreme event dyad against a full suite of dyads.

S = supply metric
P = number of publications
WQI_i = specific water quality issue, for example: point source pollution
CE_j = specific climate extreme, for example: drought

$$\boldsymbol{S} = \frac{P_{WQI_i,CE_j}}{\sum P_{WQI_i}} \qquad \textbf{Eq S4}$$

In the case where WQT_i = point source pollution and CE_j = drought, P_{WQI_i,CE_j} is the number of publications that discussed point source pollution as a water quality issue and it reported that this issue is triggered or worsened by drought. The denominator is the sum of all the documents that discussed point source pollution as an issue, despite whether they reported drought as a trigger. Results of the supply metric are reported in *Table 2* of the main manuscript.

QUADRATIC ASSIGNMENT PROCEDURE DETAILS

QAP correlations of perceived risk between statewide California and regions

To assess how similar or different perceived risk of certain water quality and climate extreme linkages was, we compared regional perceived risks against each other and against statewide perceived risk (Table S9 and Table S10). Regions with fewer than 5 survey respondents were omitted from the analysis.

Table S9. Groundwater QAP scores showing the correlation of perceived risk for science between regions and statewide California scales. Two regions, *North Coast* and *South Sierra* had fewer than 5 survey respondents and are therefore not included in the tables.

Groundwater									
	California	**Bay Area**	**North**	**North Central Valley**	**North Sierra**	**Central Coast**	**Desert**	**South Central Valley**	**South Coast**
California									
Bay Area	0.634**								

North	0.461**	0.387**							
North Central Valley	0.774**	0.541**	0.462**						
North Sierra	0.547**	0.490**	0.155	0.334*					
Central Coast	0.793**	0.721**	0.582**	0.852**	0.389**				
Desert	0.548**	0.643**	0.307*	0.646**	0.491**	0.629**			
South Central Valley	0.812**	0.651**	0.523**	0.785**	0.479**	0.762**	0.659**		
South Coast	0.583**	0.531**	0.330**	0.608**	0.333*	0.676**	0.558**	0.663**	

Table S10. Surface water QAP scores showing the correlation of perceived risk for science between regions and statewide California scales. Three regions, *North, South Sierra,* and *South Central Valley*, had fewer than 5 survey respondents and are therefore not included in the tables.

Surface Water								
	California	**Bay Area**	**North Coast**	**North Central Valley**	**North Sierra**	**Central Coast**	**Desert**	**South Coast**
California								
Bay Area	0.956**							
North Coast	0.733**	0.662**						
North Central Valley	0.904**	0.832**	0.656**					

North Sierra	0.823**	0.770**	0.515**	0.694**				
Central Coast	0.820**	0.785**	0.618**	0.641**	0.681**			
Desert	0.756**	0.728**	0.508**	0.722**	0.585**	0.529**		
South Coast	0.933**	0.842**	0.748**	0.863**	0.668**	0.694**	0.693**	

HEAT MAPS

Statewide and sub-regional alignment score heat maps

To assess whether perceived risk (survey results) matched science supply (publications), we calculated science-policy alignment scores (Eq S5) and then plotted them using heat maps. By creating heat maps, we could quickly and visually see the type (or lack) of disconnect between each water quality issue and extreme event, across both statewide and sub-region scales.

$[PR] = matrix\ of\ percevied\ risk\ scores$ (Eq 1), for example: the proportion of respondents reporting that point source pollution is triggered or worsened by drought

$[S] = matrix\ of\ supply\ scores$ (Eq 4), for example: the proportion of publications discussing point source pollution as triggered or worsened by drought

$[A] = matrix\ of\ alignment\ scores\ between\ perceived\ risk\ and\ science\ supply$

$$[\boldsymbol{A}] = [\boldsymbol{PR}] - [\boldsymbol{S}] \qquad \textbf{Eq S5}$$

In the case where [PR] = the proportion of respondents reporting that point source pollution is triggered or worsened by drought and [S] = the proportion of publications discussing point source pollution as triggered or worsened by drought, [A] is the difference between the proportion of respondents and the proportion of publications that link point source pollution and drought. The matrix of alignment scores between perceived risk and science supply, [A], ranges in value from -1 to 1. When [A] = 0, this means science supply meets perceived risk (and vice versa), creating *potential alignment*. When [A] is -1 or 1, this means science is potentially oversupplied (-1) or undersupplied (1). Alignment scores were plotted as heat maps (Figure S1–Figure S9).

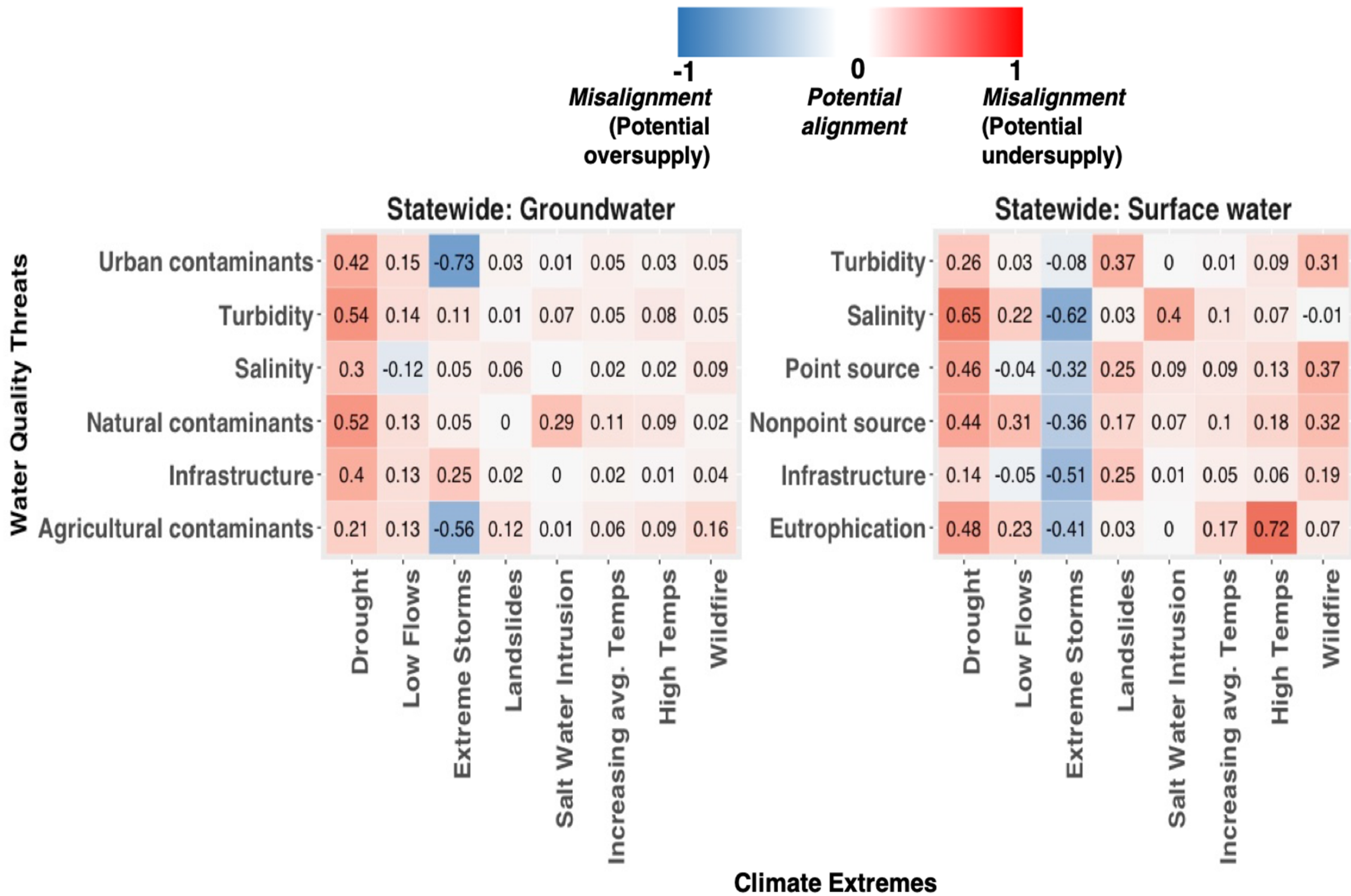

Figure S1. Alignment heat maps for California statewide for utilities with groundwater (left) and surface water (right). Alignment scores were calculated by subtracting science supply from perceived risk. Scores range from -1 to 1 where -1 is potential oversupply (poor alignment), 1 is potential undersupply (misalignment), and 0 is potential alignment.

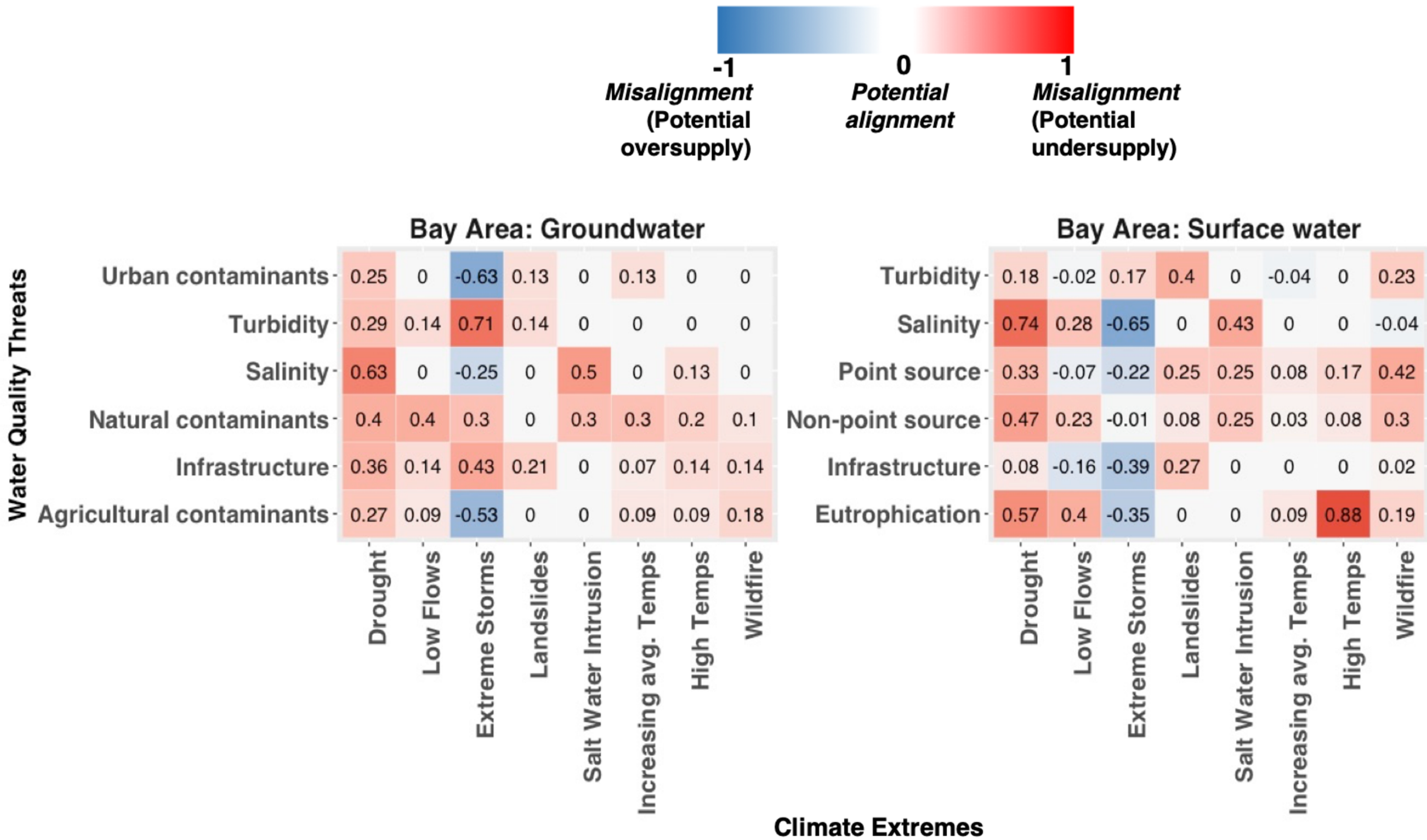

Figure S2. Alignment heat maps for the Bay Area sub-region for utilities with groundwater (left) and surface water (right). Alignment scores were calculated by subtracting science supply from perceived risk. Scores range from -1 to 1 where 1 is potential oversupply (poor alignment), 1 is potential undersupply (poor alignment), and 0 is potential alignment (good alignment).

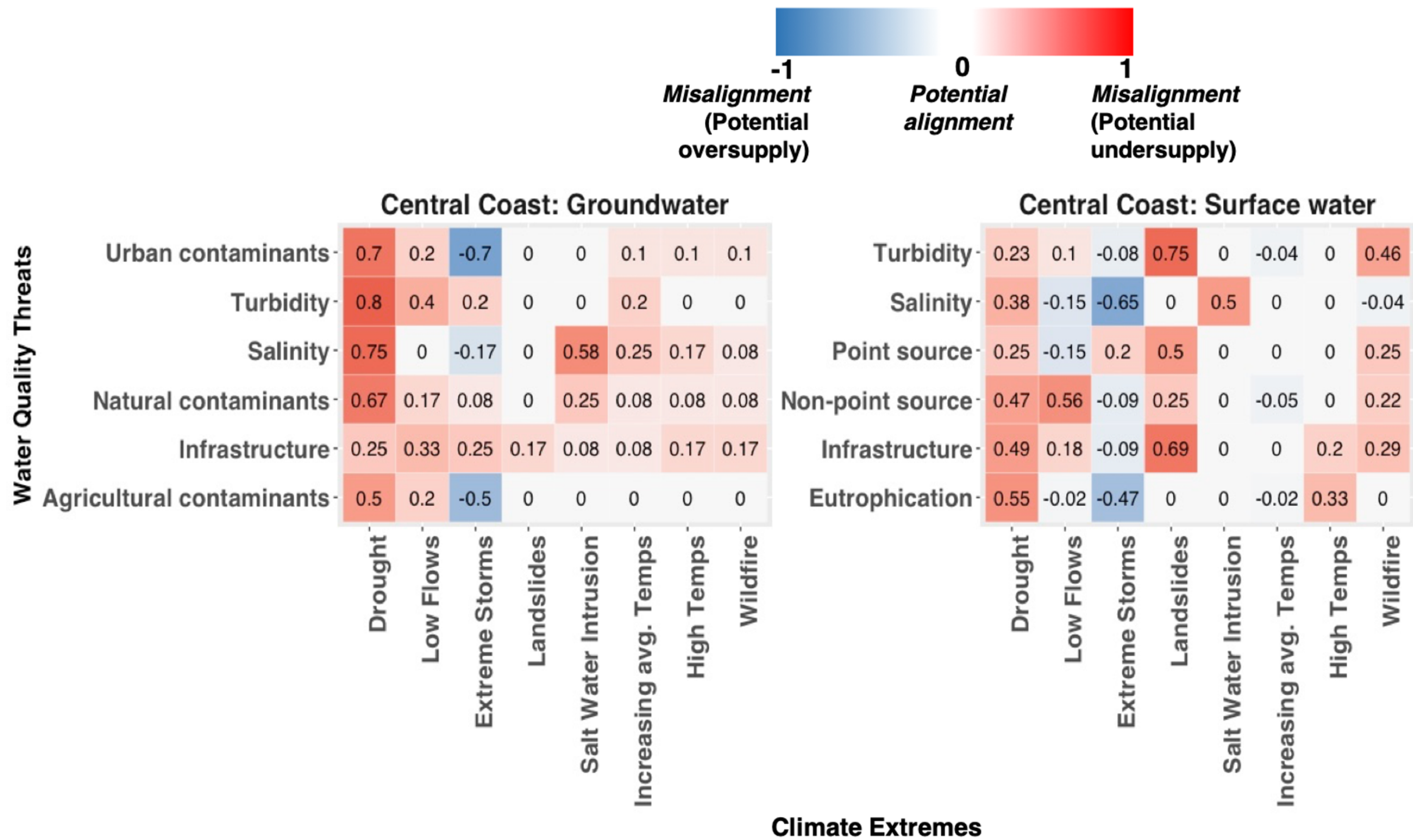

Figure S3. Alignment heat maps for the Central Coast sub-region for utilities with groundwater (left) and surface water (right). Alignment scores were calculated by subtracting science supply from perceived risk. Scores range from -1 to 1 where 1 is potential oversupply (poor alignment), 1 is potential undersupply (poor alignment), and 0 is potential alignment (good alignment).

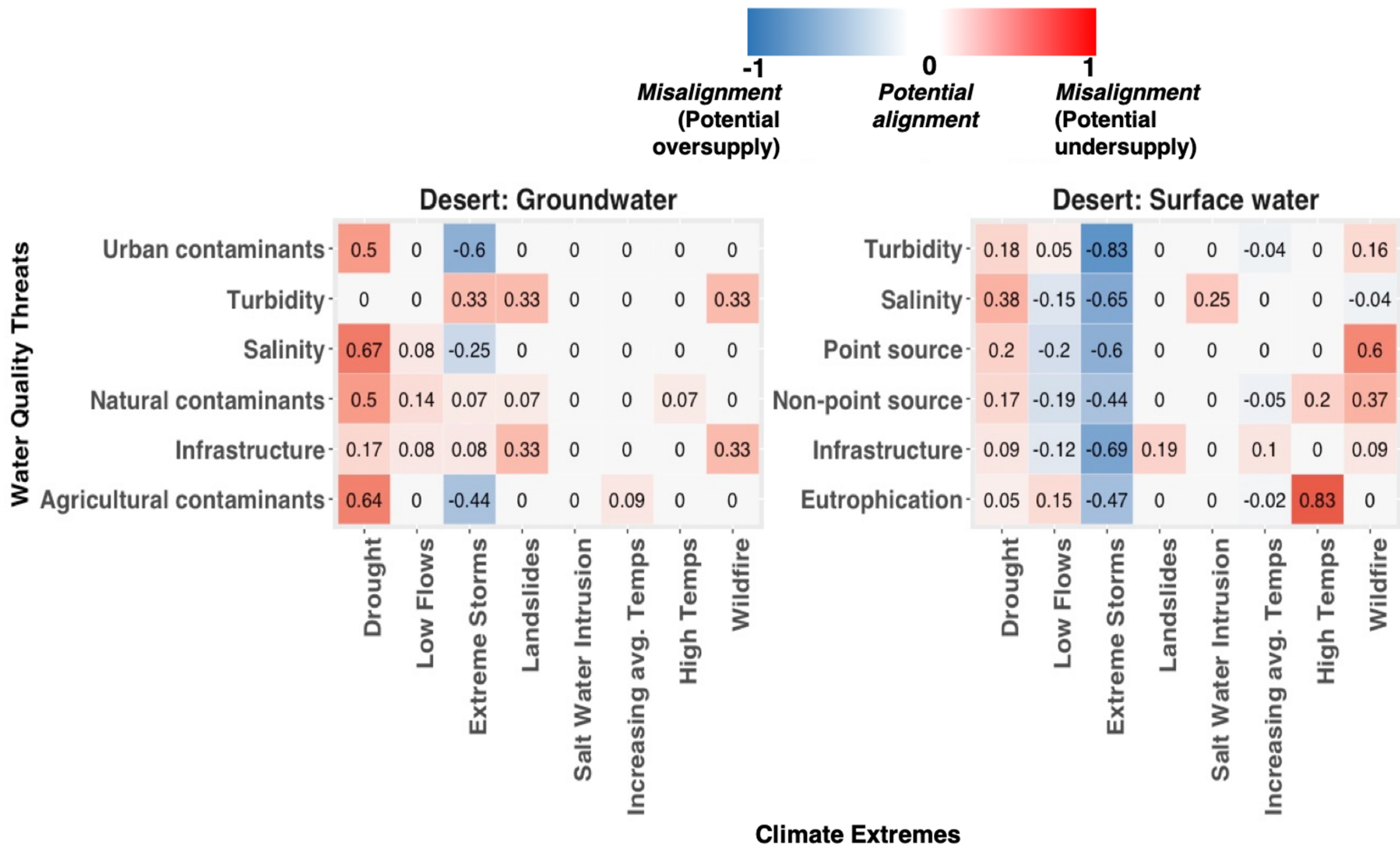

Figure S4. Alignment heat maps for the Desert sub-region for utilities with groundwater (left) and surface water (right). Alignment scores were calculated by subtracting science supply from perceived risk. Scores range from -1 to 1 where 1 is potential oversupply (poor alignment), 1 is potential undersupply (poor alignment), and 0 is potential alignment (good alignment).

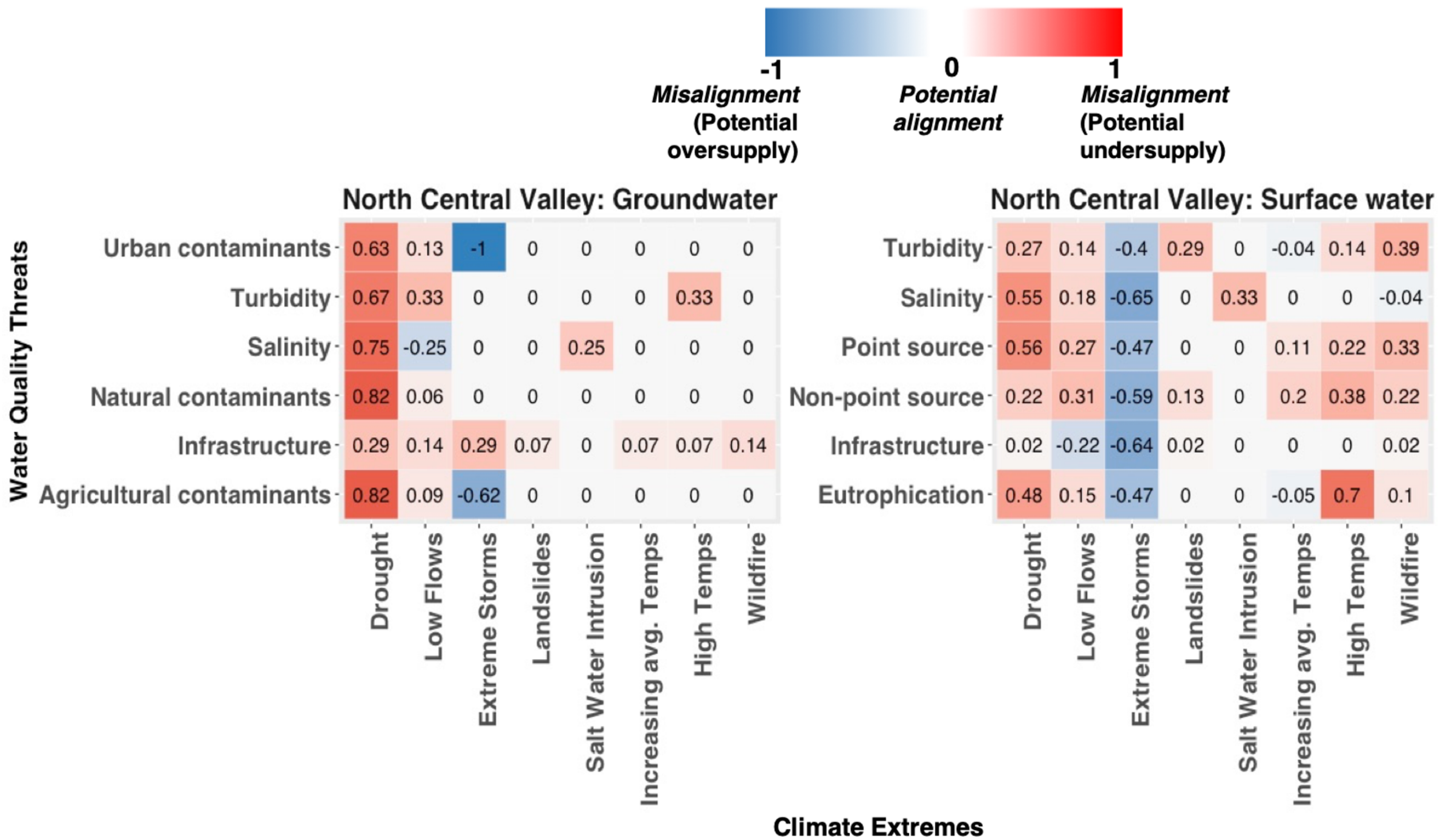

Figure S5. Alignment heat maps for the North Central Valley sub-region for utilities with groundwater (left) and surface water (right). Alignment scores were calculated by subtracting science supply from perceived risk. Scores range from -1 to 1 where 1 is potential oversupply (poor alignment), 1 is potential undersupply (poor alignment), and 0 is potential alignment (good alignment).

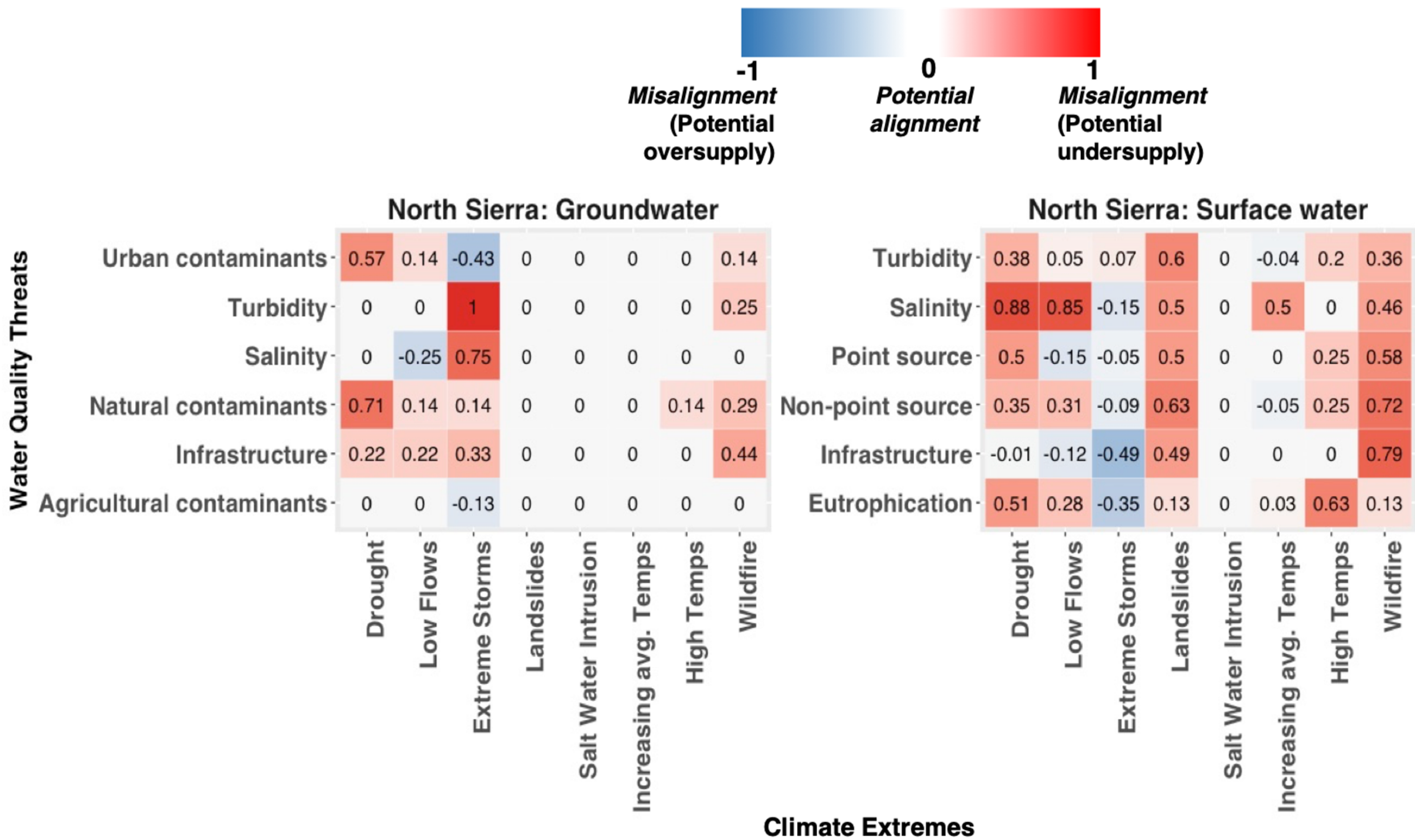

Figure S6. Alignment heat maps for the North Sierra sub-region for utilities with groundwater (left) and surface water (right). Alignment scores were calculated by subtracting science supply from perceived risk. Scores range from -1 to 1 where 1 is potential oversupply (poor alignment), 1 is potential undersupply (poor alignment), and 0 is potential alignment (good alignment).

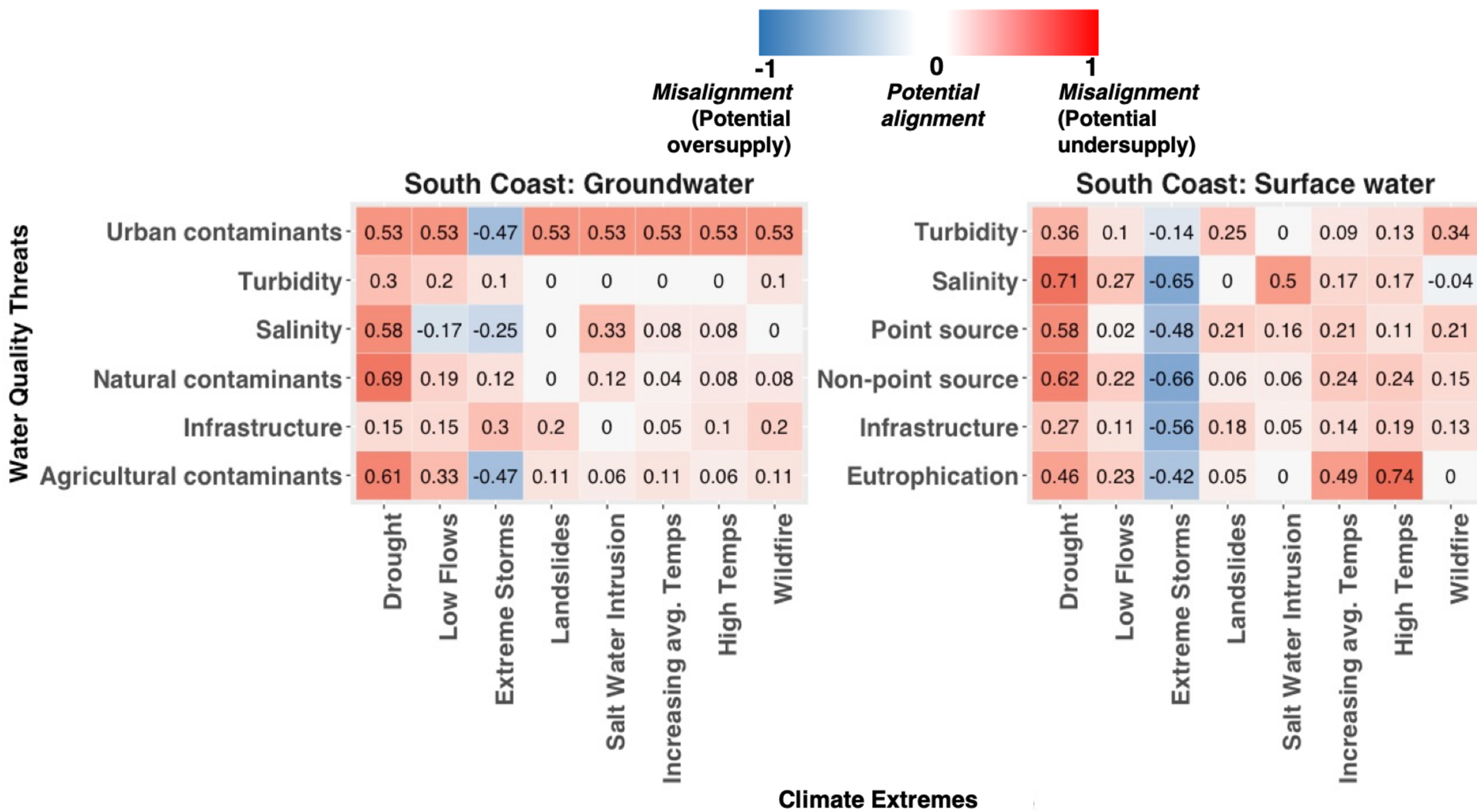

Figure S7. Alignment heat maps for the South Coast sub-region for utilities with groundwater (left) and surface water (right). Alignment scores were calculated by subtracting science supply from perceived risk. Scores range from -1 to 1 where 1 is potential oversupply (poor alignment), 1 is potential undersupply (poor alignment), and 0 is potential alignment (good alignment).

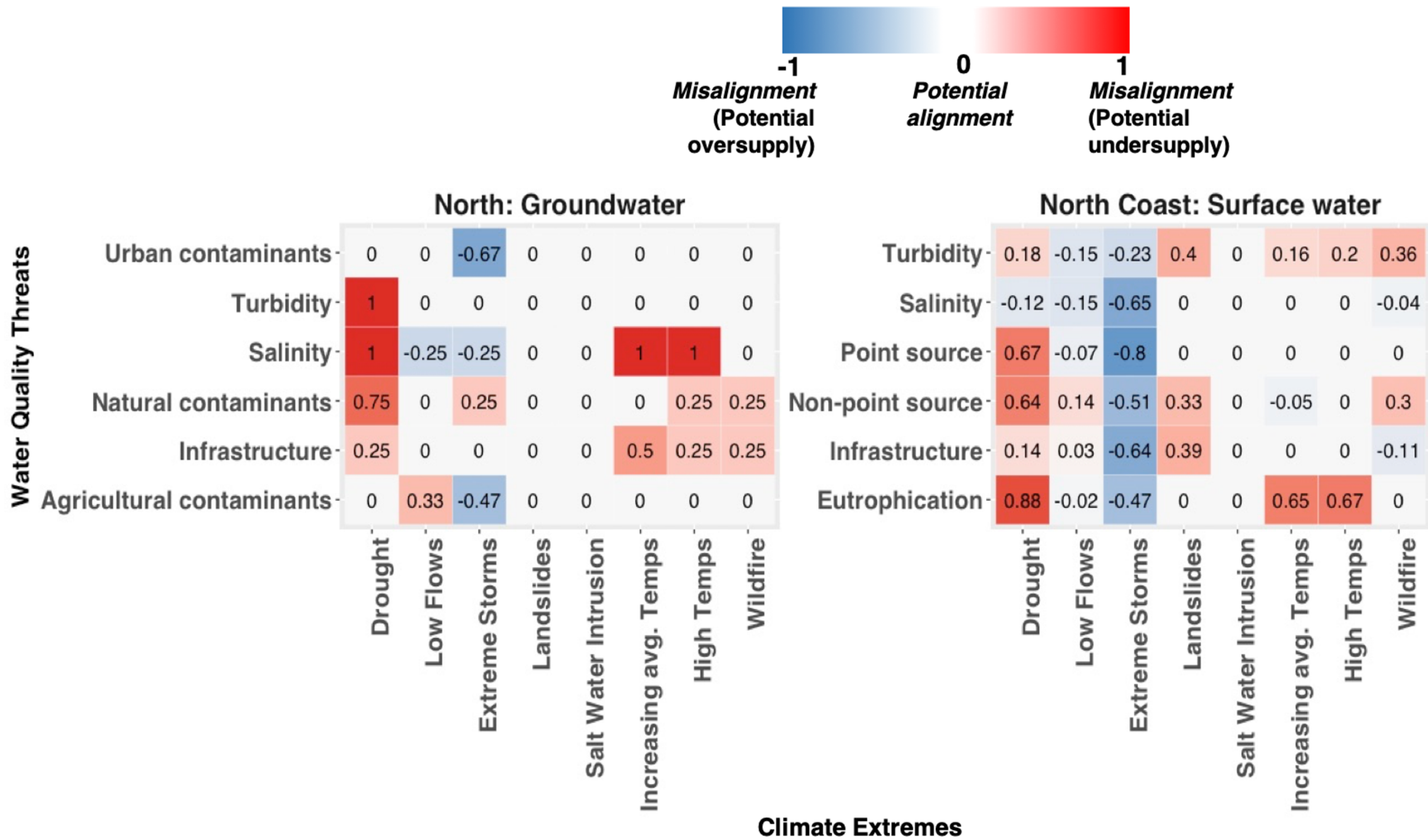

Figure S8. Alignment heat maps for the North sub-region for groundwater (left) and the North Coast sub-region for surface water (right). Alignment scores were calculated by subtracting science supply from perceived risk. Scores range from -1 to 1 where 1 is potential oversupply (poor alignment), 1 is potential undersupply (poor alignment), and 0 is potential alignment (good alignment).

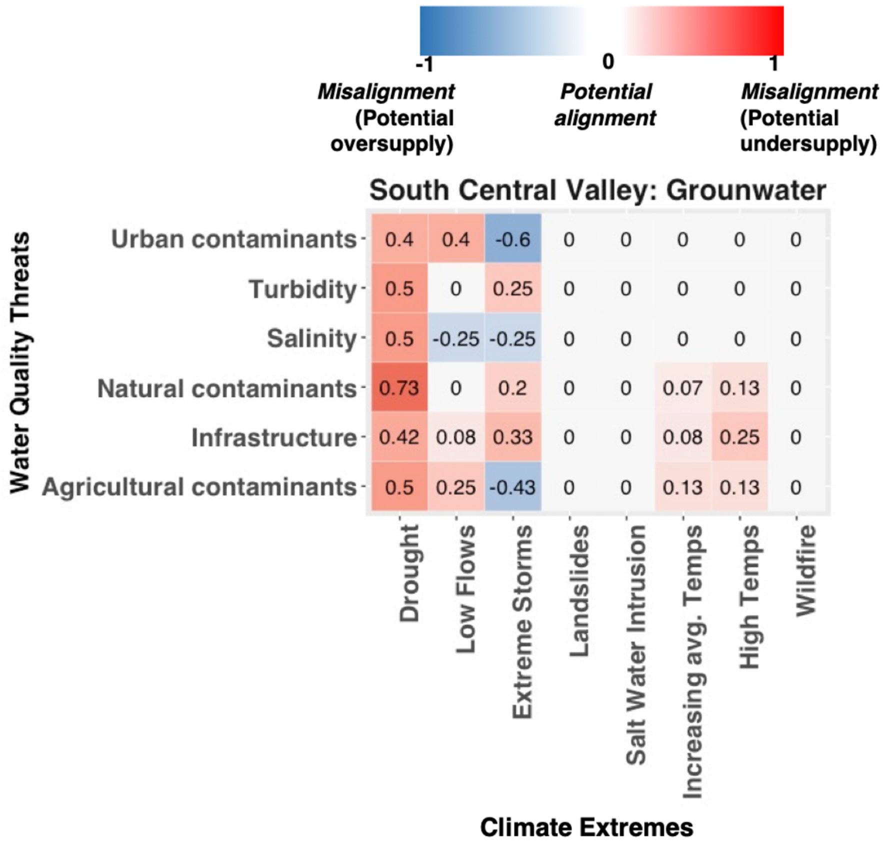

Figure S8. Alignment heat map for the South Central Valley sub-region for groundwater. Alignment scores were calculated by subtracting science supply from perceived risk. Scores range from -1 to 1 where 1 is potential oversupply (poor alignment), 1 is potential undersupply (poor alignment), and 0 is potential alignment (good alignment).

Additional investment prioritization score methodology

After examining the alignment of water quality and extreme events perceived risk and science supply, we then considered priority investments that could potentially lessen the misalignment. Using an adaptation of the alignment scores described above, we constructed an investment prioritization score using two measures: overall alignment for a specific water quality issue and overall alignment for a specific extreme event. As above, alignment, *F,* refers to the alignment between perceived risk and science supply. The metrics were calculated by taking the sum of the absolute value of each alignment, *F,* by (i) water quality issue and (ii) extreme event type. Because alignment, *F,* ranges from -1 to 1, where both negative and positive values represent *poor alignment*, we take the absolute values to calculate a total *poor alignment* score. By taking this approach, we can identify areas with the *poorest* alignment. Investment prioritization scores for both water quality issues and extreme events range from 0 to 6 where 0 represents good alignment and 6 represents the highest level of poor alignment.

$$\sum \left| \boldsymbol{F_{WQI_i}} \right| = \boldsymbol{investment\ prioritzation} \qquad \textbf{Eq S6}$$

$$F_{WQI_i} = fitness\ for\ a\ specific\ water\ quality\ issue\ (i)$$

$$\sum \left| \boldsymbol{F_{EE_j}} \right| = \boldsymbol{investment\ prioritization} \qquad \textbf{Eq S7}$$

$$F_{EE_j} = fitness\ for\ a\ specific\ extreme\ event\ (j)$$

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2. Fracked if you do, fracked if you don't: How does environmental risk shape local policy response to fracking?

INTRODUCTION

Hydraulic fracturing ("fracking") is a process of extracting oil and gas by injecting large volumes of pressurized water, sand, and other chemicals into subterranean shale rock layers, releasing hydrocarbons. Fracking offers potential benefits to local rural economies like job opportunities, reduced consumer oil and gas prices (Maniloff and Mastromonaco, 2017; Sovacool, 2014), and increased household income (Brown et al., 2019). However, fracking also poses several threats to the environment including degrading surface and groundwater quality (Burton Jr. et al., 2014; Rawlins, 2014; Soeder, 2018), impacting drinking water (Boyer et al., 2011; Hill and Ma, 2017; Holzman, 2011; Howarth, Santoro, et al., 2011; Jackson et al., 2013; Osborn et al., 2011), increasing local and regional air pollution and global warming contribution (Howarth, Ingraffea, et al., 2011; Howarth, Santoro, et al., 2011; Zhang et al., 2020; Zielinska et al., 2014), inducing localized earthquakes (Bulgarelli, 2017; Edwards et al., 2021; Ellsworth, 2013; Folger and Tiemann), and negatively impacting human health, especially in vulnerable populations like pregnant women and infants (Busby and Mangano, 2017; Casey et al., 2016; Coons and Walker, 2008; Hill, 2018; McDermott-Levy et al., 2013; Strauss et al., 2013). Every stage of the fracking process may impact the environment, but the full scope of these impacts is not yet understood. Current research focuses on distance; that is the distance from fracking wells (to water sources, drinking water, monitors, residences, etc.) at which environmental impacts can be measured (Dokshin, 2021; Hays et al., 2017; Meng, 2015; Meng and Ashby, 2014; Wilson et al., 2018). In fact, research has been so plentiful that Meng and Ashby (2015) go so far as to say that 1km from fracking wells is a critical distance for measuring environmental impacts; in other words, within 1km distance of fracking wells, environmental risk is highest.

It is reasonable to expect that jurisdictions (in this paper, we focus on sub-state jurisdictions, specifically townships, villages, boroughs, cities, and counties) may adopt policies to minimize these environmental impacts. But does actual environmental risk drive this policy adoption? Literature discusses how state regulatory structures (Davis, 2017), community and municipal capacity (Arnold and Neupane, 2017; Berry and Berry, 1990; Feiock and West, 1993; Krause, 2011b; Mooney, 2001; Ringquist, 1994; Sapat, 2004; Zahran et al., 2008), and sociodemographics (Arnold and Neupane, 2017; Barnes, 2013; Lubell et al., 2009; Scholozman et al., 2004; Verba et al., 1995; Walsh et al., 2015; Zirogiannis et al., 2014) may shape local policy adoption, however research studying how environmental risk shapes local environmental policy adoption is nascent and tends to focus on *perceived risk* (e.g., Stoutenborough et al., 2015). There is little research on how actual environmental risk, measured here as proximity from fracking wells to sub-state jurisdictional boundaries, influences local environmental policy adoption.

To address this knowledge gap, we combine fracking well data with the results of a survey distributed to government officials in Ohio, West Virginia, and Pennsylvania. Based on scientific studies of proximity and fracking, we select a range of distances that researchers argue represent the largest environmental impact. We use this range of distances as proxies for environmental risk, where distances more proximate to fracking wells represent higher environmental risk and distances more distant represent lower environmental risk. We then fit logit models to the well data, distance information, and survey data to test whether environmental risk, measured as the well density at a distance that a municipality is from fracking wells, drives local environmental policy adoption in response to fracking. In this paper, we treat policy adoption as a dichotomous dependent variable that indicates whether a sub-state jurisdiction adopted any of five different types of environmental policies in response to fracking. This research contributes to understanding the determinants of local policy adoption and more specifically, within literature on fracking, how municipalities interact with and respond to environmental risk. We begin with an overview of fracking before turning to a review of existing literature on environmental impacts of fracking and drivers of local policy adoption. We then discuss the data and methods used to explore the role of environmental risk in shaping policy adoption, before concluding with our findings and the implications for future research.

BACKGROUND AND THEORY

Overview of Fracking

Hydraulic fracturing (fracking) is a process of extracting oil and gas by injecting large volumes of pressurized water, sand, and other chemicals into subterranean shale rock layers, releasing hydrocarbons. It differs from traditional oil and gas drilling because it involves both vertical drilling and horizontal or curved drilling to access oil and gas deposits in shales. This new drilling approach, which made shale production economically feasible, spurred a fracking boom in the United States in the mid-2000s. With the promise of high economic gain from fracking, subsequent energy-related policy often erred on the side of industry, further accelerating the fracking boom (Robbins, 2012). For example, the Energy Policy Act of 2005 exempted fracking from Safe Drinking Water Act regulations, thereby reducing some regulatory constraints. In addition to promising high profits, fracking is touted for its positive economic benefits to local communities. However, with these benefits, fracking introduces myriad adverse impacts to the local and regional environment. These impacts arise from all stages of fracking.

There are six stages in the full fracking process, including site preparation, drilling, well completion, fracking, production, and well plugging. Site preparation involves designating or building access roads and constructing well pads. Suitable locations are typically between 4 and 5 acres in size, compared to tradition drilling which uses 1.5 to 3 acres (Meng, 2015). Land may need to be clear-cut if trees and vegetation will threaten well infrastructure. Heavy load trucks carry equipment like rigs, drill bits, storage tanks, and pipes, as well as water, chemicals, and other supplies, to the drilling site. Once the site is prepared, an operator drills vertically down to a *kick-off point*, approximately 100 feet below the deepest known groundwater aquifer; from here, the operator drills horizontally up to 2km from the kick-off point (Pearson, 2016). Following drilling, during the well completion stage, operators first replace the drill pipe with an impermeable steel pipe and cement it in place for fracking. Operators then lower a perforating gun loaded with explosive charges, into the well. The detonated explosives perforate the steel pipe in preparation for the fracking stage. It takes between 3 and 5 months to develop a well site from preparation to well completion (UKOOG, 2017). Following well completion, the fracking process begins with operators injecting between 1,800,000 and 4,800,000 gallons of highly pressurized fracking fluid into the well to create cracks in the shale rock (Arthur and Layne, 2008). By creating these cracks, operators release oil and natural gas deposits. The process of fracking extends along the length of the horizontal well and though repeated several times, only takes a few days to complete (Pearson, 2016). Once the entirety of the well has been fracked, operators then transition to the production stage. As hydrocarbons flow through and up the well, between 5% and 85% of the fracking fluid (Vidic et al., 2013), now combined with naturally occurring metals and contaminants returns to the surface as *produced water*. Produced water is either treated onsite, stored, and later reused, injected into deep wells, or transported offsite for treatment (Gallegos et al., 2015; Gregory et al., 2011). During the production stage, it is also possible that operators will re-frack the well to provide for better production. When a well no longer produces, potentially 20 to 40 years later (Coloradans for Responsible Energy Development, 2014), the fracking process enters its final stage, well plugging. During the well plugging stage, all temporary equipment like trucks and rigs are removed from the well site, stoppers are inserted into the well at various intervals to prevent fluid flow, and the land is reverted to pre-fracking activities. Some fracking wells may be *orphaned,* meaning left without proper plugging; there are an estimated 300,000 orphaned oil and gas wells in the United States (Nikulin and de Smet, 2019).

Environmental Impacts from Fracking

Environmental impacts may occur because of fracking operations like land clearing during site development or as spills, leaks, and other accidental events (Gordalla et al., 2013). A large emphasis in the literature focuses on measuring fracking's spatially and temporally diverse environmental impacts (e.g., Black et al., 2019; Burbidge and Adams, 2020; Dokshin, 2016; Goodman et al., 2016; Meng, 2014, 2015, 2018; Zwickl, 2019). Although results vary depending on the type and nature of the pollutant measured, studies generally find that impacts are greatest in closer proximity to fracking wells, but may still be detected at greater distances (Bonetti et al., 2021; Currie et al., 2017; Meng, 2015; Zhang et al., 2020). With this in mind, we conceptualize levels of *environmental risk* to jurisdictions as a gradient of distances based on proximity to fracking wells, where more proximate distances represent a higher environmental risk and more distant distances represent a lower environmental risk (Figure 6).

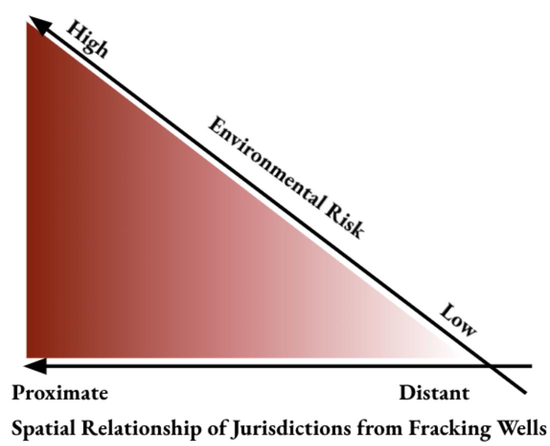


Figure 6. Conceptualization of environmental risk as ranging from low to high on the z-axis based on a jurisdiction's distance from fracking wells on the x-axis. Darker red represents higher environmental risk occurring at more proximate distances between jurisdictions and fracking wells and lighter red represents lower environmental risk occurring at more distant distances between jurisdictions and fracking wells (constructed based on research by Bonetti et al., 2021; Casey et al., 2016; Coons and Walker, 2008; Currie et al., 2017; Drollette et al., 2015; Fontenot et al., 2013; Hill and Ma, 2017; Jackson et al., 2013; Janitz et al., 2019; McKenzie et al., 2012; Meng, 2015; Meng and Ashby, 2014; Osborn et al., 2011; Rabinowitz et al., 2015; Steinzor et al., 2013; Vidic et al., 2013; Whitworth et al., 2017; Willis et al., 2021; Yan et al., 2017; Zhang et al., 2020)

Using this conceptualization of environmental risk, we review existing studies that empirically test for environmental impacts at differing distances from fracking wells and activity. We summarize this literature in Table 5. This table is not meant to be exhaustive but rather to provide an overview of distances from fracking activity at which existing researchers measured environmental impacts. Additionally, not every paper found all parameters studied (e.g., methane, particulate matter) at every distance. For example, Whitworth et al. (2017) finds greater likelihood of preterm birth when women live within 0.8km, 3.2km, or 16km compared to women who don't have any proximate fracking wells, but they did not find correlations between term birth weight at these distances; in Table 1, we report only the former results. With this in mind, in Table 5, we only discuss study findings of measured environmental impact at some distance or distances. Further, we found that some studies incorporated distance into other measurements for analysis; this is particularly prevalent in public health research that calculates some level of fracking exposure using inverse distance weights whereby distances more proximate to wells receive greater weighting (e.g., Casey et al., 2016, 2019; Whitworth et al., 2017; Willis et al., 2021). For example, Casey et al. (2019) constructed a fracking activity exposure index that divides number of wells, days of fracking stages, well depth, and volume of gas by the distance from the fracking well to the residential address. In these studies, a closer distance may result in a larger fracking exposure score. Because these studies measure environmental impact based on residences within a certain distance to fracking wells, we include them in Table 5. Below Table 5, we provide additional discussion of environmental impacts discussed in the fracking literature focusing on air quality, water quality, and public health.

Table 5. Summary table of empirical studies measuring environmental impacts of fracking. Results are discussed narratively in-text below the table. Data are categorized by environmental impact type and thus a citation may appear more than once if that paper discussed more than one environmental impact type. When studies provided distances in units other than km, we adjusted them so that all distances are in kilometer units. The *State studied* column identifies the state in which the study was conducted; it does not imply that the study was statewide. Rows shaded grey represent studies that incorporate distance into other measurements for analysis.

Citation	Impact type	Distances at which one or more parameters are found	Brief description of parameters found	State studied
(Zielinska et al., 2014)	Air Quality	0.017km, 0.067km	Distance measured from fracking well. Increased concentrations of: Isopentane, pentane, hexane,	Texas

			benzene, cyclohexane, heptane, toluene, octane, ethylbenz, m&p xylene, o xylene, nonane, 1,3-butadiene, and Volatile organic compounds (ethane, propane, n-butane, isobutane, isopentane, n-pentane). Higher concentrations closer to fracking wells.	
(Zhang et al., 2020)	Air Quality	0-2km, 2-5km, 5-10km, 3km	Distance measured from centroid of fracking well. Particulate matter (PM2.5) concentrations decrease as distance from fracking wells increases. Increased PM2.5 levels equate to 20.11 additional deaths between 2010 and 2017.	Pennsylvania
(Casey et al., 2016)	Public Health	0-20km	Distance measured from fracking well to residences and considered as denominator of fracking activity index. Exposure split into quartiles with quartiles 1-3 as lower activity. Fourth quartile associated with lower term birth weight and increased odds of high-risk pregnancy. Increased odds of preterm birth across all quartiles.	Pennsylvania
(Casey et al., 2019)	Public Health	0-20km	Distance measured from fracking well to residences and considered as denominator of fracking exposure index. Exposure split into quartiles with quartiles 1-3 as non-exposure. Fourth quartile associated with 4.3 additional preterm births per 100 women and 4.3 additional cases of antenatal anxiety or depression per 100 women. Increasing prevalence of antenatal anxiety or depression across quartiles.	Pennsylvania
(Coons and Walker, 2008)	Public Health	0-0.075km, 0-0.05km, 0-0.25km, 0-0.5km	Distance measured from fracking well in downwind direction. EPA's acceptable value for cancer risk is	Colorado

			exceeded for Benzene. Reference concentrations for Benzene, m,p-xylenes, and volatile organic compounds exceeded.	
(Currie et al., 2017)	Public Health	0-1km, 1-2km, 2-3km	Distance measured from fracking sites to residences. Increased probability of low birth weight, reduced average birth weight, and reduced infant health. Lower infant health at distances closer to fracking wells.	Pennsylvania
(Hill, 2018)	Public Health	0-2.5km, 3.5km	Distance measured from fracking sites to residences. Increased likelihood of low birth weight and small for gestational age; lower average term birth weight and birth weight. Increased likelihood of lower APGAR (metric based on newborn health where higher scores indicate better health).	Pennsylvania
(Hill, 2021)	Public Health	0-1km, 1-5km	Distance measured from fracking sites to residences. Reduced birth weight, lower average gestation length, and increased prevalence of low birth weight and premature birth. Increased gestational diabetes and hypertension in mothers. Impacts greatest closer to wells.	Colorado
(Janitz et al., 2019)	Public Health	0-8.04km, 16km	Distance measured from fracking wells to residences. Mothers split into tertiles based on fracking activity within 8.04km buffer and compared to birth mothers residing outside the 8.04km buffer (no exposure). Increased, prevalence of neural tube defects (quartile 2 and 3), and elevated prevalence of common truncus, transposition of the great arteries, pulmonary valve atresia and	Oklahoma

			stenosis, tricuspid valve atresia and stenosis, interrupted aortic arch, total anomalous pulmonary venous connection when comparing any quartile to no exposure. Increased prevalence proportion ratios for spina bifida and cleft palates (though these latter two are not significant) between all quartiles and no exposure. Some consistent impacts out to 16km. Impacts greatest closer to fracking activity.	
(McKenzie et al., 2012)	Public Health	0-0.8km, 0.8km	Distance between fracking wells and residences. Chronic and sub-chronic cancer and non-cancer health impacts higher closer to fracking activity but measurable beyond 0.8km. Pollutants driving each type of impact vary across distances and type of impact (neurological, developmental, respiratory, and hematologic). Some main pollutants studied include: 1,2,3-Trimethylbenzene, n-Hexane, n-Nonane, n-Pentane, Styrene, Toluene, Xylenes, Aliphatic hydrocarbons, Propylene, Aliphatic hydrocarbons, Aromatic hydrocarbons, Ethylbenzene, and 1,3,5-Trimethylbenzene, Cyclohexane, and n-propylbenzene) distress.	Colorado
(McKenzie et al., 2017)	Public Health	0-16.1km	Distance measured from fracking well to residences and considered as part of an inverse distance weight where more weight is given to more proximate distances. Data split into tertiles and compared to controls. Acute lympocytic leukemia (ALL) cases more likely	Colorado

			to occur in the highest tertile across all children aged 0-24. ALL cases more likely in highest tertile children aged 5-24 and likelihood of ALL increased from first to third tertile.	
(Rabinowitz et al., 2015)	Public Health	0-1km, 1-2km, >2km	Distance measured from fracking well to residences. Higher average number of reported symptoms closer to fracking wells but symptoms reported out beyond 2km. Residents closer to wells more likely to report skim conditions and upper respiratory conditions when compared with more distant residents.	Pennsylvania
(Steinzor et al., 2013)	Public Health	0.1-8km, 0.1-0.46km, 0.46km-8km	Distance measured from fracking well to residences. Percentage of respondents reporting symptoms decreases as distances from wells increases. Symptoms included throat irritation, sinus problems, and severe headaches. Of the top 20 symptoms reported, 18 were reported by a higher percentage of respondents living within 0.46km than further from wells. Symptoms included: throat irritation, sinus problems, nasal irritation, eye burning, joint pain, severe headaches, sleep disturbance, skin rashes, shortness of breath, forgetfulness, sleep disorders, loss of sense of smell, persistent cough, frequent nose bleeds, swollen painful joints, lumbar pain, muscle aches or pain, and diarrhea. Environmental testing found concentrations of benzene, toluene, ethylbenzene, xylene,	Pennsylvania

			chloromethane, carbon disulfide, trichlorethylene and acetone at households where participants reported associated symptoms. Water tests found iron, manganese, arsenic, and lead in concentrations above state limits in water well samples. Tests also found concentrations of methane, bromide, sodium, strontium, and total suspended solids but there are no current standards for these parameters.	
(Walker et al., 2018)	Public Health	0-0.8km	Distance measured from fracking well to residences and considered as denominator of fracking activity metric. Distances were constrained to 0.8km maximum. Data split into tertiles and women with no fracking within 0.8km of their residence served as the reference group. Higher likelihood of preterm birth found between each tertile and reference (highest and significant for third tertile). Higher likelihood of extremely preterm births in highest tertile.	Texas
(Whitworth et al., 2017)	Public Health	0-0.8km, 0-3.2km, 0-16km	Distance measured from fracking well to residences and considered as denominator of fracking activity metric. Fracking activity calculated for three distance buffers. Women with no wells within 16km of residence served as reference group. Each study group split into tertiles. Increased likelihood of preterm birth found in the highest tertile for all distances. Increased likelihood fetal death found at greater distances.	Texas
(Willis et al., 2021)	Public Health	0-3km, 3-10km, 1-2km vs	Distance measured from fracking well to residences. Births from	Texas

		3-10km, 2-3km vs 3-10km	mothers residing within 3km of a fracking well are exposed and births from mothers residing between 3 and 10km are the reference group. Lower birth weights and higher likelihood of term small for gestational age found closer to fracking wells but trends extend to 10km distance.	
(Bonetti et al., 2021)	Water	0-5km 0-10km 0-15km	Distance measured from fracking well to water monitoring stations. Measured concentrations of bromide, chloride, barium, and strontium are highest when wells are more proximate to monitoring stations. Concentrations persist out to at least 15km.	United States and Pennsylvania
(Drollette et al., 2015)	Water	0-1km	Distance measured from fracking well to residential groundwater wells. Significantly higher concentration of diesel range organic compounds in groundwater wells more proximate to fracking. Gasoline range organic compounds found higher within 1km of fracking (not significant). Volatile organic compounds (e.g., benzene, toluene, ethylbenzene, xylenes) found in some samples (below contaminant thresholds).	Pennsylvania
(Fontenot et al., 2013)	Water	0-3km, 3km	Distance measure from fracking well to residential drinking water wells. Higher concentrations of arsenic, selenium, strontium, and barium in drinking water wells more proximate to fracking. Arsenic, selenium, strontium, and total dissolved solids concentrations exceeded contaminant threshold in some cases. Concentrations also found at distances greater than 3km but	Texas

			generally at smaller levels.	
(Hildenbrand et al., 2016)	Water	5km	Distance measured from fracking well to residential water wells. Some cases of contaminant threshold exceedance for: total dissolved solids, pH, arsenic, beryllium, chromium, copper, iron, molybdenum, and dichloromethane. Statistically higher concentrations from reference group for pH, total organic carbon, inorganic carbon, copper, cyclohexane, ethanol, and dichloromethane. Statistically lower concentrations from reference group for dissolved oxygen, selenium, and strontium.	Texas
(Hill and Ma, 2017)	Water	0-0.5km, 1km, 1.5km, 2km, 10km	Distance measured from fracking well to community water system groundwater source intakes. Highest levels of contaminants measured at more proximate distances to fracking wells. Contaminant levels decrease as distance increases. Further distances are not statistically significant. Specific contaminants measured not identified in the manuscript.	Pennsylvania
(Jackson et al., 2013)	Water	0-1km	Distance measured from fracking well to drinking water wells. Methane, ethane, and propane concentrations found to be significantly higher in wells more proximate to fracking. Distance found to be a statistically significant determinant of contaminants.	Pennsylvania
(Osborn et al., 2011)	Water	0-1km, 1.8km	Distance measured from fracking wells to drinking water wells. Average and maximum methane	New York and Pennsylvania

			concentrations highest at closer distances to fracking wells. Concentrations decrease as distance from fracking wells increases; measurements to 1.8km.	
(Yan et al., 2017)	Water	0-1km	Distance measured from fracking wells. Study uses the National Hydrography (NHD) flowline or minor tributary of NHD flowline to identify water impacts. Calcium, chloride, methane, sodium, sulfate, iron, and manganese levels significantly higher in closer proximity to fracking wells than further.	Pennsylvania

<u>Summary of Distance Literature</u>

There are a wide range of distances at which environmental impacts have been measured by the literature. This variation is also common within each environmental impact category. Generally, research measuring environmental impacts from fracking notes that concentrations of pollutants increase as distances to fracking wells decreases (Bonetti et al., 2021; Currie et al., 2017; Fontenot et al., 2013, 2013; Hill, 2021; Hill and Ma, 2017; Jackson et al., 2013; Janitz et al., 2019; Osborn et al., 2011; Rabinowitz et al., 2015; Steinzor et al., 2013; Willis et al., 2021; Zhang et al., 2020; Zielinska et al., 2014). Air quality impacts are generally measured closer to fracking wells, however, given the potential of wind patterns, weather, and other confounding factors, fracking may have more regional impacts (Zhang et al., 2020). Comparatively, public health studies tend to consider a much larger set of distances (up to 20km), likely a reflection of limited data points available. In the literature we reviewed for this paper, the average distance at which environmental impacts are measured is about 4.79km. Other research has pointed to 1km as the key distance for measuring environmental impact (Meng and Ashby, 2014). As our literature review is not comprehensive, we do not purport to claim that 4.79km is a crucial distance. Instead, we provide it as a discussion point for future consideration. Given the wide range of distances covered in environmental impact literature, we test a series of distances from 0.5km to 20km. In this way, we explore several potentially important distances across environmental impact types. We now turn to a more explicit discussion of environmental impacts.

Air Quality Impacts

Air quality impacts from fracking begin during site development and carry through to well plugging. Supplying an individual fracking well may require an average 2,000-3,000 truck trips for transporting water and materials (Olmstead et al., 2013; Xu and Xu, 2020). Transportation in the fracking process emits volatile organic compounds (VOCs), nitrogen oxides (NOx), and PM2.5, however the emissions from transportation are much smaller compared with the emissions of these pollutants from later stages in the fracking process (Litovitz et al., 2013). Transportation of sand specifically for fracking fluid exposes drilling operators to respirable silica (Moore et al., 2014). As operators begin site clearing and constructing storage ponds, some pollutants, like PM2.5, and nitrogen oxides (NOx) may be further emitted from equipment use (Bar-Ilan et al., 2010; Kováts et al., 2013; Zielinska et al., 2004). While preparing a single well can be completed in only a few weeks, several wells may be prepped on a well pad simultaneously (Coloradans for Responsible Energy Development, 2014). Initial vertical drilling may release pockets of methane and ethane, but quantifying these emissions is difficult (Moore et al., 2014). Rigs and pumps used during the drilling and fracking stages may be responsible for between 12 and 39% of NOx emissions from the fracking process (Bar-Ilan et al., I; Litovitz et al., 2013). As produced water emerges from wells during the fracturing stage, additional heavy trucks may move wastewater offsite. This large quantity and frequency of truck trips results in air pollutant emissions, especially PM2.5, PM10, NOx, carbon dioxide, BTEX[1], PAH[2], and dust (Srebotnjak and Rotkin-Ellman, 2014). During the well completion stage, additional quantities of BTEX and NOx, as well as methane, carbon dioxide, and

[1] Benzene, toluene, ethylbenzene, xylene
[2] Polycyclic aromatic hydrocarbons

hydrogen sulfide may be emitted during venting and flaring (ATSDR, 2019; McKenzie et al., 2012; Moore et al., 2014). As production begins and hydrocarbons are extracted and processed, air quality concerns focus on equipment faults, leaks, flares, maintenance emissions, and compressor stations (used in processing). This stage of fracking may produce the highest quantity of air emissions in terms of VOCs, NOx, PM2.5, and sulfur oxides (Litovitz et al., 2013), but also produces carbon dioxide and methane (Srebotnjak and Rotkin-Ellman, 2014). In studies measuring air quality impacts at different distances from fracking operations, Zhang et al. (2014) found that concentrations of PM2.5 are highest within 2km of fracking wells but may be measurable out to 30km. Zielinska et al. (2014) on the other hand, found that air pollutant concentrations return to background levels at distances beyond 0.1km downwind of a well; however, they noted that topography and wind direction may lead to variations in air impacts. Methane emitted from fracking is particularly important to quantify given its global warming potential; methane can capture 25 times more heat than carbon dioxide (USEPA, 2016). However, quantifying methane emissions from fracking is difficult and modeled results claim that anywhere between 4% (Tollefson, 2012) and 7.9% (Howarth, Santoro, et al., 2011) of methane emitted during gas production is lost to the atmosphere. Another study of seven fracking well pads found that 34g of methane per well are emitted each day (Caulton et al., 2014). None of these studies explicitly consider distance from fracking wells at which impacts are measured, most likely because the contribution of methane to global warming is better measured on a global scale, in which distance may not factor.

Water Quality Impacts

Both water quality and water quantity are impacted by fracking activities (Torres et al., 2016). Fracking requires immense quantities of water for initial drilling, the fracking process, and well infrastructure; each well may demand between 1 million and 13 million gallons (Cooley and Donnelly, 2014; Nicot et al., 2011; Robbins, 2012). The amount required is a function of well construction and design and the geology of the well site (Torres et al., 2016). Between 2013 and 2018, the total amount of water required by fracking in the United

States increased from 75.6 billion gallons to 205.8 billion gallons (Rystad Energy, 2021). As a result of the huge water demand, local groundwater and surface water sources may be impacted and some fracking operations have turned to reuse and recycling to meet their needs (Groom, 2015). Most of the water is used during the fracking stage to break up shale layers and release hydrocarbons. Fracking involves injecting a pressurized proprietary blend of water, sand (or another proppant), and chemicals into shale formations; about 750 different chemicals were used in proprietary blends between 2005 and 2009 (Ferrer and Thurman, 2015). There are three primary water quality concerns stemming from the fracking stage. First, well sites may experience spills or leakage of fracking fluid blends into the surrounding environment and water resources. While fracking typically occurs thousands of feet away from groundwater resources, drilling proceeds through shallower groundwater aquifers, potentially threatening water quality (Torres et al., 2016). Second, as the fluid fractures shale to release hydrocarbons, it may also accidentally infiltrate groundwater resources (Jackson et al., 2013; Osborn et al., 2011). Third, about 75% of injected fluid returns to the surface as produced water (Mooney, 2011), which may contain salt, oil and grease, chemical additives, and naturally-occurring organic and inorganic compounds and radioactive materials that are released during underground agitation (USEPA ORD, 2012). If produced water is not properly managed as waste, it can contaminate local soils and waters. Much of the research measuring water quality impacts from fracking, aims to capture pollutants associated with the fracking fluid and produced water.

Impacts of fracking fluid on drinking water are of particular concern given the number of people living proximate to fracking wells that obtain water from drinking water wells; in the United States, more than half of fracking wells are located within 2-3km of a domestic well (Jasechko and Perrone, 2017). Many of the studies measuring the impacts of fracking on drinking water quality compare the pollutant concentrations of drinking water samples at varying distances from fracking wells (Fontenot et al., 2013; Hildenbrand et al., 2016; Hill and Ma, 2017; Jackson et al., 2013; Osborn et al., 2011). These studies find that drinking water wells located closer to fracking wells have poorer water quality (measured as higher pollutant concentrations). Hill and Ma (2014) found that pollutant concentrations were highest in drinking water wells when located within 0.5km of a fracking well, followed by drinking water wells located within 1km of a fracking well. While pollutant concentrations were highest in drinking water wells more proximate to fracking wells, Hill and Ma (2014) also found elevated pollutant concentrations in wells up to 10km away from fracking. Several studies compare pollutant concentration levels in residential drinking water wells located within 1km of a fracking well to concentration levels in drinking water wells located more than 1km from fracking. These studies find higher pollutant concentrations in drinking water wells located within 1km of fracking for gasoline, organic compounds, and diesel (Drollette et al., 2015), calcium, chloride, sulfate, iron, total dissolved solids, conductivity, sodium, and chloride (Yan et al., 2017), and methane in drinking water walls (Jackson et al., 2013; Osborn et al., 2011). Several methane concentrations found in these latter two studies exceeded the 10mg/L hazard mitigation concentration level (Jackson et al., 2013; Osborn et al., 2011; Vengosh et al., 2013) Fontenot et al. (2013) compared pollutant concentration levels in drinking water wells within 3km of a fracking well to drinking water wells further than 3km from a fracking well and found that arsenic, selenium, strontium, and total dissolved solids exceeded maximum contaminant levels in some samples drawn from drinking water wells within 3km of fracking wells but remained *below* maximum contaminant levels in drinking water wells located more than 3km from fracking wells. More broadly, Bonetti et al. (2021) assessed levels of salts (bromide, chloride, barium, and strontium) associated with fracking brines in surface water samples collected in known fracking regions across the United States; they found elevated concentrations of all four salts in surface water samples taken out to 30km from fracking wells, with the highest concentrations in samples collected within 5km of fracking wells.

Public Health Impacts

Public health impacts from fracking operations stem from air pollution from equipment, venting, and fugitive emissions, water contamination from spills, accidents, and produced water, and noise-pollution (Casey et al., 2019; Hays et al., 2017; Srebotnjak and Rotkin-Ellman, 2014). While public health impacts may be felt both locally and regionally, a main focus of research has been on those living in closer proximity to fracking (Adgate et al., 2014; Casey et al., 2016, 2019; Currie et al., 2017; Hill, 2018, 2021; Janitz et al., 2019; McKenzie et al., 2017; Steinzor et al., 2012, 2013; Walker et al., 2018; Whitworth et al., 2017). Drilling operators may be exposed to an even greater number of pollutants (and in higher concentrations) than those residing nearby because of their persistent exposure to well processes and contaminants at the well site (Adgate et al., 2014). For example, drilling operators are particularly exposed to respirable silica from large quantities of sand transported onsite for fracking fluid (Moore et al., 2014) and hydrogen sulfide which naturally occurs in natural gas and is an explosive and toxic hazard (33-35). One study on silica at fracking sites found that 51% of samples exceeded the Occupational and Safety Health Administrations' exposure limit (Esswein et al). Exposure to respirable silica has been linked to lung cancer, tuberculosis, kidney disease, and autoimmune disease (16).

Community members are also susceptible to fracking-related public health impacts; fracking may increase exposure to particulate matter, heavy metals, volatile organic compounds, and other toxins can result in eye, nose, and throat irritation, respiratory and cardiovascular problems, headaches and disorientation, vomiting, fatigue, cancers, and negative impacts to fetal and child development and reproductive systems (Adgate et al., 2014; Srebotnjak and Rotkin-Ellman, 2014). McKenzie et al. (2012) found chronic hazards (e.g., 1,2,3-Trimethylbenzene, n-Hexane, Toluene, Xylenes) and sub-chronic hazards (e.g., propylene, aliphatic hydrocarbons, aromatic hydrocarbons, and ethylbenzene) are measurable at distances greater than 0.8km between residences and fracking wells but are greatest within 0.8km. In this study, chronic was defined as exposure to pollutants for 360 months (estimated using well completion and production time) and sub-chronic was defined as exposure to pollutants for 20 months (estimated using well completion time). Several studies also reported respiratory, behavioral, neurological, digestive, skin, and vision impacts in people residing within 1km of fracking wells (Rabinowitz et al., 2015; Steinzor et al., 2013). Rabinowitz et al. (2015) found that skin and respiratory impacts specifically are common in people living as much as 2km from fracking wells; 13% of residents within 1km versus 3% of residents living more than 2km away for skin conditions and 39% of residents living within 1km versus 18% of residents living more than 2km away for respiratory symptoms. McKenzie et al. (2017) found a similar trend in that the likelihoods of having acute lymphocytic leukemia, non-hodgkin lymphoma, or non-hematologic cancer is increased in people residing closer to fracking wells, even though increased likelihood persists in people up to 16.1km from fracking activity compared to control groups.

Negative health impacts are especially concerning for vulnerable populations like pregnant women and their babies. The odds of babies having low birth weight, lower average birth weight, and worse overall infant health are increased for babies born to mothers residing within 1km of fracking wells (Currie et al., 2017; Hill, 2021) and within 2.5km of fracking wells (Hill, 2018). Babies are also more likely to be small for gestational age and have lower term birth weight, when they are born to mothers residing within 0.8km (Whitworth et al., 2017) and 2.5km of fracking wells (Hill, 2018). Similarly, Willis et al. (2021) found the odds of a baby having lower term birth weight are greatest when they are born to mothers living within 3km of fracking wells. Further, the likelihood of low birth weight (Currie et al., 2017; Hill, 2018), lower term birth weight (Currie et al., 2017; Hill, 2018; Whitworth et al., 2017), and small for gestational age (Whitworth et al., 2017) may persist to mothers living out to 16km from fracking wells. Lower average gestation length in babies and increased likelihood of gestational diabetes and hypertension in pregnant women has also been found in mothers residing within 1km of fracking wells (Hill, 2021). Finally, in babies born to mothers living within 8.04km of fracking wells when they gave birth, Janitz et al. (2019) found increased prevalence of neural tube defects, truncus, transposition of the great arteries, pulmonary valve atresia and stenosis, tricuspid valve atresia and stenosis, interrupted aortic arch, and total anomalous pulmonary venous connection.

Local Policy Response

Sub-state jurisdictions may choose to adopt one or more policies to minimize their residents' exposure to environmental impacts from fracking. What sub-state jurisdictions can do, however, is in part shaped by the state regulatory structure. Primary authority over fracking at the state level may rest with an environmental agency, an oil and gas commission, or both, such is the case in Texas (Davis, 2017). State approaches to managing fracking are of varied stringency and may or may not influence sub-state jurisdictions' ability to regulate fracking (Fisk, 2016; Wiseman, 2014). Overall, states cede different levels of authority to sub-state jurisdictions. For example, in some places, local governments can *ban or prohibit* fracking activity (Taylor and Kaplan, 2014), while in others, local governments can only rely on land use regulations to constrain or shape fracking operations (Loh and Osland, 2016). Further, when states leave a policy void, sub-state jurisdictions may be motivated to enact policy in response (Riverstone-Newell, 2012). The policies that sub-state jurisdictions adopt may be shaped by state constraints or limits (Perry and Kingdon, 1985), social learning from, mimicry of, or competitive advantages over neighboring jurisdiction activity (Berry and Berry, 1990; Karch, 2007; Shipan and Volden, 2008), internal determinants, like capacity and sociodemographics, or, as we argue, environmental risk. In this paper, we do not discuss the role of state constraints or neighboring jurisdiction diffusion effects because we do not have those data available; however, we encourage future research to consider the potential interacting influences of these determinants.

The Role of Environmental Risk in Decision-Making

There is a dearth of research on the role of environmental risk in shaping local policy adoption, particularly related to fracking (though see for example, Stoutenborough et al., 2015 on drought or Leiserowitz, 2006 on supporting climate change action) or discusses the role that experience with a previous hazard may exert on likelihood of policy adoption (Birkland, 1997, 1998). Loh and Osland (2016) found that a sub-state jurisdiction's experience with a previous fracking-related accident results in a much stronger likelihood of the jurisdiction adopting *restrictive* fracking policies but found a weaker (though still significant) relationship between fracking-accident experience and adopting *any* fracking policy. In this paper, we conceptualize risk as actual measured impact where proximity to fracking wells equates to larger impact and thus, larger risk. Inherent in this conceptualization is that risks may only exist insofar as they are socially ascribed as such (Hurlbert and Gupta, 2016). In the context of policy adoption to respond to environmental impacts of fracking, decision-makers must recognize an environmental risk and choose to address it. This recognition of an environmental risk is at least in part driven by the robustness of the evidence available and the level of pressure and claim that the problem exists (Hoppe, 2011). When uncertainty around the problem is minimized, the problem is more clearly structured for consideration by decision-makers (Hurlbert and Gupta, 2016). Decision-makers therefore seek information that reduces uncertainty and increases concrete evidence when faced with a policy choice (Bradshaw and Borchers, 2000; Evensen, 2015). Information about potential impacts needs to be timely and reliable (Adger et al., 2005; Buizer et al., 2016; Sarewitz and Pielke, 2007).

However, literature shows that decision-makers may not follow this rational-choice approach whereby they have access to all information available *and* utilize all that information (Ezrahi, 1980; Ronen et al., 2012). For example, decision-makers may only use information if it is salient, legitimate, and reliable (Buizer et al., 2016). On the other hand, decision-makers may not trust the information sources or the information may not interplay with their current decision-making information (Callahan et al., 1999; Lemos et al., 2012; Lowrey et al., 2009; Patt and Gwata, 2002; Rayner et al., 2005; Rice et al., 2009). In these instances, decision-makers may choose to only focus on information that is consistent with their underlying beliefs, experiences, and perceptions (Blake, 1999; Rickards et al., 2014; van Wyk et al., 2008). Decision-makers use their belief systems as heuristics that reflect their own evaluations of the causes and severity of the problem under consideration

(Jenkins-Smith and Kunreuther, 2001; Kahneman et al., 1982; Weible and Sabatier, 2009). These heuristics of problem severity are informed by and align with actual measured problem severity (Kalesnikaite and Neshkova, 2021). In turn, decision-makers use these heuristics to make policy choices based on their own best available knowledge (Jones 2017). When the problem severity is sufficiently high, policy response is more likely.

The link between problem severity and policy response is consistent in literature on climate change (see for example, (Kettle and Dow, 2016; O'Connor et al., 1999; Page and Dilling, 2020; Sharp et al., 2011), sustainability (Hughes et al., 2018a), likelihood of local collaboration to solve complex problems (Kalesnikaite and Neshkova, 2021; McGuire and Silvia, 2010), and pollution control regulation adoption (Lester et al., 1983; Lester and Lombard, 1990; Ringquist, 1993, 1994). However, redistributive policy, that is policy in which costs are born by a smaller and different population than the benefits (e.g., environmental justice policy), suggests there is no relationship between problem severity and state level policy adoption (Ringquist and Clark, 2002). Problem severity has also been linked to adoption of policy innovations (see for example (Gray, 1973; Nice, 1994; Savage, 1978; Walker, 1969). In all cases (except environmental justice as mentioned above), problem severity has a positive correlation with policy response. In other words, as problem severity increases, so does policy adoption. Based on our literature review of actual measured environmental impacts from fracking, we found that the greater environmental risk is measured closest to fracking wells and that this environmental risk decreases as distance from fracking wells increases. Relatedly, literature argues that proximity can catalyze policy response. Specifically, psychological distance theory argues that as proximity, in terms of time, space, distance, and likely impact, decreases, so too does the likelihood of action (Hughes et al., 2018b; Trope and Liberman, 2010). Given that we conceptualize environmental risk in this way, we hypothesize the following:

Jurisdictions are more like to adopt environmental policies when facing greater environmental risk (closer proximity to fracking wells) than less environmental risk (further proximity from fracking wells)

Other Determinants of Local Policy Adoption

There is a rich literature on the internal determinants of local policy adoption. One of the strongest predictors of local policy adoption is capacity (e.g., resources available). Jurisdictions with larger capacity (more staff or financial resources) are more likely to adopt policies because they are able to address a broader range of priorities (Mohr, 1969). This holds true for environmental policies specifically; as human and financial capacity increases, so does the likelihood of policy adoption (Betsill, 2001; Chapin and Connerly, 2004; Krause, 2012; Loh and Osland, 2016). Jurisdiction population size one indicator of capacity because it represents the tax base and thus potential funds available for implementing policies. Several studies have found a positive correlation between population size and policy adoption (Arnold and Long, 2019; Opp et al., 2014; Portney and Berry, 2010; Walsh et al., 2015; Zirogiannis et al., 2014). For example, Portney and Berry (2010) found that larger cities are more likely to adopt sustainable policies than smaller cities. Jurisdictional wealth is another indicator of capacity, again representing potential funding available for policy implementation and support (Dye, 1966; Gray, 1973; Lubell et al., 2009; Sapat, 2004). For example, Sapat (2004) found that state wealth is a determinant of hazard waste policy innovation, while Lubell et al. (2009) found that wealthier California cities located in the Central Valley are more likely to adopt sustainable practices when compared to cities with lower fiscal wealth. Resident wealth is typically more likely to adopt pro-environmental policies (Arnold and Long, 2019; Boehmke and Witmer, 2012; Krause, 2011b; Opp et al., 2014; Ringquist, 1994; Shipan and Volden, 2008) as it may be an indication of long-term capacity to respond to environmental impacts (Krause, 2011b; Krause et al., 2019) or ability to civically engage (Krause, 2011a; Rothenberg, 2002; Verba et al., 1995). However, Davis (2017) finds a weak connection between family income and environmental protection action, consistent with other research showing that wealth may not correlate with attitudes towards offshore drilling (Smith, 2001).

Sociodemographics of a jurisdiction's polity or government officials themselves can also play a role in whether jurisdictions adopt environmental policies. Political ideology, specifically greater liberalism of residents and/or local officials, consistently increases the likelihood of a jurisdiction adopting pro-environmental policy (Arnold and Neupane, 2017; Davis, 2017; Dokshin, 2016; Heath and Gifford, 2006; Jones and Dunlap, 1992; Krause, 2011b; Ringquist, 1994; Walsh et al., 2015). More liberal leaning jurisdictions may support pro-environmental policies because political liberals may be more likely than conservative leaning jurisdictions to work in concert with government institutions (Daley, 2008). Finally, higher education levels are also positively correlated with pro-environmental policies (Jones and Dunlap, 1992; Krause, 2011b; Opp et al., 2014; Portney, 2003; Portney and Berry, 2010; Ringquist, 1994; Walsh et al., 2015). Higher levels of education may translate into greater environmental awareness (Daley and Garand, 2005; Wood, 2011) or interest group activity (Galston, 2001; Opp et al., 2014; Portney and Berry, 2010), which may in turn translate into local policy adoption as government officials seek to represent their constituents' interests. However, education is not a significant predictor of state-level fracking policy adoption (Davis, 2017). Finally, jurisdictions with lower unemployment rates may be more likely to adopt environmental policies because low unemployment indicates less economic need, thus less dependency on fracking activity to boost the local economy (Davis, 2012).

DATA AND METHODS

This analysis combines fracking well data, literature review data, and data from an original survey of sub-state jurisdiction officials in Ohio, West Virginia, and Pennsylvania, with sociodemographic data from the U.S. Census Bureau.

Survey

The survey targeted 662 local government officials in counties across Ohio, Pennsylvania, and West Virginia that overlay Marcellus and/or Utica shales. These three states were selected because the Marcellus and Utica shales are two of the three highest dry shale gas production overlays in the United States as of September 2021 (EIA, 2021). Marcellus shale is 5,000 to 9,000 feet underground and is estimated to contain between 168 and 516 trillion cubic feet of natural gas (PSU Extension), while Utica shale is 2,000 to 8,000[3] feet underground and is estimated to contain between 38 and 728 trillion cubic feet of natural gas (NGI, 2021). Survey recipients were selected using stratified random sampling to ensure our survey reached sub-state jurisdictions of varying sizes and types. The survey consisted of 27 questions about fracking's local impacts, governance, and community support (or opposition). The survey was mailed to prospective respondents in November and December 2020. In January 2021, we identified phone numbers and email addresses of non-respondents and followed up with an opportunity to take a digital version of the survey programmed in Qualtrics. We received a total of 145 survey responses (125 paper, 20 digital), both completed and partially completed. Of these, one survey response was missing a CASEID and could not be linked to the initial participant list. Our overall response rate was 18.93%.

Twenty-three jurisdictions had multiple respondents complete some portion of the survey. Our unit of analysis is the jurisdiction and as such, we used one respondent's responses from each jurisdiction. In selecting which response to include, we first prioritized whichever survey was more complete. In two cases where multiple respondents in the same jurisdiction completed the same number of questions, we chose the individual holding the governmental role most prevalent in the data. In this way, we prioritized land use officials over township supervisors.

Dependent Variable

The dependent variable was constructed by asking survey respondents about types of environmental policies their jurisdiction might have implemented in response to fracking activity (Table 6). For each policy type, we assessed whether a jurisdiction had implemented it (1) or not (0). We constructed a sixth dichotomous variable to measure whether the respondent's jurisdiction implemented *any* environmental policy in response to

[3] Although note that some believe Utica shale may be up to 14,000 feet deep in Pennsylvania

fracking. If, for example, a jurisdiction implemented a zoning setback policy and a policy to monitor public health impacts of fracking, they took a *1* on this sixth variable.

Table 6. Environmental policy types

Environmental Policy Type (Dependent Variable)
Zoning setbacks affecting fracking
Monitoring public health impacts of fracking, such as air, water or soil pollution
Providing water to residents affected by fracking-linked water contamination
Increasing spending on public health, which might be used for educational campaigns or health clinics
Establishing a community bill of rights, which is a policy statement regarding rights of residents to safe water, clean air, and other environmental amenities
One or more of the above environmental policies

Independent Variables

To test our hypotheses, we examined the density of wells at varying distances from jurisdictional boundaries. We focus on five distances (0.5km, 1km, 3km, 5km, and 20km) representative of the range of distances used in prior investigations into fracking's environmental impacts. We also consider several sociodemographic variables as controls. We discuss each independent variable below in further detail.

Fracking Activity Distance Risk Analysis

We first obtained TIGER/Line jurisdictional (municipality, county[4]) boundary GIS layers for Ohio[5], Pennsylvania[6], and West Virginia[7]. Data layers were imported into QGIS and reprojected to Conus Albers 83 for mapping and spatial analysis. Enverus (2021) provides location data of myriad drilling well types. To obtain

[4] County data layers came from ArcGIS (2021)

[5] Ohio data layers came from the Ohio Department of Transportation (2018).

[6] Pennsylvania data layers came from the Commonwealth of Pennsylvania (PennDOT 2021).

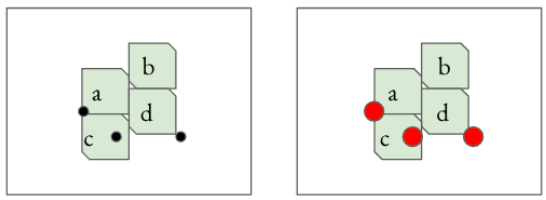
[7] West Virginia data layers came from the West Virginia GIS Technical Center (2021).

fracking well data, we filtered for *oil and gas* wells and wells with either a *horizontal* or *directional* drill type[8]. We then filtered the fracking well data for fracking wells permitted during the 2005-2020 timeframe. This resulted in 17,282 wells in our dataset. We limited the focus to 2005-2020 because the Energy Policy Act of 2005 exempted fracking from Safe Drinking Water Act underground injection regulations and fracking subsequently expanded rapidly in Ohio, Pennsylvania, and Virginia (see Supplemental Information for more detail). We selected 2020 as the end date to align with when the survey ended, so our results reflect what happened in the region over a roughly 15-year time period. We downloaded the fracking well data and plotted locations in QGIS using surface hole latitude and longitude coordinates, reproducing fracking well data to Conus Albers 83 to match the jurisdictional boundary data.

We next conducted a distance risk analysis for our subset of crucial distances (simplified example in Figure 7). Using QGIS, we first overlayed the fracking well data points onto the jurisdictional boundary layers (Figure 7, Step 1). We then created a data layer for each distance, with each buffer centered around the point where the vertical component of the fracking wellbore entered the ground (Figure 7, Step 2). We then intersected each buffer layer with the municipality and county boundary layers to ascertain how many wells intersected each jurisdiction at each distance (Figure 7, Step 2). We did not restrict intersection based on some level of overlap, instead if a well's buffer touched, intersected, or completely overlapped a jurisdiction, it was associated with that jurisdiction. If a buffered well touched two jurisdictions, then that well counted towards each of the jurisdiction's total well count. We then summed the total number of wells intersecting each jurisdiction for the given distance (Figure 7, Step 3). This process was repeated for each distance of interest. Once the risk analysis was completed, we calculated the density of wells for each distance by dividing the total count of wells intersecting a jurisdiction by the jurisdiction's area in square kilometers. For example, if a

[8] While it's possible that fracking wells may also use a vertical approach, there is no way to distinguish between vertical fracking and vertical other drilling in the Enverus data set.

jurisdiction had 5 wells intersect it at the 0.5km distance and the jurisdiction had an area of 5 square kilometers, the well density for that jurisdiction at a distance of 0.5km would be 0.5/5 or 0.1. We capture this variable as *Density of Wells at Distance* in each of our models. In this way, we use one variable to consider both well density *and* distance.



Municipality	Well Count
Municipality a	1 Well
Municipality b	0 Wells
Municipality c	2 Wells
Municipality d	1 Well

Step 1: Plot wells over jurisdiction boundary layers

Step 2: Add 0.5km buffer around each well

Step 3: Count number of buffered wells intersecting each municipality

Figure 7. Simplified visualization of the distance risk analysis process: 1) in step 1, we plotted the well points on the jurisdictional boundary layers; 2) in step 2, we created buffers around each well point for the specified distance and intersected them with the jurisdictional boundary layers; and 3) in step 3, we counted the total number of wells intersecting each jurisdiction for a given distance.

<u>Sociodemographic Data (Controls)</u>

Drawing on local policy adoption literature, we selected several sociodemographic variables as controls (see Table 7 for descriptive statistics). To capture sub-state jurisdiction capacity, we include *Per Capita Income* (in 1000s of U.S. dollars, 2006-2010). *Per Capita Income* gives an indication of resident wealth, which we expect to be positively correlated with environmental policy adoption (Arnold and Long, 2019; Boehmke and Witmer, 2012; Krause, 2011a; Opp et al., 2014; Ringquist, 1994; Shipan and Volden, 2008). Additionally, counties may have more capacity than smaller jurisdictions, therefore, we expect that counties will be more likely to adopt environmental policies than small jurisdictions. To capture political ideology, we included the percentage of voters in each jurisdiction[9] that voted for Donald J. Trump in the 2016 Presidential election (*Percent Trump Votes*). Given existing research on the relationship between ideology and environmental attitudes (Arnold and

[9] In one case, we were unable to parse a jurisdiction's votes from precinct data because the precinct served voters in multiple jurisdictions. In this case, we used the percentage of trump voters from the entire precinct as a proxy.

Neupane, 2017; Davis, 2017; Dokshin, 2016; Heath and Gifford, 2006; Jones and Dunlap, 1992; Krause, 2011b; Ringquist, 1994; Walsh et al., 2015), we expect that sub-state jurisdictions with lower percentages of trump voters are more likely to adopt environmental policies. Next, to capture resident affluence, we include both the rate of unemployment (*Unemployment*) and the percentage of each jurisdiction aged 25 or older who graduated from high school (*Percent HS Graduates*). We expect to find a negative correlation between unemployment rate and environmental policy adoption (Davis, 2012) and a positive correlation between education and environmental policy adoption (Jones and Dunlap, 1992; Krause, 2011b; Opp et al., 2014; Portney, 2003; Portney and Berry, 2010; Ringquist, 1994; Walsh et al., 2015). Finally, we include a *County Identifier* denoting whether the survey respondent represented a county or a smaller entity such as a town, village, or borough. We ran pairwise correlations on the independent variables to check for collinearity and confirmed that all variable pairs have less than high correlation (|r| > 0.70).

Table 7. Descriptive statistics for the regression variables. *Density of Wells at Distance* is the main variable of interest; other variables are controls.

Variables	Min	Max	Mean	Description and Data Source
Density of Wells at Distance	0	2815.00*	Varies with distance	Count of wells intersecting a jurisdiction divided by the jurisdiction's area in square kilometers. *For each distance, we removed outliers using the equation: cut off = IQR(well density)*1.5 + Q3, where IQR is the interquartile range and Q3 is the third quartiele. Sources: Enverus 2021 (Enverus, 2021, wells) and (US Census Bureau, 2021b, jurisdiction area).
Unemployment (2006-2010)	0.00	14.30	4.95	Number of unemployed people as a percentage of the civilian workforce based on the 2006-2010 timeframe. Source: (US Census Bureau, 2021b)
Percent HS Graduates	41.5	100.00	86.81	Percentage of people aged 25 and above in

(2006-2010)				each jurisdiction are high school graduates or higher. Source: American Community Survey (US Census Bureau, 2021a)
Percent Trump Voters (2016)	20.84	83.11	65.77	Count of votes cast in each jurisdiction for Donald J. Trump divided by the total number of votes cast in that jurisdiction. One jurisdiction uses the percentage of its precinct (two jurisdictions) because we were unable to parse out votes for the jurisdiction. We used several sources to calculate voting percentage and aligned the survey respondent jurisdictions with precinct, county, and state data. Sources: Offices of Secretaries of States and County Assessor, Recorder, Clerk, and Election Offices.
Per Capita Income (2006-2010)	7.82	43.69	21.62	Per capita income adjusted to be in 1000s of U.S. Dollars. Source: American Community Survey (US Census Bureau, 2021a)
County Identifier	0	1	N/A	A “1” signifies that the jurisdiction is smaller than a county (e.g, village, city, borough, township). A “0” signifies that the jurisdiction is a county.

Logit Modeling

We ran logistic regression models, one for each buffer distance and environmental policy combination (5 individual environmental policy categories and 1 overall environmental policy category). We compared the coefficients for the *Well Density at Distance* variables across each model for each policy type. If our hypothesis is supported, we expect to see that that coefficient size decreases as the distance increases. To ensure proper model fitting, we also ran models with alternative measures of the independent variables (e.g., substituting median household income for median family income) and reviewed AIC scores to ensure we selected the best fitting models.

RESULTS

We present the results of our logit models in Tables 8-13; results are presented as coefficient values and standard errors for the six environmental policy dependent variables at distances of 0.5km, 1km, 3km, 5km, and 20km. All values are presented as probabilities where a value higher than 0.500 means that a one unit change in that variable increases the likelihood of policy adoption and a value lower than 0.500 means a one unit change in the variable decreases the likelihood of a policy being adopted. Below we discuss the results around each of our hypotheses, followed by overall model results.

Table 8. Determinants of Adopting a Zoning Setback Policy

	0.5km	**1km**	**3km**	**5km**	**20km**
Unemployment	0.130 (0.140)	0.452 (0.141)	0.447 (0.148)	0.451 (0.148)	0.434 (0.167)
Percent HS Graduates	0.513 (0.076)	0.513 (0.076)	0.512 (0.082)	0.510 (0.081)	0.517 (0.092)
Density of Wells at Distance	0.492 (2.804)	0.614 (2.014)	0.417 (0.525)	0.499 (0.231)	0.979 (0.029)
Percent Trump Voters	0.500 (0.034)	0.501 (0.034)	0.501 (0.035)	0.501 (0.035)	0.501 (0.038)
Per Capita Income	0.543*** (0.079)	0.544*** (0.080)	0.551*** (0.084)	0.551*** (0.084)	0.549*** (0.091)
County Identifier	0.656 (0.876)	0.639 (0.831)	0.668 (0.824)	0.673 (0.831)	0.652 (0.871)
Constant	0.000 (7.045)	0.000 (7.070)	0.000 (7.787)	0.000 (7.664)	0.000 (8.662)
Observations	90	92	88	86	86

*p<0.10, **p<0.05, ***p <0.01

Table 9. Determinants of Adopting a Policy to Monitor Public Health Impacts

	0.5km	**1km**	**3km**	**5km**	**20km**
Unemployment	0.490 (0.143)	0.494 (0.136)	0.501 (0.109)	0.504 (0.110)	0.489 (0.118)
Percent HS Graduates	0.502 (0.072)	0.504 (0.074)	0.497 (0.050)	0.498 (0.053)	0.501 (0.054)
Density of Wells at Distance	1.000*** (4.122)	0.990 (3.053)	0.665 (0.528)	0.597 (0.309)	0.491 (0.034)
Percent Trump Voters	0.490 (0.031)	0.490 (0.030)	0.497 (0.029)	0.497 (0.029)	0.497 (0.029)
Per Capita Income	0.515 (0.069)	0.518 (0.069)	0.524 (0.061)	0.523 (0.061)	0.520 (0.062)
County Identifier	0.822* (0.912)	0.877** (0.842)	0.889*** (0.784)	0.885*** (0.788)	0.842** (0.797)
Constant	0.198 (6.092)	0.083 (6.184)	0.118 (4.674)	0.071 (4.892)	0.103 (4.957)
Observations	83	84	82	78	79

*p<0.10, **p<0.05, ***p <0.01

Table 10. Determinants of Adopting a Policy to Provide Water to Residents with Contaminated Drinking Water

	0.5km	1km	3km	5km	20km
Unemployment	0.478 (0.262)	0.502 (0.265)	0.461 (0.209)	0.471 (0.234)	0.469 (0.223)
Percent HS Graduates	0.530 (0.152)	0.508 (0.153)	0.497 (0.097)	0.486 (0.076)	0.503 (0.109)
Density of Wells at Distance	1.000* (6.064)	0.968 (5.072)	0.836** (0.782)	0.770** (0.545)	0.509 (0.029)
Percent Trump Voters	0.492 (0.059)	0.450 (0.065)	0.502 (0.058)	0.511 (0.078)	0.509 (0.067)
Per Capita Income	0.486 (0.122)	0.509 (0.134)	0.511 (0.105)	0.526 (0.119)	0.512 (0.106)
County Identifier	0.720 (1.438)	0.900* (1.237)	0.912** (1.131)	0.956** (1.389)	0.900* (1.125)
Constant	0.000 (12.494)	0.001 (12.921)	0.026 (9.431)	0.012 (8.730)	0.000 (11.198)
Observations	84	85	83	79	80

*p<0.10, **p<0.05, ***p <0.01

Table 11. Determinants of Adopting a Policy to Increase Spending on Public Health

	0.5km	1km	3km	5km	20km
Unemployment	0.579 (0.355)	0.590 (0.353)	0.560 (0.274)	0.664 (0.488)	0.538 (0.245)
Percent HS Graduates	0.507 (0.214)	0.511 (0.222)	0.485 (0.099)	0.479 (0.145)	0.500 (0.124)
Density of Wells at Distance	1.000* (8.266)	1.000 (6.150)	0.977** (1.630)	1.00** (1.812)	0.513 (0.067)
Percent Trump Voters	0.497 (0.087)	0.499 (0.091)	0.545 (0.150)	0.610 (0.267)	0.577 (0.157)
Per Capita Income	0.513 (0.185)	0.519 (0.188)	0.555 (0.158)	0.602* (0.239)	0.561 (0.156)
County Identifier	0.944 (1.935)	0.978** (1.744)	0.996*** (2.080)	1.000* (3.434)	0.991** (1.896)
Constant	0.000 (17.414)	0.000 (18.378)	0.000 (15.760)	0.000 (28.012)	0.000 16.929)
Observations	82	83	81	77	78

*p<0.10, **p<0.05, ***p <0.01

Table 12. Determinants of Adopting a Policy to Establish a Community Bill of Rights to Protect Public Health, Water Quality, Air Quality, etc.

	0.5km	1km	3km	5km	20km
Unemployment	0.503 (0.363)	0.518 (0.405)	0.502 (0.164)	0.508 (0.166)	0.512 (0.168)
Percent HS Graduates	0.547 (0.199)	0.548 (0.207)	0.498 (0.074)	0.499 (0.077)	0.500 (0.076)
Density of Wells at Distance	0.000 (130.386)	0.000 (117.056)	0.738 (0.787)	0.643 (0.491)	0.504 (0.041)
Percent Trump Voters	0.526 (0.109)	0.526 (0.109)	0.530 (0.084)	0.531 (0.081)	0.532 (0.087)
Per Capita Income	0.633 (0.422)	0.660 (0.500)	0.522 (0.104)	0.521 (0.081)	0.523 (0.108)
County Identifier	0.000 (4,041.545)	0.000 (4,023.079)	0.000 (3,496.490)	0.000 (3,499.379)	0.000 (3,504.195)
Constant	0.000 (26.199)	0.000 (28.898)	0.000 (9.272)	0.000 (9.138)	0.000 (9.718)
Observations	83	84	82	78	79

*p<0.10, **p<0.05, ***p <0.01

Table 13. Determinants of Adopting any Environmental Policy

	0.5km	**1km**	**3km**	**5km**	**20km**
Unemployment	0.460 (0.118)	0.458 (0.199)	0.477 (0.105)	0.479 (0.102)	0.481 (0.109)
Percent HS Graduates	0.507 (0.062)	0.507 (0.062)	0.503 (0.057)	0.052 (0.056)	0.057 (0.062)
Density of Wells at Distance	0.604 (2.638)	0.592 (1.882)	0.541 (0.388)	0.554 (0.200)	0.499 (0.013)
Percent Trump Voters	0.489 (0.026)	0.489* (0.027)	0.493 (0.025)	0.492 (0.025)	0.494 (0.026)
Per Capita Income	0.534* (0.071)	0.536** (0.071)	0.543** (0.072)	0.542** (0.072)	0.542** (0.074)
County Identifier	0.829* (0.812)	0.835** (0.768)	0.833** (0.744)	0.842** (0.752)	0.840** (0.766)
Constant	0.052 (5.368)	0.056 (5.420)	0.030 (5.120)	0.038 (5.003)	0.007 (5.597)
Observations	91	93	90	88	88

*p<0.10, **p<0.05, ***p <0.01

Overall Model Results

County Identifier is generally the most significant and positive predictor of local environmental policy adoption across all environmental policies *except* a zoning setback. *Per Capita Income (2006-2010)* is the strongest predictor of adopting a zoning setback policy; as per capita increases, so does the likelihood of a jurisdiction adopting a zoning setback policy. *Percentage of Trump Voters (2016)*, a measure of political ideology, has some mixed influence; there is a significant positive correlation between *Percentage of Trump Voters (2016)* and adoption of a policy to increase spending on public health (Table 11, at the 5km and 20km distances), but a significant negative correlation between *Percentage of Trump Voters (2016)* and adoption of any environmental policy (Table 13, at the 1km distance). Lastly, we find that none of our independent variables significantly predict whether a jurisdiction adopts a community bill of rights for water, air, or environmental amenities (Table 12).

Comparing Environmental Risk Across Distances and Models

To understand how geographic distance influences policy adoption, we compare the size of the coefficients for well density at each distance for each policy model. If policy adoption responds to the size of environmental risk as determined by distance, the influence of well density on the likelihood of policy adoption should decrease as the distance increases. In other words, we would expect to see the largest well density coefficient for the 0.5km distance models and the smallest well density coefficient for the 20km distance models. We find mixed results pertaining to our second hypothesis. First, we find that for both predicting adoption of a zoning setback policy and of a community bill of rights, distance does not matter and the coefficient of well density is seemingly random. However, for all other policy types, the well density coefficient generally decreases from 0.5km to 20km, indicating support for our hypothesis. This trend is strongest when predicting whether a jurisdiction will adopt a policy to monitor public health impacts from air, water, and soil pollution (probability is 1.000 at 0.5km vs -0.491 at 20km) and whether a jurisdiction will adopt a policy to provide water to residents impacted by water contamination from fracking (probability of 1.000 at 0.5km vs 0.509 at 20km). In other words, there is almost a 100% probability that jurisdictions that have at least one fracking well within 0.5km of their administrative boundaries will adopt a policy to monitor public health or to provide water to residents with contaminated drinking water. Further, the probability that jurisdictions adopt these types of policies decreases as we increase the distance threshold from administrative boundaries to fracking wells.

DISCUSSION

Fracking is touted as a solution to energy security in the United States, costing less to both produce and consume than imported oil and gas (Sovacool, 2014). However, fracking also has a multitude of potential negative impacts, particularly to the environment and public health. Research to understand environmental impacts from fracking typically uses distance as a measure of potential environmental risk. Fracking's benefits and burdens are distributed unequally across scales; benefits in the form of cheaper energy are felt nationally while local jurisdictions experience both immediate benefits but also frequently short and long-term environmental and public health burdens. It would stand to reason, then, that local jurisdictions would respond to these risks with policies intended to reduce them or mitigate their impacts. If local policymaking is not driven by risk assessment, what motivates local policy choices around fracking impacts? Below we discuss the three themes that emerge from our analysis of local environmental policy adoption drivers in Ohio, Pennsylvania, and

West Virginia: 1) not all local environmental policies are equal, 2) wealth and "not in my backyard" (NIMBYism) may drive *some* local environmental policy adoption, and 3) environmental risk has at least some influence on local environmental policy adoption.

Not all environmental policies are created equal

Much of the existing literature on drivers of fracking-related local policy adoption evaluates a single policy type or outcome (e.g., (Arnold and Neupane, 2017; Dokshin, 2016; Hall et al., 2018). Even studies which take a more nuanced approach (e.g., Loh and Osland 2016) they still typically focus on broad categories of policies, for example by evaluating factors that encourage a jurisdiction to adopt more or less restrictive measures (Loh and Osland, 2016). See, however, Arnold and Long (2018) who consider four sub-types of policies, as an exception. When scholars take a more granular approach, they tend to find that drivers of policy adoption vary across policy domain and scale (Rosenblatt et al. *Under Review*; Hughes et al., 2018; Opp et al., 2014). We advance this line of inquiry by examining drivers of adoption for different types of environmental policies. Our findings support what others have found: different parameters matter for different policies. Overall, we find that whether a jurisdiction is a county or not is a stronger predictor of environmental policy adoption, both when analyzing if a jurisdiction adopts *any* environmental policy and if a jurisdiction adopts policies to monitor public health, increase spending on public health, or provide water to those with contaminated drinking water. This may be because counties typically have greater capacity than sub-county jurisdictions, in terms of financial resources and human capital, and have political responsibility for a larger number of people than in smaller jurisdictions (see for example, Pitt and Bassett, 2014, relating larger jurisdictions to higher likelihood of adopting energy policy).

We find that the polity's political partisanship correlates with adoption for some policy types. Higher levels of conservatism translate to a *reduced likelihood* of adopting *any* environmental policy, consistent with a large body of scholarship suggesting that conservative voters do not prioritize environmental policymaking. We also find that higher levels of conservatism correlates to an *increased likelihood* of adopting environmental policies aimed at increasing spending on public health. This finding is initially surprising because conservative voters often disapprove of government spending and public health policies have many similarities to environmental policies in terms of their goals (protecting and improving quality of life). We posit that this unexpected finding may be related to government trust: regardless of political ideology, if individuals have more trust in their government, they may be more likely to support increased government spending on things like environmental protections and health care. In turn, elected officials will also support increased government spending, to meet constituent desires. There is some support for this in the literature; Rudolph and Evans (2005) examines the interaction and role of political ideology and government trust on supporting increased government spending for distributive and redistributive policies; they find that if government trust is high, conservatives are 32-33% more likely to support increased government spending on policies like environmental protection and health care than when they have low trust in government. While we did not measure government trust in this study our normative assumption is that local jurisdiction politics are less polarized (Jensen et al., 2021) and therefore, constituents will have more trust in government.

No variables significantly predict whether a jurisdiction adopts a community bill of rights to protect environmental amenities, but we do note that the probability of a jurisdiction adopting a community bill of rights is predicted to be 0% if the jurisdiction is a county. Indeed, none of the survey respondents that are counties reported adopting a community bill of rights and only four respondents in total reported adopting a community bill of rights. This is likely because community bills of rights are relatively controversial and tend to pit local governments against state governments by challenging the latter's preemption (Buday, 2017). Finally, wealth, measured as per capita income, appears on to matter when predicting whether a jurisdiction will adopt a zoning setback policy (discussed further in the next section).

Wealth, local policy adoption, and "Not in my backyard"

Zoning setback policies require drilling operations to be built at some specified distance away from waterways, homes, and/or other infrastructure. Specific setback distances vary greatly, influenced by geographic and political context. For example, in Pennsylvania, natural gas wells must be at least 200 feet from private water wells and 100 feet from watercourses (Negro, 2012), while Collier Township (in Pennsylvania) prohibits drilling within 300 feet of a property line or 1,000 feet of a school or day care center (without proprietor consent) (Ordinance No. 592). Comparatively, in Texas, the city of Arlington requires well pads to be at least 600 feet from public lands (Ordinance No. 10-012), while in Coppell, drilling has to be more 1,000 feet from residences (Ordinance No. 2009-1228). We found a positive correlation between per capita income and the likelihood that a jurisdiction will adopt a zoning setback policy. While statistically significant, the probability is around 0.54-0.55 meaning there is some indication that as per capita income increases, so does the likelihood of a jurisdiction adopting a zoning setback policy. We posit that this positive link between wealth and zoning policy adoption may stem from at least two factors. First is the "not in my backyard" (NIMBY) sentiment; NIMBYism occurs when an activity has localized costs but geographically diffuse benefits, and those who stand to bear the costs resist their imposition, if they have sufficient political or financial capacity to do so. For example, in Cape Cod, wealthy communities argued against a wind farm development under the auspices of environmentalism, while really lobbying against development to protect their view of Nantucket Sound (Kempton et al., 2005; Martin, 2009). NUMBY (not under my backyard) sentiment may also shape likelihood of fracking policy adoption, describing "…the reaction of local homeowners who object to further development within their community, fearing that such development might reduce the market value of their homes or change the character of the community." (Salkin and Ostrow, 2009). As our literature review explained, fracking may contaminate groundwater aquifers well below the land surface (Jasechko and Perrone, 2017; Yan et al., 2017). Therefore, it is possible that ideas of NUMBYism also influence decisions to adopt environmental policies.

The second potential explanation for the influence of per capita wealth on zoning setback adoption concerns jurisdictional capacity. In addition to wealthier residents being more likely to adopt environmental policies (Arnold and Long, 2019; Boehmke and Witmer, 2012; Krause, 2011b; Opp et al., 2014; Ringquist, 1994; Shipan and Volden, 2008), resident wealth may also be an indicator of long-term capacity to respond to environmental impacts (Krause, 2011b; Krause et al., 2019). In other words, residents have more disposable income to spend on environmental protections. Additionally, several studies link resident wealth to civic engagement, arguing that, given the chance, wealthier residents are more likely to participate in decision-making process (Krause, 2011a; Rothenberg, 2002; Verba et al., 1995). As such, wealthier residents may demand environmental protections like zoning setbacks as opposed to jurisdictions with poorer residents who may rely on the fracking industry for their livelihood (Christopherson and Rightor, 2012). Further even though existing research finds that wealth may have a positive effect (Arnold and Neupane, 2017; Kostandini and Centner, 2016; Locke and Rissman, 2015; Loh and Osland, 2016) or a negative effect (Zirogiannis et al., 2015) on the likelihood of local environmental policy adoption (fracking-related or otherwise), higher citizen affluence and capacity often translates into pro-environmental attitudes (Daley and Garand, 2005; Jones and Dunlap, 1992; Wood, 2011). These attitudes, in turn, may reinforce NIMBY or NUMBY sentiment as residents seek to protect the market value of their homes and the protection of their communities (Salkin and Ostrow 2009); this in turn, may drive zoning setback policy adoption.

Measured Environmental Risk…matters?

We find overall, some support that environmental risk does influence the likelihood of local policy adoption in response to potential environmental impacts from fracking. However, the relationship between risk and policy adoption varies across both the type of environmental policy and type of environmental risk. Across environmental policies, unsurprisingly, environmental risk appears to best (in terms of statistical significance) predict policies to provide drinking water to residents with contaminated water and policies to increase spending on public health. Both types of policies tend to be directly responsive to actual fracking impacts that require short-term, coping actions. This pattern of jurisdictions pursuing coping responses when faced with an emergency (such as fracking-contaminated drinking water) is seen consistently in studies of extreme event impacts and climate adaptation planning (see for example, Ekstrom et al., 2018; Fencl, 2019; Filho et al., 2019; Fletcher et al., 2013; Moser and Ekstrom, 2010). As such, we see that there is a positive correlation between environmental risk (the well density variable) and policy adoption, meaning that as well density increases, so does likelihood of policy response. In fact, there is a probability of 0.770-1.000 that a jurisdiction will adopt a policy to provide drinking water (0.5km) or a policy increasing public health spending (0.5km, 3km, 5km).

Existing research measuring the distance at which environmental impacts from fracking are felt generally analyze a range of distances, typically concluding that impacts are greater closer to fracking activity and dissipate as distance from fracking increases. It follows, then, that we should expect our environmental risk coefficients (represented by well density variable at different distances) to decrease across distance models. In other words, if environmental risk matters, the highest probability of policy adoption should be measured at 0.5km and the lowest probability of policy adoption should be measured at 20km. In fact, we find general support for this argument; coefficients decrease as distance increases across most of the models (including adopting *any* environmental policy); the exceptions are adopting a zoning setback policy and adopting a community bill of rights policy. We, therefore, cautiously conclude that environmental risk, defined as distance from fracking wells, does influence environmental policy adoption generally, and plays a larger or smaller role depending on the policy in question. Further, we note that the role that environmental risk plays in shaping local policy adoption varies across policy type. Future researchers should be cognizant of this trend and avoid more simplistic models that consider environmental risk in adopting *only* fracking bans. There is nuance in the relationship between environmental risk and type of policy response. This may be one explanation for why Walsh et al. (2015) found that jurisdictions with greater numbers of water resources (wetlands and at-risk watersheds) may be less likely to adopt fracking *bans.* While their results may at first glance suggest that jurisdictions don't consider environmental risk, a more nuanced look at the policies these jurisdictions *do adopt* could yield differing results.

LIMITATIONS AND FUTURE RESEARCH

There are a few limitations to our study. First, we do not consider regional determinants of policy adoption like neighboring jurisdiction activity. Existing literature argues that sub-state jurisdictional policy action may be shaped by social learning from, mimicry of, or competitive advantage over neighboring jurisdictions (Berry and Berry, 1990; Karch, 2007; Shipan and Volden, 2008). We did not have these data available, given the structure of our survey, and therefore we did not test for neighborhood effects in this study. Additionally, we did not consider the institutional structure of the sub-state jurisdictions (e.g., city manager versus mayoral system). Research shows for example, that manager-organized governance structures may yield different policy adoption strategies than mayoral-council organized governance structures (Lubell et al., 2009). Finally, we measured environmental risk using well density and distance from fracking wells to measured environmental impacts based on literature. This is just one conceptualization of environmental risk. For example, future researchers may want to consider the proportion of a jurisdiction's populations that lives within different distances of fracking wells. One could posit, for example, that when a larger proportion of the population resides within 0.5km of fracking wells, the likelihood of adopting an environmental policy is higher.

CONCLUSION

In this paper, we set out to explore how (if at all) environmental risk from fracking influences local environmental policy adoption. We conceptualized environmental risk as the distance from fracking wells to measured environmental impact. We calculated the density of wells within different distances of jurisdictional boundaries. We analyzed survey and well data to ascertain whether environmental risk drives different types of local environmental policymaking. Overall, there is support that environmental risk increases the likelihood of local policy adoption for some environmental policies and that the likelihood of policy adoption decreases as environmental risk decreases. More generally, determinants of policy adoption vary across types of environmental policy, with both wealth and whether a jurisdiction is a county or not being statistically significant predictors. We look forward to future research that considers other measures of environmental risk. More broadly, researchers interested in studying local fracking policy response should investigate how the influence of different determinants, including environmental risk, varies across policy type, rather than assuming that all environmental policy adoption is driven by a common set of predictors. This paper contributes to scholarly literature on local environmental policy adoption and environmental risk. It highlights the need for further empirical testing into the types of environmental risk that matter for driving policy adoption *and* the need for exploring the drivers of individual environmental policies and how they vary across policies.

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SUPPLEMENTAL INFORMATION

Fracking well expansion following 2005

Fracking expanded quite broadly following the passing of the Energy Policy Act of 2005. Among other things, this Act, passed by the 109th Congress, exempted fracking operations from following Safe Drinking Water Act underground injection regulations. The regulatory leniency, combined with technological advances drove expansion of fracking. Figure S9 plots the number of oil and gas wells in Ohio, West Virginia, and Pennsylvania based on the year they were spudded between 2000 and 2021. Fracking well data comes from Enverus (2021).

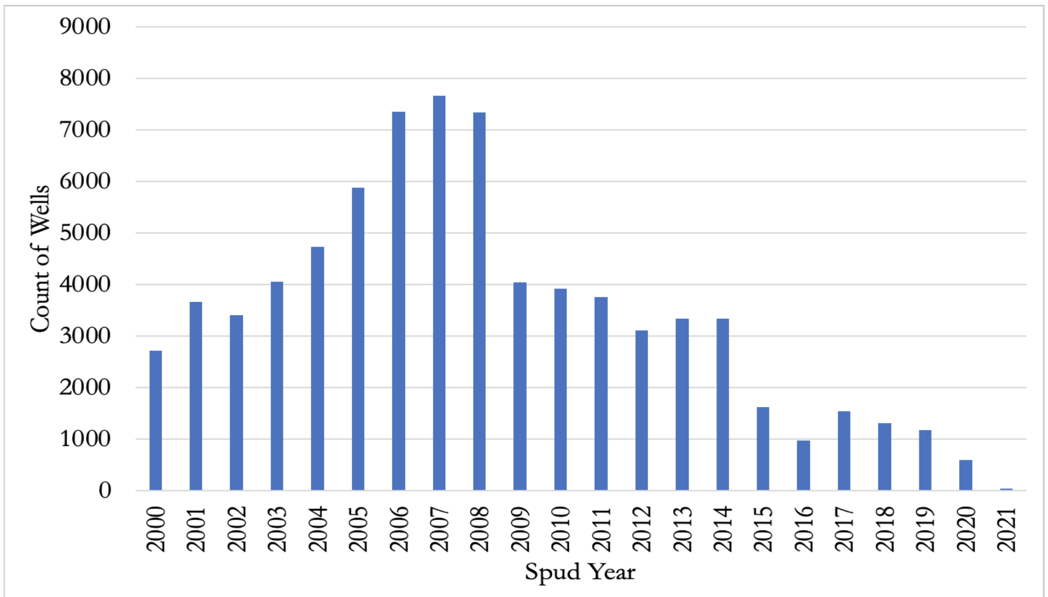


Figure S9. Count of oil and gas wells across Ohio, Pennsylvania, and West Virginia over the 2000-2021 timeframe.

WELL DENSITY OUTLIERS

Our data contained 17,282 wells data points across Ohio, Pennsylvania, and West Virginia for the 2005-2020 timeframe. When we calculated the density of wells at each buffer distance, we ended up with a wide range of densities from 0 to 2815. The variance in density came about for several reasons. First, some jurisdictions were relatively large in size but far removed from proximate drilling. Second, some jurisdictions were relatively small in size and were located in regions with heavy drilling and proximate to well pads with multiple wells in very close proximity. To help with improving our model fit, we used interquartile ranges to remove outlier densities at each distance. We conducted these processes in R using the IQR function as part of the stats package which is in base R (R Core Team 2021). Following (Tukey 1977), we multiplied the IQR result by 1.5 and added it to the third quartile to obtain the cutoff. Any well densities above this cutoff were deemed to be outliers and removed from the model run. Because well densities varied across distances, the number of observations removed from each model varied.

3. (HAB)itual challenges: how does environmental risk shape Lake Erie harmful algal bloom governance?

INTRODUCTION

Wicked environmental challenges are complex and difficult to solve, at best offering only temporary solutions (Harmon and Mayer 1986). A classic example of a wicked problem is nonpoint source pollution in which pollution sources are diffuse, occurring in a heterogeneous manner across the landscape. The impacts of nonpoint source pollution occur at locations distant from the sources of the problem; therefore, there is both a need to pursue solutions in multiple places *and* there is an overall lack of alignment between the overlaying governance system and the underlying ecological processes. Collaborative governance approaches are often touted as effective solutions to wicked problems such as nonpoint source pollution (Folke et al. 2005, Provan and Kenis 2007, Fish et al. 2010, Klijn and Koppenjan 2015, Bodin et al. 2016, 2020). However, governance actors take part in multiple management games at the same time, meaning they have limited capacity to participate in and address any one problem (Lubell 2013). To address wicked problems, governance actors must weigh the costs and benefits of working with other governance actors *and* pursuing different types of management strategies like information sharing and building new institutions (North 1984, 1991, Jones et al. 1997, Lubell et al. 2010, 2017, Bodin et al. 2020). Transaction costs may be higher if multiple organizations have authority or are otherwise involved in addressing the problem (Laurenceau 2012, McCann 2013). Decisions to collaborate may also be shaped by the underlying ecological processes of the particular situation (Pahl-Wostl et al. 2007, Bodin and Crona 2009, Treml et al. 2015, Bodin 2017). Additionally, as the size of the problem increases, overall costs may also increase (Rørstad et al. 2007, McCann and Hafdahl 2007, Krutilla and Krause 2011, Laurenceau 2012, Roberts et al. 2012, Garrick and Aylward 2012, McCann 2013). Despite this literature acknowledging that problem severity influences decision-making processes, research into how environmental risk shapes decisions of collaborative relationships is nascent (Kalesnikaite and Neshkova 2021).

The decisions of management deliberations are perhaps best explored through network analysis that visualizes and measures the connections between and among governance actors (hereafter referred to as social actors). Using network analysis, governance scholars can begin to unravel not only what leads to certain management approaches being pursued, but also which network structures lead to more positive environmental outcomes. Using the case of Lake Erie harmful algal blooms (HABs), we argue that in addition to weighing potential transaction costs when deciding which management approaches to pursue and with whom, social actors *also consider* the level of environmental risk, conceptualized here by heterogenous nonpoint source pollution inputs across the landscape. To study the relationship between environmental risk and network structure, we construct social-ecological networks that represent low, medium, and high transaction cost relationships in a low environmental risk region (Central Basin of Lake Erie) and a high environmental risk region (Western Basin of Lake Erie). Social-ecological networks are networks that consists of three levels: a social network level, an ecological network, and a social-ecological network level. We first use exponential random graph models (ERGMs) to analyze the social network level of each relationship and environmental risk combination to ascertain what drives the social network structure. We then use these fitted ERGMs to simulate social-ecological networks as a baseline comparison to our observed network. Research shows that network ties do not occur randomly and instead are the result of numerous mechanisms like homophily (a tie between two similar nodes) and transitivity (a friend of a friend is a friend) (Lusher et al. 2013). By fitting ERGMs to our network data, we can examine the social processes that give rise to the governance system of Lake Erie HABs and second, precondition the social-ecological networks based on what we see happening in the social network level of the governance system. In other words, the probability of a tie in our social network is a function of the endogenous and exogenous social processes and the probability of a tie in our social-ecological network is a function of *both* social network processes and social-ecological network processes. Finally, we examine the frequency of social-ecological motifs in our observed networks against those found in simulated networks to understand how environmental risk shapes the overall social-ecological structure of the Lake Erie HABs governance system (hereinafter referred to as the social network). Below, we begin with a review of the pertinent literature informing our study, followed by a presentation of our methodology and results, and finally, discussion and implications for future research.

BACKGROUND AND THEORY

This research contributes to existing bodies of scholarship on environmental governance networks (Bulkeley 2005, Sandström and Carlsson 2008, Bodin and Prell 2011, Bodin et al. 2016, Schoon et al. 2017), policy networks (Provan and Kenis 2007, Berardo and Scholz 2010, Lubell et al. 2010, McGuire and Silvia 2010, Berardo and Lubell 2016, 2019), and complex social-ecological systems (Gunderson and Holling 2002, Berkes et al. 2008, Ostrom 2009, Bodin and Crona 2009, Bodin and Tengö 2012, McGinnis and Ostrom 2014, McAllister et al. 2015, 2017, Epstein et al. 2015, 2020, Bodin 2017). Environmental governance networks are formed by diverse actors interacting in different ways to solve problems that can't be easily solved alone. In these networks, social actors interact through formal, informal, and financially incentivized institutional arrangements (Ostrom 1990, Sabatier et al. 2005) to make decisions (North 1991). Social interactions result in new information, increased capacity, and potentially attitude changes as social actors process what they gain through these connections (Borgatti et al. 2009, Borgatti and Halgin 2011). As a result, social actors need to be aware of what the institutions are, that they are expected to be in compliance with these institutions (North 1991), and institutional compliance will be monitored and enforced (Ostrom 1990). The structure of the social networks arises from social actors making choices about with whom to engage, when to engage with them, and how to engage with them (Crona and Bodin 2006, Bodin and Crona 2009, Bodin and Tengö 2012, Lubell 2013, Baggio and Hillis 2016, 2018). These governance decisions are critical to addressing the persistent question of how best to solve wicked problems (Folke et al. 2005, Janssen et al. 2006, Bodin and Crona 2009, Bodin and Prell 2011, Sayles and Baggio 2017, Bodin 2017). Adding to claims that transaction costs and ecological connectedness shape networks, we argue that environmental risk also shapes social actors' decisions to connect with other social actors.

In this paper, we conceptualize environmental risk as the severity of the problem that social actors are trying to solve. Social actors evaluate this problem severity when making decisions on how to act; this is particularly true for wicked problems (Bryson et al. 2006, Emerson and Nabatchi 2015). Existing literature shows that environmental risk can be a precursor to collaboration (McGuire and Silvia 2010, Emerson and Nabatchi 2015) and may also be particularly relevant for driving higher levels of collaboration (Kalesnikaite and Neshkova 2021). In terms of policy response, studies of local sustainability action show that problem severity may drive local actors' decision to adopt policies (Mullin and Rubado 2017, Hughes et al. 2018, Kwon and Bailey 2019). In the case of wicked problems, like nonpoint source pollution that are heterogeneously distributed across the landscape, we argue that social actors may be more active in higher environmental risk regions (e.g., regions with higher concentrations of pollutants) as the potential benefit of solving the problem is greater. Additionally, because time lags between pollutant inputs and measured changes in the environment increase overall costs of acting (Perry and Easter 2004, McCann 2013), we argue that higher levels of collaboration like institution building, which can lower transaction costs in the long run by designing rules and enforcement mechanisms, are critical in management efforts within higher environmental risk regions. Therefore, we hypothesize the following:

H1: *High levels of collaboration (e.g., institution building) are more active in high environmental risk regions than low environmental risk region*

Environmental problems do not occur in a vacuum; social actors are faced with multiple and overlapping problems and their actions on one issue may negatively or positively influence their actions on and the outcomes of another issue (Lubell 2013). In deciding which problems to address and how, social actors must consider their available time, funding, staff, expertise, and other resource capacity. These considerations translate into *transaction costs* or the costs associated with searching for and developing relationships, negotiating and bargaining towards particular policy responses, and the final benefit (or burden) of the policy response (Williamson 1981, North 1991, Lubell et al. 2014). Different collaborative management approaches may demand different levels of transaction costs. For example, building new institutions may involve creating or re-defining the formal rules with which management of an environmental problem is pursued. The process of institution building may be time-consuming as social actors with opposing interests and opinions negotiate to leverage the best individual outcome (Gatzweiler and Hagedorn 2002, Parkins 2011, Torfing 2012, Mitchell 2015). Comparatively, lower levels of collaboration like information sharing generally represent lower transaction costs, requiring only a social actor who has information sending it or providing it to another social actor (no reciprocal relationship). These *transaction costs* may drive social actors to collaborate with others to expand capacity (e.g., funding, staff, expertise) or knowledge (e.g., social learning). A key strand of literature on collaborative governance assesses how transaction costs shape social actors' decisions to collaborate and in what ways (Krueger 2005, King 2007, Lubell et al. 2017, Boschet and Rambonilaza 2018, Hileman and Bodin 2019, Klasic and Lubell 2020). This literature finds that generally, when social actors perceive transaction costs to be high, such as with higher levels of collaborative relationships like building new institutions, social actors seek out reinforcing connections with those they trust and who are less likely to defect (Renn and Levine 1991, Ostrom 1998, Burt and Burt 2005, Sandström and Carlsson 2008, Blair et al. 2013, McAllister et al. 2015). Social actors may also seek out trusting and reciprocal relationships when faced with wicked problems that are polarizing and lack a clear solution (Jenkins-Smith and Sabatier 1994). This may be especially true when environmental risk is high because of the magnitude of the implications if the problem is not solved.

Network analysis allows scholars to study the social processes and patterns that give rise to a social-ecological governance system by examining endogenous and exogenous variables. One of the hallmarks of network theory is that similar social actors are more likely to be connected than dissimilar social actors, referred to as *birds of a feather flock together* (McPherson et al. 2001). Homophily can help reduce transaction costs associated with collaborative partnerships (Kalesnikaite and Neshkova 2021). Two important types of homophily in governance networks are scale homophily (see for example, Hamilton and Lubell 2018, Hileman and Lubell 2018), meaning social actors at the same governance level work together, and organizational type homophily (see for example, Alexander et al. 2018). Scale and type homophily may be differentially important depending on the type of management relationship being pursued. For example, collaboration networks may show a greater tendency for homophily than information sharing networks because information networks preference bridging structures that allow social actors to learn from and leverage distant parts of the network (Ramirez-Sanchez and Pinkerton 2009, Bodin and Crona 2009, Wukich et al. 2019).

H2: *Homophily is a stronger predictor of collaboration networks than information sharing networks*

In addition to endogenous variables like homophily, network analysis allows for the examination of network motifs. Motifs are basic network building blocks composed of social actors or social and ecological actors, and the links between and among them. There are two main types of motifs, closed and open. In a social network, the most basic closed network motifs are represented by three social actors that are all connected to each other (Figure 8a), while the most basic open network motifs are represented by three social actors that are *not* all connected to one another (Figure 8b). In social-ecological networks, the most basic closed network motif is two social actors that are communicating with each other *and* managing one ecological actor (e.g., watershed) (Figure 8c), while the most basic open network motif is two social actors managing one ecological actor but *not* communicating (Figure 8d). In this way, closed network motifs represent connectivity between all social actors involved, while open networks imply a lack of connectivity. Closed and open network motifs are representative of different social processes (Berardo and Scholz 2010). While both closed and open network motifs are important in collaborative networks, a rich strand of literature has developed discussing the properties and determinants of closed and open network structures (Coleman 1990, Putnam 1993, Ostrom 1998, Burt and

Burt 2005, Berardo and Scholz 2010, Bodin and Prell 2011, Berardo 2014) as well as the implications these structures have for solving wicked environmental problems (Cheng et al. 2006, Bergsten et al. 2014, Epstein et al. 2015, Bodin et al. 2016, Bodin 2017, Dey et al. 2019).

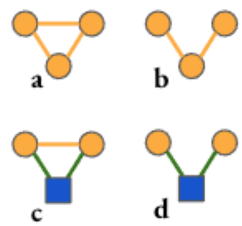


Figure 8. The most basic closed (9a, 9c) and open (9b, 9d) network motifs in social networks (9a, 9b) and social-ecological networks (9c, 9d). Orange nodes and links represent social actors and connections between them; blue squares represent ecological nodes (e.g., watersheds); green links indicate that the connected social actor manages the ecological cator.

Social Networks: Closed and Open Motifs

Networks described as having many open motifs are often sparser than networks with closed motifs. Open network motifs facilitate connections between social actors without requiring a large investment (Bodin 2017). The simplest open network motif consists of three actors in a star shape where at least two of the actors are not connected to one another. Open network motifs imply that some actors have more connections and are therefore more centrally located in the network than others (Bodin 2017). These open network motifs promote learning and innovation (Granovetter 1973, McAllister et al. 2015) and enable actors to access resources available through more distant connections (Putnam 1993, Burt and Burt 2005). Network researchers argue that coordination problems often relate more to open network motifs (McAllister et al. 2015). In coordination problems, most of the actors involved often agree on what should be done and how it should be done, with the goal being to find the most efficient and effective way to reach the overarching objective (Berardo and Scholz 2010, Berardo 2014, Bodin et al. 2020). Higher transaction costs from open network motifs may emerge because social actors are further removed from more distant parts of the network, however open motifs may offer access to unknown resources (Sandström and Carlsson 2008), and boundary actors who disparate parts of the network may help reduce transaction costs (McCann 2013). Additionally, open network motifs may be useful in addressing emergencies because they allow for more rapid diffusion of information (Lubell et al. 2017).

At the opposite extreme, closed network motifs, at their most simple level, involve three actors that are each linked to one another; in a sense, a friend of a friend is a friend (Bodin 2017). Closed network motifs reinforce trust and a willingness to collaborate (Putnam 1993, Ostrom 1998, Burt and Burt 2005, Berardo and Scholz 2010, Berardo 2014), but may also facilitate learning (Prell and Lo 2016). Closed network motifs are likely to arise when the chance of defection or free riding is high (McAllister et al. 2015) because social actors will pursue densely connected and reinforced relationships that increase trust, facilitate a shared understanding of expectations, and exert pressure on social actors to comply with the institutions in place (Casella and Rauch 2000, Bodin 2017, Bodin et al. 2019). Trust, while time-demanding, can decrease transaction costs, making collaboration more desirable (Ostrom and Walker 2003, Emerson et al. 2012, Kamieniecki and Kraft 2013, Klasic and Lubell 2020). Network theorists often describe closed network motifs as being more likely to emerge from cooperation problems when diverse actors with varying and sometimes opposing opinions and priorities must negotiate and compromise in order to solve a collective action problem (Coleman 1990, Putnam 1993, Ostrom 1998, Bodin 2017). When the collective action is politicized or otherwise doesn't have a clear solution, research shows that social actors may seek out reciprocal relationships with those who uphold their own ideals and priorities (Jenkins-Smith and Sabatier 1994, Sabatier et al. 2005, Lubell et al. 2017). Additionally, as the number of social actors involved in decision-making increases, so to do associated transaction costs (Laurenceau 2012, McCann 2013, Mitchell 2015). The desire for trusting, reinforcing relationships may be even more pronounced when social actors participate in high levels of collaboration (e.g., institution building) in higher environmental risk regions that may carry higher transaction costs and a greater chance of failure. While targeted solutions to addressing nonpoint source pollution may be theoretically efficient, they may actually have higher overall transaction costs (Rørstad et al. 2007). With all of these points in mind, we hypothesize the following:

> ***H3:*** *In high environmental risk regions, social actors pursuing higher levels of collaboration (e.g., institution building) are more likely to seek out reciprocal ties, resulting in networks with more closed motifs than in lower environmental risk regions.*

Social-Ecological Networks: Closed and Open Motifs

Social-ecological systems research argues that management decisions are the outcome of feedback and relationships between and among social and ecological processes (Young and Gasser 2002, Ekstrom and Young 2009, Bodin and Tengö 2012, Bergsten et al. 2014, Treml et al. 2015, Barnes et al. 2017). Much of the scholarship explores this idea through *fit*, arguing that when ecological processes either transcend traditional social boundaries or are not managed at an appropriate scale, there is a misalignment (misfit) and that there exists a more ideal management approach (Cumming et al. 2006, Termeer et al. 2010, Pelosi et al. 2010, Bergsten et al. 2014). Expanding on motif ideas in social network literature, social-ecological fit can be discussed in terms of closed and open social-ecological network motifs. In social-ecological networks, motifs describe the relationships among social actors (e.g., organizations), among ecological actors (e.g., watersheds), and between social and ecological actors. A common relationship between a social actor and an ecological actor as described in this manuscript, is location of management effort. For example, an organization that plays a role in managing a watershed is represented by a tie between that organization and that watershed (social-ecological tie).

Figure 9 depicts four sets of open and closed social-ecological motifs that are important to consider when analyzing social-ecological networks. Each set of motifs represents different styles of management, with open network motifs generally referring to social-ecological contexts in which management could be improved through cooperative ties between social actors. The four social-ecological contexts symbolized in Figure 9 and discussed further in this manuscript below are categorized based on the nature of the ecological units (e.g., watersheds) and the type of management being pursued; these management types include: social learning, shared management, shared management and social learning (together), and shared management of interconnected resources.

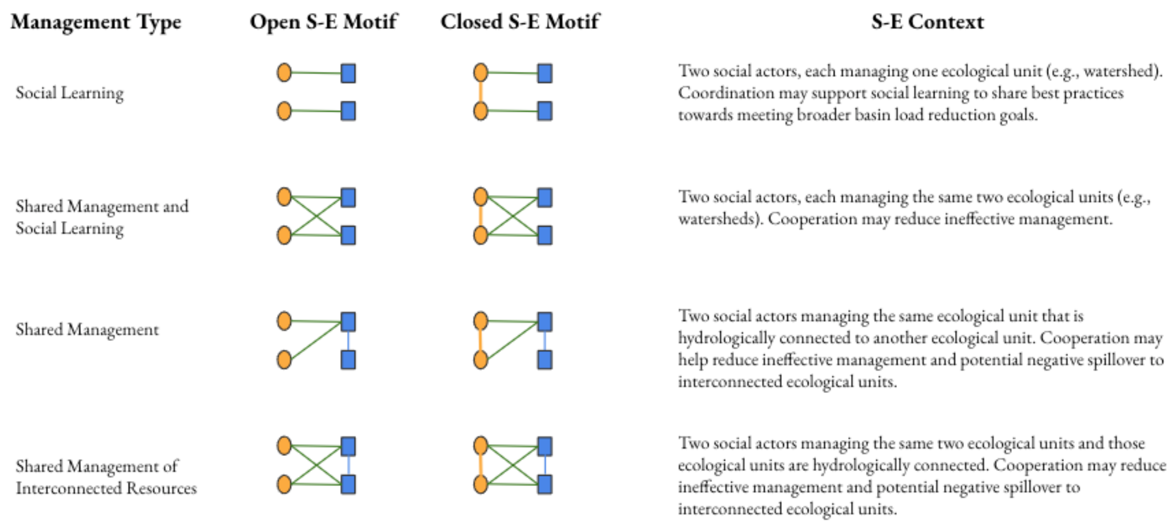


Figure 9. Conceptualizing different management types within social-ecological systems using open and closed social-ecological motifs.

<u>Social Learning Across Disconnected Ecological Actors</u>

When ecological actors are disconnected, they may be treated as separate ecological units that do not influence one another. For example, the watershed approach argues that managing nutrient loading within a watershed's boundaries is important because what happens upstream accumulates downstream (Crumpton 2001). There may be less of an impetus for social actors managing separate watersheds to cooperate because they are focused on their defined ecological boundaries (open network motif). However, when social actors managing separate ecological actors are cooperating, there may be an increased likelihood of social learning and innovation (Abers 2007, Patterson et al. 2013). Therefore, while cooperation between social actors may not be inherently needed to manage the individual ecological actors, it can be helpful in sharing strategies and lessons learned and may ultimately result in better social-ecological alignment across the landscape (closed network motif).

Shared Management and Social Learning Across Disconnected Ecological Actors

In contexts in which ecological actors are disconnected but more than one social actor is sharing the management of each individual ecological actor, cooperation among the social actors could lead not only to social learning and innovation, but also coordinated management efforts. Social-ecological alignment across disconnected ecological actors may also be especially important in addressing fragmented management systems arising when ecological processes do not follow administrative boundaries (Young and Gasser 2002, Ekstrom and Young 2009, Treml et al. 2015). For example, if an ecological actor such as a watershed overlays two states, the governance structures for managing that watershed may contradict or otherwise undermine one another (Sabatier et al. 2005). In this social-ecological context, an open network motif, in which the social actors managing the same resources are not cooperating, may result in poorer management, while a closed network motif, in which the social actors managing the same resources *are* cooperating, may result in more effective management.

Shared Management of Interconnected Ecological Actors

Open social-ecological network motifs involving interconnected ecological actors may indicate poor management design because social actors are not sharing information or the management practices or actions they are pursuing (Guerrero et al. 2015b). However, interconnected ecological actors may exert positive or negative influence on one another regardless of the cooperation state of the social actors managing the ecological actor or actors. For example, we can consider the case of nonpoint source pollution and more specifically, phosphorus loading from agricultural fields across a set of watersheds. If phosphorus loading is occurring within a single watershed that drains to a lake, then management approaches that address runoff in that watershed may be the best approach to reducing impacts on the lake. However, if that watershed is hydrologically upstream and connected to a second downstream watershed and that second downstream watershed flows into the lake, management of the upstream watershed alone may not be enough. If, for example, best management practices are placed onto agricultural fields in the upstream watershed, but nothing is done in the downstream watershed, then the management efforts in the upstream watershed may be for naught. Alternatively, if social actors are cooperating (thus forming a closed-social ecological network motif), then the system is more likely to reflect aligned management and may result in better overall environmental outcomes (see for example, Barnes et al. 2019). Closed social-ecological network motifs may be beneficial to environmental problem-solving because management approaches occurring in one ecological area (e.g., a watershed) may have positive or negative consequences for interconnected ecological areas (e.g., another watershed) (Guerrero et al. 2015b). Additionally, when two social actors are managing the same interconnected ecological actors, social actors may each individually possess local ecological knowledge that the other does not but that may be beneficial to their own management approach (Crona and Bodin 2006). To minimize potential negative feedback and maximize benefit, researchers hypothesize that social actors should work together. We argue that in high environmental risk regions, social actors will purposefully plan to collaborate in a way that emphasizes closed network motif structures to address the fragmented nature of the governance system and the underlying ecological processes. We therefore hypothesize the following:

H4: *In high environmental risk regions, social-ecological networks will show a propensity for social-ecological fit or closed network motifs over open network motifs*

METHODS AND DATA COLLECTION

Case: Lake Erie Harmful Algal Bloom Management

We test our hypotheses using the case of Lake Erie harmful algal bloom (HAB) management. Lake Erie is the shallowest and warmest of the five Laurentian Great Lakes of North America, bordering Canada and the United States. Lake Erie is surrounded by five states (Ohio, Pennsylvania, New York, Michigan, and Indiana), one province (Ontario), and five urban centers (Buffalo, Erie, Toledo, Cleveland, and Detroit). Lake Erie is a crucial source of drinking water for 10M people, supports a $12.9B fishing and tourism industry, and offers a critical habitat for migratory birds, endemic and endangered species, and aquatic life (USEPA GLNO et al. 2018).

Seasonal HABs threaten Lake Erie's diverse and unique social-ecological system. HABs are prolific growths of toxic algae driven by excessive nutrients. What makes HABs especially difficult to address is that in addition to the complexities of nonpoint source pollution loading, HABs are also driven by factors like temperature, water depth, spring precipitation over which managers have little to no control. Of the five Great Lakes, Lake Erie receives the highest loading of phosphorus and is exposed to the greatest amount of urbanization, industrialization, and agriculture (USEPA GLNO et al. 2018). Ecologically, Lake Erie consists of three drainage basins, identified as Eastern, Central, and Western. These three basins are composed of more than 30 watersheds, some of which are interconnected prior to draining into the lake. The Western Basin is responsible for 61% of the total phosphorus loading into Lake Erie, while the Central Basin and Eastern Basins are responsible for 28% and 11% respectively (USEPA GLNO et al. 2018). In this paper, we treat the Western Basin as having *high environmental risk* and the Central Basin as having *low environmental risk*.

Lake Erie has a long history of dealing with HABs that dates back to at least the 1960s. In 1972, policy efforts stemming from point source pollution control in the Clean Water Act and the Great Lakes Water Quality Agreement (GLWQA), a binational agreement between the United States and Canada, resulted in an extreme decline of HABs on the lake (Jetoo 2015). However, in the 1990s, HABs began reappearing and have steadily increased over time, especially over the last 10 years (USEPA GLNO et al. 2018). Lake Erie HABs came to a head in 2011 when the largest bloom on record resulted in a *do not drink advisory* for half a million people in Toledo, Ohio (Michalak et al. 2013). As point source pollutants (especially wastewater outflow) have been controlled through permitting processes, present day HABs are linked to excessive nonpoint source pollution loading. More specifically, phosphorus is the limiting factor for HABs occurrence in Lake Erie, stemming primarily from intensive agricultural land use in the larger watershed (Ludsin et al. 2001, Scavia et al. 2014).

With a basin that overlays 5 states, a province, and two countries (not to mention numerous cities, towns, and other governance level jurisdictions), Lake Erie HABs management can be described as polycentric. More broadly it exemplifies a fragmented social-ecological system plagued by misalignment between the underlying ecological processes and the social processes. As a result, the governance system employs both top-down and bottom-up approaches. The GLWQA provides the overarching framework for Great Lakes management and represents a set of formalized institutions within which HABs management (and other priorities) occurs. Canada and the United States use the GLWQA as a guide for developing national Great Lakes and Lake Erie plans. The national plans, in turn, guide state and province-level domestic action plan development that in turn shapes local level action. The most recent version of the binational agreement, *the 2012 GLWQA* was signed into force in February 2013 (Binational n.d.). The 2012 GLWQA identifies nine general objectives, one of which explicitly discusses reducing and eliminating nutrients from human activities in amounts that result in detrimental human and aquatic impacts from algae and cyanobacteria growth. Following the 2012 GLWQA signing, the United States and Canada, through a robust science-based process that included public participation, set a phosphorus loading reduction target of 40% for the Central (low environmental risk) and Western (high environmental risk) basins of Lake Erie. The Eastern Basin was not included because it has low levels of agricultural land use and it is deeper on average, resulting in fewer (often not present) seasonal HABs. Despite Canada contributing much less phosphorus to Lake Erie than the United States, Ontario put forth a plan and commitment to reduce their contributions of phosphorus by 40%, in alignment with the GLWQA process, by 2025; Ohio and Michigan have taken similar approaches (IJC 2019). Bottom-up approaches to Lake Erie HABs management are also present; for example, several private and public entities (and citizens) in key phosphorus contributing watersheds across Ohio, Michigan, and Indiana formed the

Maumee Watershed Alliance (formerly the Tri-State Watershed Alliance) to coordinate activities (Berardo et al. 2019). An important feature of Lake Erie HABs governance, however, is that there are no enforcement mechanisms associated with the phosphorus reduction targets; countries and states have flexibility in how best to achieve these goals, however if they fail to reach them, there are no concrete penalties. This design feature can increase transaction costs and risk of defection for managers pursuing HABs management strategies and partnerships.

Data Collection

The work carried out in this study depends on publicly available planning documents. Data collection consisted of a four-step approach. First, we identified the universe of documents related to HABs planning in the western and central basins of Lake Erie. Second, we hand coded the document set for social and ecological network data. Third, we cleaned and aggregated inductive codes to broader categories. Finally, we collected attributes (ways of describing network data) and formed and analyzed the social-ecological networks (SENs). Each of these steps is discussed below in further detail.

Step 1. Identifying the Universe of HAB Planning Documents

We conducted internet searches for Lake Erie HABs-related documents for the 2007-2017 timeframe. Each search that was completed contained "Lake Erie", a Geographic Scope (e.g., Ohio, Ontario), a keyword or phrase related to harmful algal blooms (e.g., harmful algal bloom, algae), and a document type (e.g., plan, strategy). For example, one search was "Lake Erie" + "Ohio" + "Harmful Algal Bloom" + "Plan". We made two purposeful decisions in conducting our searches. First, we did not include a timeframe limit to help avoid planning documents that were posted earlier or later than our time period of interest. For example, a strategic plan for 2012 may be finalized and posted in 2011. Second, we initially included several document types in our search (e.g., plan, meeting, workshop, conference, colloquium), because not all planning documents are called plans. News and other media articles were removed from our results (see Supplemental Information for additional detail). All documents were downloaded and placed into a Zotero reference manager library.

Additional details on the search protocol are included in the Supplemental Information. We narrowed our data set in this paper to the 2012–2017-time frame to focus on activities planned in response to the 2012 Great Lakes Water Quality Agreement (GLWQA). The GLWQA is a binational agreement between the United States and Canada that outlines priorities for the Great Lakes. The 2012 update expanded the priorities from restoration activities to restoration and protection activities. Documents downloaded into Zotero were reviewed and those items pertaining to 2012-2017 were ultimately used for this analysis.

Step 2. Coding Planning Documents

Because of the geographic scope of the Lake Erie Central (low environmental risk) and Western (high environmental risk) basins (multiple states and a province, multiple nations) combined with the lack of previous analysis on actors involved in Lake Erie harmful algal bloom management at this broad a scale, we opted to code the planning documents manually and inductively in Excel. Inductive coding is a process of interpreting or looking for patterns in raw textual data rather than using theory to inform what is coded (Creswell and Poth 2016). In this manner, we first identified text excerpts in the documents and then extracted social actors (organizations), relationships between those social actors, ecological actors (where the social actors planned to work), and the ecological focus (e.g., harmful algal blooms, water quality, biodiversity, etc.). We also made a note of whether the ecological actor was defined within the excerpt or implied from contextual text surrounding the excerpt. This coding approach was iterative in that the coders had to re-read sections of the planning documents to ensure segments of text were coded appropriately.

An added benefit of inductive coding was that coders were not biased into trying to fit social relationships into specific relational categories from the start (Gioia et al. 2013). We opted for a text excerpt coding approach as opposed to presence/absence coding (e.g., do actors co-appear in a document or not) because we were most interested in the diversity of relationship types and which organizations are involved in which of these relationships over what space. In this manner, we were also able to garner two benefits: 1) we separated out actors involved in HABs-related planning from those involved in other unrelated activities and 2) we focused on actors planning to take an action as opposed to those who had already completed an action (e.g., will collaborate vs. collaborated previously). By focusing on planned action, as opposed to completed action, we aimed to capture activity that reflects on what had been accomplished previously, combined with the adjusted 2012 GLWQA directive. Our coding team consisted of 6 coders. We coded three documents together and discussed questions and concerns related to the coding process. As we proceeded with coding, we met weekly to discuss any issues or challenges that arose.

Step 3. Defining and Cleaning Actor and Relationship Data

Once all the documents were coded, we cleaned the data. Social actors were reviewed to ensure consistent spelling. In cases where an organization name had changed over time, we collapsed names into one common nomenclature. began the process of cleaning the data. Ecological actor codes were linked to HUC10 watersheds based on hydrologic flow maps.

Social relationship codes were categorized into 10 initial relationship categories using a process called margin coding, in which text is reviewed and aggregated into broader themes by making notes in the margins and then iteratively reviewing and aggregating again (Forman and Damschroder 2007). Based on an initial review, our team developed loose definitions of these themes through discussions and literature review. These relationships were further collapsed into six relationship types. We selected three of these relationships for analysis and evaluation in this paper (defined in Table 14). The three relationship choices, information sharing, collaboration, and institution building, represent low, medium, and high levels of transaction costs.

Table 14. Definitions of the three relationship types analyzed in this paper.

Final Relationship Category	Definitions
Information Sharing and Engagement	Excerpts in this category either 1) explicitly used the terms information sharing or engagement, 2) discussed education and training, 3) discussed data sharing, or 4) discussed generally engaging organizations.
Collaboration	Excerpts in this category either 1) explicitly used the terms collaborate or cooperate, or 2) discussed partnering or working with other organizations, but *did not* mention creating any new institutions.
Building New Institutions	Excerpts in this category discussed organizations creating new institutions, strategies, planning or implementation documents, or programs of some sort.

Step 4. Collecting attribution data

Finally, we collected attribution data on our social actors from Internet searches of each organization. Social attributes included information on the type (e.g., governmental, agricultural) and governance level (e.g., local, regions, national). In cases where organizations were composed of actors representing multiple levels of governance, we coded them as the highest level of governance. Additionally, for working groups or other non-formalized organizations that were designed as multiple separate actors working towards a cause, we identified all the individual organizations and added them to our dataset as partners along with their attributes.

Characterizing Lake Erie HABs Social-Ecological Network

To analyze how social relationships vary across space, we built multi-level social-ecological networks (SENs). SENs allow social and ecological systems to be integrated in a way that can explain their interdependencies (Bodin and Tengö 2012, Bodin 2017). While the proposal of using SENs to study social-ecological systems is not new (see for example, Cumming et al. 2006, Janssen et al. 2006), empirical and theoretical work to advance SEN scholarship remains nascent (see Sayles et al. 2019). Multi-level SENs allow researchers to study how different numbers and kinds of nodes relate; however, there can only be one type of relationship between any two nodes (Zappa and Lomi 2015). We define our multilevel SEN using social nodes (organizations), links between them (who are they working with), ecological nodes (watersheds), links between them (hydrologic flow), and links between social and ecological nodes (where are organizations working). In this way, our SEN analysis creates three interdependent networks: a social network, an ecological network, and a social-ecological network. Each SEN in our paper reflects the actors involved in that particular basin and relationship. For example, to appear in the information sharing SEN for the Central Basin, social actor nodes must have been included in the HABs planning documents as participating in information sharing in one or more of the watersheds that is part of the Central Basin. In this way, the total number of nodes in each SEN varies across relationship types and basins. Using SENs, we are able to study the underlying motifs that build or compose management of social-ecological systems (Rathwell and Peterson 2012, Bodin and Tengö 2012, Bergsten et al. 2014, Guerrero et al. 2015a). In this paper, we are specifically interested in how the level of ecological risk shapes these network motifs. Table 15 defines each of the three networks used in this paper.

Table 15. Our data defined three networks: 1) a social network representing the relationships between organizations, 2) an ecological network representing hydrologic flow between watersheds, and 3) a social-ecological network representing where organizations plan to work.

Network	Nodes	Links
Social Network	Organizations involved in Lake Erie HABs work	The planned relationship between the organizations
Ecological Network	Watersheds of the Central and Western Basins of Lake Erie	The hydrologic flow between watersheds
Social-Ecological Network	Organizations involved in Lake Erie HABs work and the Watersheds of the Central and Western Basins of Lake Erie	The watershed in which the organization planned to do Lake Erie HABs work

Analytical Methods: Combining Exponential and Multilevel Exponential Random Graph Modeling

To analyze our SENs, we employed a two-step process in which we first run exponential random graph models (ERGMs) on the social network of each relationship type and then we use the specified ERGMs as baselines in a multilevel network process to further examine the processes driving our observed networks. In the first step, we fit exponential random graph models (ERGM) to each of our networks (each relationship in each base for a total of 12 networks) in R using the *ergm* package (Handcock et al. 2021). ERGMs use markov chain monte carlo (MCMC) simulations to allow for networks forming from both endogenous (the ties influence whether other ties exist) and exogenous (node attributes influence whether ties exist) processes. ERGMs consider the observed network to be one possible outcome of a stochastic network process (Lusher et al. 2013) and estimate the frequency of observed motifs (combinations of nodes and links) in a network compared to the frequency of motifs in other random networks of the same size. Positive ERGM coefficients indicate that motifs occur in the observed network at a higher frequency than what is expected at random. In fitting ERGMs, we initially sought to include the same variables across all ERGMs (Table 16), however the final set of variables included in each ERGM varied based on convergence and goodness of fit.

Table 16. Variables included the ERGMs and their descriptions.

Variable	Description
gwesp	Measures propensity for triangles in the network.
gwdegree	Measures the variation in node connections across the network.
nodematch	Measures homophily of connected nodes. We tested for both scale and organization type homophily. Scale homophily included: local, state, regional, and national levels. Local governance actors represented sub-state entities, regional governance actors represented sub-national but supra-state entities, and national governance actors represented Canada, United States, and Tribe/First Nations/Métis entities. Organization type homophily included: government, agriculture, industry, not-for-profit, research, private citizen groups, and Tribe/First Nation/Métis.

We calculated descriptive statistics, including density, betweenness centrality, and global transitivity for each of the networks in the Central and Western basins. Density represents governance activity across the network, centrality presents a proxy for how spread out the network is, and transitivity measures the propensity of triangles (closed network motifs) in the governance network.

Following ERGM specification, we used the *motifr* package (Angst and Seppelt 2020) to compare the frequency of motifs in our observed social-ecological network to a simulation of 100 simulated random social-ecological networks of the same size. We then calculated the percentage difference between the frequency of each observed network motif and the average frequency of that same network motif from the simulated networks. There were two added benefits of using *motifr*. First, we were able to use our specified ERGMs as the baseline for comparison, which allowed us to reflect the social processes of our case more accurately, and second, we were able to hold the ecological network static. In our case of Lake Erie, we connect watersheds based on hydrological flow. It is extremely unlikely that hydrologic flow between these watersheds will change. Holding the ecological network static allows us to better represent the real-world context. One drawback to using *motifr* is that in addition to holding the ecological network layer static, it also holds the social-ecological network level constant. We initially tried to run our multilevel network analysis in *MPNet*, a software system that can allow for specifying variability and stability for each individual network level, however, we could not achieve a high enough goodness of fit for our data using this approach. Sufficiently fitting and modeling social, ecological, and social-ecological network data together is particularly challenging given that technological approaches to multilevel network analysis are nascent.

RESULTS

Below we present three sets of results: 1) descriptive statistics about the social networks, 2) the coefficients and standard errors for our ERGMs, and 3) a summary of the multilevel motif process.

Lake Erie Social-Ecological Networks

Our search ultimately yielded 770 documents of which 220 were planning documents (meaning they contained the word plan in their titles or otherwise were aimed at actions they hoped to accomplish in the future, such as a strategy). Of these 220 planning documents, 69 were ultimately included in our analysis because they were unique (duplicate documents removed), fit our amended time range (2012-2017), and they contained terms related to harmful algal blooms. Within the 69 planning documents, we identified 1,080 organizations (social actors) and 27 watersheds (ecological actors) of the Central and Western Basins of Lake Erie. For this analysis, we focus on three types of relationships: information sharing, collaboration, and institution building (definitions outlined above in Table 14). We selected these three relationships to represent low, medium, and high transaction costs, respectively. Table 17 presents descriptive statistics on social network density, betweenness centrality, and transitivity for each of the three relationships (see Supplemental Information for additional details on the networks and descriptive statistics). All three statistics allow us to understand the connectedness of the network in some way. We note again that the total count of nodes in each SEN varies by relationship type and basin, so that social actor nodes only appear in the SEN if they were found to participate in that particular relationship in the planning documents. Density measures the number of observed edges and divides it by the total number of possible edges (Wasserman and Faust 1994); in this way, density can be thought of as a proxy for activity, higher density (higher observed to possible edges) equates to higher activity. Betweenness centrality measures the role of a particular node in the network; it calculates the number of shortest paths that must go through the node (Golbeck 2013). Finally, transitivity is a network measure to capture the prevalence of triangles, that is the idea of a friend of a friend is a friend. If node *a* is connected to node *b*, and node *b* is connected to node *c,* a triangle is formed if node *a* is also connected to node *c.* Triangles are a ubiquitous occurrence in social networks (Wasserman and Faust 1994). It follows then, that networks are more clustered together if they have more triangles.

Overall, all of our networks are sparse, however for both collaboration and institution building, all three network metrics are higher in the Western Basin (higher ecological risk) than the Central Basin (lower ecological risk). We note here again that each network is composed of only those social actors that are involved in the relationship being depicted. In other words, the number of nodes varies across networks, so that an organization involved in information sharing but not institution building will only appear in the information sharing network. With this in mind, as we look across relationships, we find that density is highest for institution building (0.0784 in the Central Basin, 0.1110 in the Western Basin) followed by collaboration (0.0067 in the Central Basin, 0.0267 in the Western Basin), and information sharing (0.0314 in the Central Basin, 0.0071 in the Western Basin). Information sharing networks may benefit from less dense and more *spread out* network structures; this idea is captured as the strength of weak ties, which argues that weak or more bridging ties may increase innovation (Granovetter 1973).

Table 17. Density of each relationship's social network in the Central (low ecological risk) and Western (high ecological risk) Basins of Lake Erie.

	Density		**Betweenness Centrality**		**Global Average Transitivity**	
Relationship Type	Central Basin (Low Risk)	Western Basin (High Risk)	Central Basin (Low Risk)	Western Basin (High Risk)	Central Basin (Low Risk)	Western Basin (High Risk)
Information Sharing	0.0314	0.0071	69.1268	595.1690	0.0211	0.0675
Collaboration	0.0067	0.0267	503.9361	825.4183	0.0206	0.9039
Institution Building	0.0784	0.1110	1.1111	40.3220	0	0.8481

Exponential Random Graph Models

Table 18 presents the results of the ERGM estimations for each of three relationships across the Central (low environmental risk) and Western (high environmental risk) basins. We interpret the variable coefficients as conditional log odds, or the likelihood of observing the specified motif or formation in the network given all other formations in the model. While we initially sought to include all variables across all ERGMs, we ultimately removed certain variables from models when: 1) no actors met the specific variable condition in the observed network or 2) MCMC convergence was not reached.

Overall, we find support for hypotheses on scale homophily and type homophily for the collaboration networks, particularly related to social actors working at the local scale (1.1443 in the Central Basin, 0.9680 in the Western Basin, both statistically significant $p<0.00$) and across all organization types except government. Coefficients are generally smaller in the Western Basin (higher ecological risk) than the Central Basin (lower ecological risk), indicating that homophily is a stronger predictor of network structure for the Central Basin. Both information sharing and institution building network homophily varies across basins. For information sharing, scale homophily is a strong predictor in the Western Basin (higher ecological risk) for the local level (0.6406, $p<0.000$) and the national (e.g., Canada, United States) level (0.2550, $p<0.001$). Regional actors, however, have a negative significant coefficient (-0.8522, $p<0.000$), indicating that regional actors may work across scales. In the Central Basin (lower ecological risk), information sharing shows a positive and statistically significant coefficient for nonprofit organizations (0.9991, $p<0.05$), indicating nonprofits tend to work together. Concerning institution building, there is little support for the type homophily hypothesis in the Western Basin (higher ecological risk) specifically; coefficients for agriculture (-0.1178), research (-0.6673, $p<0.00$), and nonprofit (-0.6798, $p<0.05$) are all negative, indicating that these types of organizations are working with dissimilar organization types. Finally, we found support for our hypothesis that higher environmental risk regions produce more closed network motifs. Looking across relationship types *and* basins, we find positive, statistically significant, coefficients for triangles (*gwesp*), in the Western Basin (higher ecological risk) for all three relationship types. Further, the coefficient for triangles in the Western Basin (higher ecological risk) for collaboration building (2.4147, $p<0.000$) is *higher* than in the Central Basin (0.9133, $p<0.000$), and there are *no* observed triangles in the information sharing and institution building networks in the Central Basin (lower ecological risk).

Table 18. ERGM results for each relationship network (information sharing, collaboration, and institution building) for the central basin (low ecological risk) and the western basin (high ecological risk) (see Supplemental Information for further detail on social actor categorization).

	Information Sharing		**Collaboration**		**Institution Building**	
	Central Basin (Low Risk)	**Western Basin (High Risk)**	**Central Basin (Low Risk)**	**Western Basin (High Risk)**	**Central Basin (Low Risk)**	**Western Basin (High Risk)**
Edges	-8.0219*** (1.6195)	-5.9418*** (0.3270)	-8.7456*** (0.4748)	-9.315*** (0.3431)	-4.3876* (1.7580)	-3.7247*** (0.4782)
Gwesp(0.25)	No Triangles	1.1205*** (0.0614)	0.9133*** (0.0806)	2.4147*** (0.0661)	No Triangles	1.3989*** (0.2042)
Gwdegree(0.25)	0.7653 (0.4782)	-0.0138 (0.1756)	0.3863* (0.1886)	No Convergence	No Convergence	No Convergence
Within Scale Homophily						
Local	0.3998 (0.2856)	0.6406*** (0.0762)	1.1443*** (0.1107)	0.9860*** (0.0363)	0.4270 (0.8255)	0.0936 (0.5233)
State	No Convergence	No Convergence	No Convergence	0.0320 (0.0370)	-1.3098 (1.1202)	No Convergence
Regional	0.5236 (1.1587)	-0.8522*** (0.0895)	-0.8417*** (0.1216)	-0.1670*** (0.0468)	No Regional Actors	No Regional Actors
National	0.7858* (0.3072)	0.2550** (0.0970)	0.7806*** (0.1319)	0.0049 (0.0404)	0.7211 (1.1776)	0.5759** (0.2062)
Within Type Homophily						
Agriculture	0.5691 (0.3464	0.1196 (0.0991)	0.9594*** (0.1648)	0.2579*** (0.0618)	1.2225 (1.0983)	-0.1178 (0.1688)
Industry	1.0431 (0.6606)	0.6702** (0.2213)	1.0871*** (0.1621)	0.5471*** (0.1020)	No Industry Actors	No Convegence
Government	-0.1715 (0.2535)	-0.2034* (0.0854)	-0.3623** (0.1225)	0.4168*** (0.0495)	2.0478 (1.3045)	0.2819. (0.1640)
Research	0.4027 (0.4848)	0.0700 (0.1115)	0.5741*** (0.1713)	0.0962*** (0.0590)	No Research Actors	-0.6673*** (0.1757)
Not-for-Profit	0.9991* (0.5045)	0.0897 (0.0878)	0.4861*** (0.1403)	0.0039 (0.0522)	-0.6217 (1.5612)	-0.6798* (0.2846)
Private Citizens	0.3857 (0.3950)	-0.0008 (0.0985)	0.3168 (0.2483)	0.4663*** (0.1034)	-0.6375 (0.9046)	0.4376* (0.1998)
Tribal/First Nations	No Tribal/Métis/First Nation Actors	No Tribal/Métis/First Nation Actors	No Convergence	0.6547* (0.2862)	No Tribal/Métis/First Nation Actors	No Tribal/Métis/First Nation Actors
AIC	694.2	7114	4806	30369	92.29	1064

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Multilevel Social-Ecological Motif Analysis

The results of our multilevel social-ecological motif analysis are presented in Table 19 and Table 20. The results are organized to reflect the table of social-ecological network motifs presented in the theory and background section of this manuscript. Motifs are presented as pairs (open and closed) for each management type (e.g., social learning or shared management). Table 19 presents results pertaining to social-ecological motifs in which the ecological actors (watersheds) are disconnected. These motifs appear in both the low environmental risk Central Basin and the high environmental risk Western Basin. Table 20 presents results pertaining to social-ecological motifs in which the ecological actors (watersheds) are hydrologically connected. Hydrologically connected watersheds only appear in the Western Basin and as such, the Central Basin is not represented in Table 20. Network motifs are represented by orange and blue nodes and links and green links. Orange nodes and links represent the social network, blue nodes and links represent the ecological network, and green links between orange and blue nodes represent the social-ecological network. Results are presented as shaded cells containing the frequency of the specified motif found in the observed network and in parentheses, the percentage difference between the observed motif frequency and the average motif frequency based on the simulated network analysis. Cell colors represent the results of a significance test between observed network motif frequency and simulated network motif frequency. The motif frequency in the observed network is statistically significant if it falls above (positive significance; green shading) or below (negative significance; red shading) the 95% confidence interval of the average frequency in the simulated social-ecological networks (see Supplemental Information for breakdown of calculations). Yellow cells represent cases where the observed frequency of motifs fell within the 95% confidence interval of the simulated networks.

Table 19. Results of the multi-level social-ecological network motif analysis for disconnected ecological actors (watersheds). Each square represents the frequency of that motif in the observed social-ecological network. Values in parentheses are the percent difference from the mean. Positive values indicate that the frequency of that motif in the observed network was greater than the average simulated frequency of that motif. Motifs are organized by open management type and open versus closed structure. Colors represent results of the significance test between observed network motif frequency and simulated network motif frequency: 1) yellow- observed network frequency falls *within* two standard deviations of the mean in simulated networks, 2) red- observed network frequency falls *below* two standard deviations of the mean in simulated networks, and 3) green- observed network frequency falls *above* two standard deviations of the mean in simulated networks.

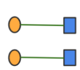
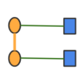
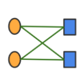
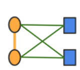
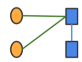
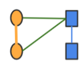
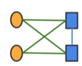
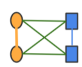
Management Type		**S-E Motif**	**Information Sharing** Central Basin (Low Risk)	Western Basin (High Risk)	**Collaboration** Central Basin (Low Risk)	Western Basin (High Risk)	**Institution Building** Central Basin (Low Risk)	Western Basin (High Risk)
Social Learning	Open Motif		2548 (+3.33%)	264260 (+0.60%)	64 (+0.61%)	414719 (+2.93%)	40 (+9.89%)	881 (+12.06%)
	Closed Motif		0 (-100.00%)	24 (-98.51%)	0 (-100.00%)	5 (-99.96%)	0 (-100.00%)	0 (-100.00%)
Shared Management and Social Learning	Open Motif		9682 (-1.58%)	633309 (-1.81%)	16327 (-4.44%)	1343016 (-2.14%)	679 (-7.05%)	28678 (-0.20%)
	Closed Motif		543 (+39.98%)	16976 (+221.00%)	902 (+526.39%)	47066 (+166.54%)	119 (+76.07%)	3141 (+1.88%)

Table 20. Results of the multi-level social-ecological network motif analysis for management of interconnected (hydrologically) ecological actors (watersheds). Each square represents the frequency of that motif in the observed social-ecological network. Values in parentheses are the percent difference from the mean. Positive values indicate that the frequency of that motif in the observed network was greater than the average simulated frequency of that motif. Motifs are organized by open management type and open versus closed structure. Colors represent results of the significance test between observed network motif frequency and simulated network motif frequency: 1) yellow- observed network frequency falls *within* two standard deviations of the mean in simulated networks, 2) red- observed network frequency falls *below* two standard deviations of the mean in simulated networks, and 3) green- observed network frequency falls *above* two standard deviations of the mean in simulated networks.

Management Type		S-E Motif	Information Sharing	Collaboration	Institution Building
			Western Basin (High Risk)	Western Basin (High Risk)	Western Basin (High Risk)
Shared Management of Interconnected Resources	Open Motif		19346 (-1.64%)	24839 (-22.22%)	44 (-14.93%)
	Closed Motif		456 (+240.30%)	8467 (+517.58%)	14 (+122.93%)
	Open Motif		59368 (-0.86%)	101510 (-0.82%)	1646 (-2.49%)
	Closed Motif		1078 (+15.67%)	1920 (+77.94%)	134 (+27.41%)

Generally, we find some support for our hypothesis that in the higher environmental risk region (Western Basin), there is a preference for closed (aligned) social-ecological network motifs regardless of whether the ecological actors (watersheds) are hydrologically connected. We find this support specifically where there is shared interest in a watershed or watersheds (e.g., two social actors managing the same watershed or watersheds). We do not find support for our hypothesis or the preference for closed (aligned) network motifs when social actors do not have shared interests (e.g., when they do not comanage a watershed or watersheds). Below we more specifically discuss the results by management type (shared management and social learning; shared management of interconnected resources).

<u>Shared Management and Social Learning Across Disconnected Ecological Actors</u>

Table 19 presents the results of managing disconnected watersheds. Overall, we find that information sharing is more prevalent in the higher risk Western Basin (16,976 motif frequency; 221.00% higher than expected)) than in the lower risk Central Basin (543 motif frequency; 39.98% higher than expected). We also find that across the higher environmental risk Western Basin, information sharing between social actors engaged in shared management and social learning is more prevalent (motif frequency is 221.00% higher than expected) than collaboration (motif frequency is 166.54% higher than expected) and institution building (motif frequency is 1.88% higher than expected). We found mixed support for our hypothesis on environmental risk related to the Collaboration network. Generally, the collaboration network reflects that it is rare to have shared management interests, but when those shared management interests do appear, there is a preference for collaborating. We also found little support for our hypothesis on environmental risk related to the Institution Building network. In the Institution Building network, shared interest is about as expected (motif frequency 0.20% lower than the average motif frequency) and likewise, so is the likelihood of building institutions (motif frequency 1.88% higher than the average motif frequency).

Shared Management of Interconnected Ecological Actors

When considering network motifs representing hydrologically interconnected watersheds, we found that consistent with our hypothesis of environmental risk and network structure, across all three relationship types, there is a preference for closed network motifs (positive and statistically significant motif frequencies). However, we also found that collaboration was the dominant relationship type, rather than information sharing. This is true in cases where social actors co-manage a single (frequency of closed collaboration motifs is 8,467 and 517.58% higher than expected) or multiple (frequency of closed collaboration motifs is 1,920 and 77.94% higher than expected) watersheds. This may suggest a shift along the pathway from information sharing towards institution building. In other words, our results suggest that it is not just environmental risk that shapes the relationships pursued, but perhaps some combination of environmental risk, transaction costs, and priorities that matters.

DISCUSSION

We modeled three governance relationships by combining social and ecological data about where organizations plan to work and with whom they plan to work with to address Lake Erie HABs. We analyzed these networks across two basins (low and high environmental risk) with the goal of evaluating how environmental risk shapes management networks. In doing so, we also considered concepts of open and closed network structures, transaction costs, homophily, and ecological connectedness. Overall, we found: 1) the role of scale and organization type homophily varies across governance networks, 2) governance networks are denser and show a preference for more closed network motifs in higher environmental risk regions regardless of transaction cost level, and 3) governance networks in the high environmental risk region (Western Basin) generally have a propensity for closed (aligned) social-ecological network motifs, but environmental risk alone does not fully explain network structure and relationships pusued. Below, we discuss each of these findings.

Scale and Organization Homophily

Local actors (e.g., municipal governments or nonprofit organizations) and agricultural actors (farming operations and other agribusinesses) show a tendency for homophilous connectivity in information networks and collaboration networks in the Western Basin (high environmental risk). The homophilous tendency of local actors also carries over to the Western Basin (high environmental risk) for collaboration. While there have been several major statewide (e.g., H2Ohio) and national level (e.g., Clean Water Act Section 319) initiatives to support nonpoint source pollution reduction through agricultural best management practices (BMPs), the onus of recruiting farming operations to implement BMPs which may incur additional undesirable costs often falls to local organizations and leaders (Forster and Rausch 2002, Lamba et al. 2008, Wilson et al. 2013, Rudnick et al. 2021). Research shows that awareness of BMPs may increase adoption rate (Napier et al. 1988, Lubell and Fulton 2008) and this awareness may be driven by information sharing and educational programs that decrease uncertainty around the proposed BMPs (Feather and Amacher 1994). In Lake Erie specifically, Zhang et al. (2016) showed that farming operations in the Maumee Watershed (largest contributor of Phosphorus loading in the Lake Erie Basins) whose managers believe that BMPs will reduce nutrient runoff, were more likely to adopt those BMPs. Therefore, it is perhaps not surprising that local actors, including nonprofits, agri-businesses, and farming operations, are more likely to share information and otherwise collaborate to try and implement broad scale nutrient reduction strategies.

We also found that national level actors (e.g., the U.S. Environmental Protection Agency and Environment and Climate Change Canada) tend to build new institutions in the Western Basin (high environmental risk). Given the longstanding history of binational effort in the Lake Erie region (IJC 2018) , it is interesting that despite the number of institutions designed over the years to manage Lake Erie (e.g., Great Lakes Water Quality Agreement, International Joint Commission, Nutrients Annex 4 Committee), the United States and Canada are still pursuing building *new* institutions. This finding could indicate that the United States and Canada are participating in social learning processes and amending institutions to better align with the new information and understanding they gain. Processing information and changing approaches to management are hallmarks of the adaptation process (Moser and Ekstrom 2010). In addition to this ongoing homophilous tendency at the national level, research and nonprofit organizations both have negative (and significant) coefficients for homophily in the Western Basin (high environmental risk) Institution Building network. It could be that research and nonprofit organizations that typically collect and produce data, are working with and supplying this new information to the national level organizations to help in amending institutions.

Finally, homophily appears to be most significant in the Collaboration networks, compared to both Information Sharing and Institution Building. This is unsurprising given that collaboration networks typically represent two ongoing social processes, cooperation and coordination (Berardo and Scholz 2010). As a typically mid-level transaction cost relationship, collaboration involves actors working together with those they trust (coordination), while simultaneously seeking cooperative relationships with those who are different.

Structurally, these relationships appear as both open and closed network motifs. In comparison, information sharing networks often depend on heterogeneous relationships to educate disparate parts of the network and leverage additional capacity (e.g., funding for data collection).

Greater Activity in Western Basin (High Environmental Risk)

We found greater activity in the Western Basin (high environmental risk) than the Central Basin (low environmental risk) for both collaborative and institution building networks. Greater activity may be occurring in the Western Basin (high environmental risk) because of the structure of policy agenda. The top-down policy structure of Lake Erie places more emphasis on addressing phosphorus inputs from the Western Basin (high environmental risk) than the Central Basin (low environmental risk). Despite the GLWQA calling for phosphorus reduction targets and subsequent national-level plans calling for a 40% reduction in phosphorus loading for *both* the Central (low environmental risk) and Western (high environmental) basins, practically, there is more nuance in how these targets are implemented. The nutrient annex of the GLWQA, for example, identifies priority tributaries to focus phosphorus reduction efforts; the majority of these tributaries flow into the Western Basin (high environmental risk) (Blue Acounting n.d.). Additionally, the Maumee River, which drains into the Western Basin (high environmental risk), is the largest contributor of phosphorus loading into Lake Erie (Obenour et al. 2014, Scavia et al. 2014, 2016, Kerr et al. 2016). The United States Action Plan for Lake Erie emphasizes the contribution of the Maumee River and notes that phosphorus loading from the Maumee River is a strong predictor of algal bloom severity (USEPA GLNO et al. 2018). Further, even though the target loading reductions are both set to 40%, because there is so much more phosphorus input in the Western Basin (high environmental risk), actual required phosphorus load reductions are higher in the Western Basin (high environmental risk) than the Central Basin (low environmental risk) (USEPA GLNO et al. 2018). Finally, despite the Western Basin (high environmental risk) being largely composed of United States territory, the Canada-Ontario Lake Erie Action Plan that shapes Ontario's approach to managing Lake Erie, also emphasizes contributions and work in the Western Basin (high environmental risk). The plan specifically identifies two priority tributaries, both draining into the Western Basin (high environmental risk), that contribute to Lake Erie HABs (Environment and Climate Change Canada). Along with these driving policy documents, funding programs designed to address nonpoint source pollution problems in the Lake Erie Region prioritize Western Basin (high environmental risk) watersheds. For example, the H2Ohio program (ODNR 2019), an effort by Governor Mike DeWine to curb agricultural runoff into waterways by providing funding to farmers, prioritized the Maumee Watersheds located in the Western Basin (high environmental risk). These policy and funding program emphases may *set the agenda* for where work should be pursued across the broader Lake Erie Basin (Pralle 2009).

Governance Networks and Closed Network Motifs

We found that closed network motifs, specifically triangles, are more prevalent in typically higher transaction cost relationships like institution building than in lower transaction cost relationships like information sharing. Our findings reinforce what existing literature suggests, that high transaction cost relationships spur social actors to pursue relationships with those they know and trust, thus networks reflecting this concept are denser and have more triangles, as governance actors seek to minimize likelihood of defection and reinforce shared norms and trust (Renn and Levine 1991, Putnam 1993, Ostrom 1998, Burt and Burt 2005, Lubell et al. 2017). However, we also found that regardless of relationship type, there is a preference for closed network motifs (triangles) in the Western Basin (high environmental risk) over the Central Basin (low environmental risk). In fact, in two of the Central Basin (low environmental risk) networks (information sharing and institution building) there were *no* triangle structures at all in the social networks. The prevalence of closed network motifs in the social networks is potentially driven by two mechanisms: focusing events and coalitions of like-minded individuals. Focusing events are sudden harmful events occurring in a defined region that captivate policy makers and the public simultaneously (Birkland 1998). Focusing events are important determinants of shifting priority policy issues (Walker 1977, Cobb and Elder 1983, Kingdon 1995, Baumgartner and Jones 2010). In August 2014, Lake Erie experienced a particularly severe HAB (in terms of toxicity) that resulted in a *do not drink* order for almost half a million residents in Toledo, Ohio, located in the Western Basin (high environmental risk) (Michalak et al. 2013). This event brought focused and immediate attention to the Lake Erie HABs and specifically, the Western Basin (high environmental risk). Miles (2020) showed that following the Toledo water crisis, the social network was much more active (both larger and denser) *and* exhibited much stronger bonding ties than prior to the crisis. In the time since the 2014 Toledo Water Crisis, approaches to address Lake Erie HABs in the Western Basin (high environmental risk) have become increasingly polarized (Anonymous Interviewee from Lake Erie Western Basin, 2020). Bottom-up efforts to prioritize Lake Erie health and combat HABs by private citizen groups, may have further polarized certain social actors in the region (e.g., agricultural actors) by pursuing a *Lake Erie Bill of Rights* (Citizens of Toledo 2019). In 2019, citizens of Toledo voted to approve the Bill of Rights, only to have a farmer immediately file a lawsuit. The farmer claimed the bill was an "…unlawful assault on the fundamental rights of family farms in the Lake Erie Watershed…" (Johnston et al. 2019). Theory using the advocacy coalition framework (ACF) argues that when a public policy problem is particularly polarized or otherwise intense, actors will form advocacy coalitions with other actors that share their beliefs and opinions (Fischer and Miller 2006, Sabatier and Weible 2014). These tightly formed coalitions of actors who trust each other and reinforce each other's heuristics may appear as closed motifs in social networks (Weible and Nohrstedt 2012). Therefore, the abundance of closed network motifs in Western Basin (high environmental risk) social networks may be explained by focusing events and subsequent coalition building. Future research could more robustly consider temporality as a driver of Lake Erie social-ecological network structure.

Closed Social-Ecological Network Motifs in the Western Basin (High Environmental Risk)

Finally, consistent with our hypothesis, we generally found that social-ecological networks show a preference for social-ecological network closure (fit or alignment) in the high environmental risk Western Basin. Social-ecological network research theorizes that social-ecological alignment is important for achieving better environmental outcomes (see for example, Bodin and Crona 2009, Barnes et al. 2019). When social actors with shared interest in ecological actors (e.g., watersheds) are themselves connected, it may result in social learning and sharing ultimately minimizing adverse and spillover adverse impacts (Bodin and Tengö 2012, Bergsten et al. 2014, Bodin et al. 2014, 2016, Guerrero et al. 2015a). This is especially important in the context of hydrologically connected watersheds, whereby pollutant loadings and land use upstream accumulate downstream. Reducing phosphorus loading and minimizing nutrient impact downstream, requires some set of coordinated activities. We argue that social-ecological alignment is likely prevalent in the Western Basin (high ecological risk) because actors managing Lake Erie HABs are knowledgeable on and pursue watershed and basin approaches to solving nonpoint source pollution. Because social actors are knowledgeable about the implications of watershed connectivity relative to phosphorus loading and transport, they may be more likely to seek relationships that form closed network motifs during the planning process. In this way, social actors are *proactive* in pursuing social-ecological alignment, as evidenced by the governance networks in our study.

While we found some evidence that environmental risk does at least in part shape overall social-ecological network structure, we also found nuance in the drivers of network structure for social actors managing connected watersheds (which are only present in the high environmental risk Western Basin). Specifically, when we look across relationship networks, we found that collaboration was the dominant relationship type, suggesting both a shift from information sharing towards institution building *and* the potential role of transaction costs, resource availability, and priorities in shaping network structure. In the Western Basin of Lake Erie, most of the hydrologically connected watersheds are part of the larger Maumee watershed. Mentioned earlier, the Maumee watershed contributes the largest phosphorus loading into Lake Erie and overlays three states (Ohio, Michigan, and Indiana). Given the fragmented governance structure of the Maumee watershed, it is conceivable that collaborative relationships are prioritized to coordinate activities across the landscape. In fact, Lubell et al. (2017) argue that social actors involved in coordination over longer periods of time may find reduced transaction costs and as a result, a more stable system. Therefore, to better align social and ecological systems and accomplish basin-wide phosphorus reduction goals within a fragmented governance system, social actors may be prioritizing collaborative relationships in the higher environmental risk Western Basin. In this way, we argue that in the case of Lake Erie HABs, it is not *just* environmental risk that drives social-ecological alignment, but environmental risk and transaction costs, priority activities and goals.

Mechanisms are somewhat different for disconnected ecological resources. There is an impetus for actors to collaborate when they are both managing the same resource; this *shared management* may prevent over harvesting, or more likely in our case, ineffective management (Ostrom 1990, Sabatier et al. 2005, Bergsten et al. 2014, Bodin et al. 2014, 2014, Berardo 2014, Guerrero et al. 2015a). Shared management of individual watersheds is particularly important because *random acts of individual restoration* could potentially undermine one another or be a waste of limited resources. For example, Sabatier et al. (2005) showed that ineffective management of watersheds likely arises when watersheds overlap more than one jurisdiction and the jurisdictions do not coordinate efforts. In Lake Erie, we found that when two social actors work in the same two watersheds, even if those watersheds are not interconnected, social actors are more likely to work together. We argue here that like interconnected watershed approaches, social actors are cognizant of the importance of social-ecological alignment and therefore, purposefully plan to coordinate with actors in their watersheds. This has interesting implications for social-ecological systems research theorizing that certain motifs will result in better or worse environmental outcomes (e.g., Bergsten et al. 2014, Bodin et al. 2014, Guerrero et al. 2015a, Treml et al. 2015). If instead, governance actors purposefully design planning documents with an eye towards social-ecological alignment, what happens between planning and implementation to change the network structure?

LIMITATIONS AND FUTURE RESEARCH

There is one main limitation to our study. In the approach we used for analyzing social-ecological networks, we held the social-ecological network static; this was a function of the technological limitations of the analytical method; more specifically, *motifr (Angst and Seppelt 2020)* is not yet capable of varying multiple networks in its analysis. As a result, it is likely that our randomly generated social-ecological networks were underfitting our observed network data. We hope that in future research, this capability will be built in or otherwise addressed through other analytical approaches.

We propose three potential future research areas. First, we encourage researchers to test our hypotheses in other complex social-ecological systems to further understand how environmental risk shapes governance networks. Second, research could explore environmental risk at other governance levels. For example, given the heterogeneous distribution of phosphorus loading across the Western Basin of Lake Erie, do our hypotheses hold true in studies of the governance networks within each watershed? In other words, do higher phosphorus loading watersheds show a preference for closed network structures in line with the basin scale view that we took? Finally, researchers should explore what drives network structure change between planning and implementation.

CONCLUSION

In this paper we sought to understand the role that environmental risk plays in shaping the Lake Erie harmful algal bloom social-ecological governance system. Using a combination of exponential random graph modeling and multi-level motif analysis, we explored three social-ecological governance networks in a low ecological risk (Central Basin) and high ecological risk (Western Basin) context. We first analyzed the governance networks and found that both scale and organization type homophily is greatest in collaboration networks and that higher transaction cost relationships, like institution building, reflect governance actors' preference for closed network structures that promote trust, learning, and shared norms. We then analyzed network descriptive statistics and found that governance activity is greater in the high environmental risk region (Western Basin) than in the low environmental risk region (Central Basin). Within the high environmental risk region, we found that governance actors show a preference for closed network structures that may have higher transaction costs upfront but could decrease transaction costs in the long-term. Next, we analyzed the social-ecological governance networks and generally found that when planning for how to address Lake Erie harmful algal blooms, governance actors seek out relationships with other social actors that will result in social-ecological alignment represented by network closure. This preference for planned network closure may reflect governance actor knowledge of the importance of the watershed approach for addressing phosphorus loading in the Lake Erie region. Finally, we found that in the context of hydrologically interconnected watersheds (in the high environmental risk Western Basin), social actors in Lake Erie show a preference for collaborative relationships over information sharing and institution building. This preference may reflect social actors' varying priorities, estimated transaction costs, and efforts to overcome fragmented governance and social-ecological misalignment.

This research has interesting implications for social-ecological systems scholarship, particularly related to how planned governance relationships translate (or don't) into implemented governance relationships. While existing research argues that closed social-ecological network motifs are important for aligning institutions and ecological processes towards better overall environmental outcomes, this research shows that governance actors are not only aware of the importance of social-ecological alignment, but actively plan future partnerships and collaborations based on social-ecological alignment. Further, our research shows that environmental risk does shape social-ecological alignment, however there is nuance in the degree to which it drives network structure. In fact, we found overall that it is the combination of environmental risk, transaction costs, and prioritization that shapes social-ecological governance networks.

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SUPPLEMENTAL INFORMATION

EXPANDED METHODOLOGY

Search Process for Planning Documents

Our initial search for documents was much broader than the documents and timeframe used in this manuscript. We conducted multiple internet searches for any documents posted between 2007 and 2017 that met a set list of criteria. Each search that was completed contained terms from four overarching categories including Regional Scope, Geographic Scope, Water Quality Focus, and Document Type. Table S11 shows the terms that align with the overarching categories and were therefore used in the internet searches. For example, one search would include "Lake Erie (Regional Scope) + Indiana (Geographic Scope) + harmful algal blooms (Water Quality Focus) + Plan (Document Type)".

Table S11. Documents included in our analysis were identified through internet searches for key terms related to four overarching categories: Regional Scope, Geographic Scope, Water Quality Focus, and Document Type.

	General Terms	Search Terms
Regional Scope	Great Lakes	Lake Erie
Geographic Scope	Political Boundary	First Nations Indiana Métis Michigan Ohio Ontario Tribal
	Ecological Boundary	Ashtabula-Chagrin Watershed Auglaize Watershed Big Watershed Black-Rocky Watershed Blanchard Watershed Cedar Watershed Cedar-Portage Watershed Clinton Watershed Cuyahoga Watershed Detroit Watershed Grand Watershed Huron Watershed Huron-Vermillion Watershed Lake St. Clair Watershed Lower Maumee Watershed Lower Thames Ottawa-Stony Watershed Raisin Watershed Rondeau Watershed

		Sandusky Watershed St. Clair Watershed St. Marys Watershed St. Joseph Watershed Sydenham Watershed Tiffin Watershed Upper Maumee Watershed Upper Thames *Note we also searched for Thames and Maumee without the Upper/Lower qualifiers
Water Quality Focus	Water Quality	Harmful Algal Blooms
Document Type		Plan Meeting Workshop Conference Colloquium

Internet search results were reviewed and assessed using a "three click" approach to identifying pertinent documents (shown in Figure S10). We clicked on each link ("click one") and reviewed the Webpage search result. There were three possible outcomes on the first click: 1) the search result led directly to a document; 2) the search result led to a Webpage with no hyperlinks; or 3) the search result led to a Webpage with hyperlinks. The next steps depended on the "click one" outcome. If the search result led to a non-news or media article, it was downloaded, otherwise it was ignored. If the search result led to a Webpage with no hyperlinks, no further action was taken. If the search result led to a Webpage with hyperlinks, "click two" was triggered. At this point, the aforementioned decision process was repeated. If the new Webpage was a non-news or media article it was downloaded. If the new Webpage was another Webpage with no hyperlinks, no further action was taken. If the Webpage however led another Webpage with hyperlinks, the final "click three" was triggered. At this final stage, if the link led to a non-news or media document it was downloaded, otherwise no further action was taken. All documents downloaded were placed into a group Zotero library.

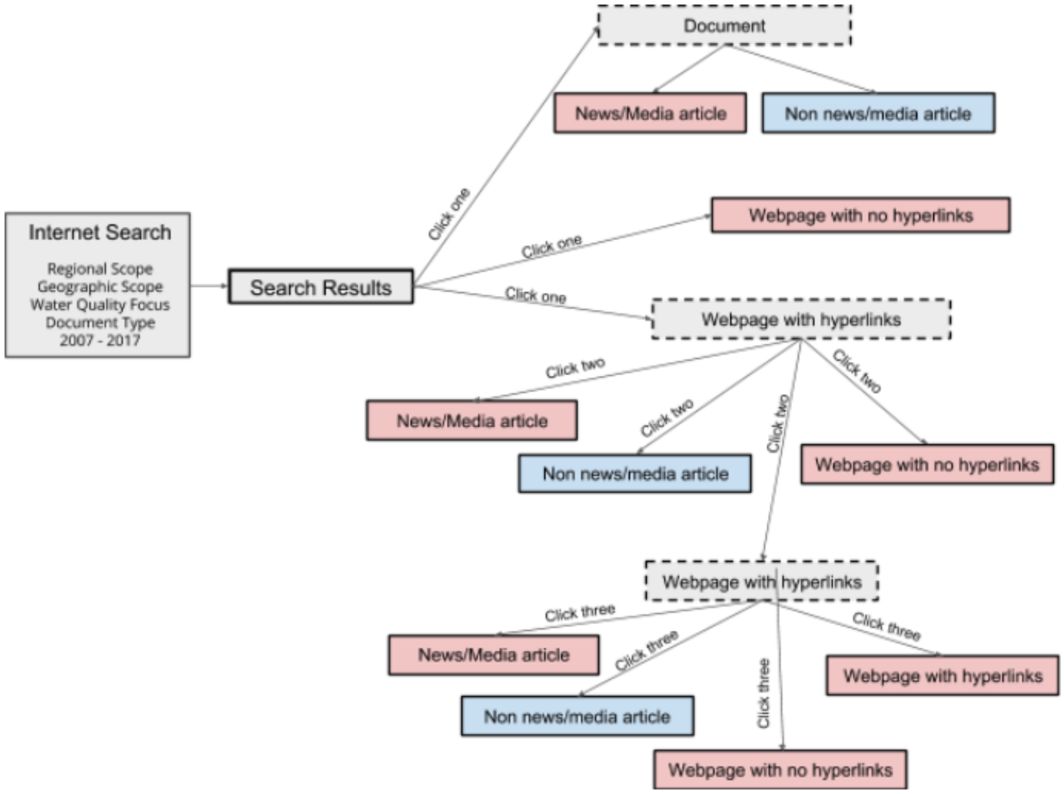


Figure S10. Process of identifying Lake Erie western and central basin harmful algal bloom documents to code. Boxes outlined in dashes represent the initial decision points after "click one". Red boxes indicate that documents were **not** downloaded. Blue boxes indicate documents that **were** downloaded.

Coding

We initially conducted a cursory internet search for potential organizations and entities that could be involved in Lake Erie HABs planning. This yielded thousands of potential results. We attempted to create a deductive codebook in MaxQDA, but ultimately decided against this approach as MaxQDA could not seem to handle the immensity of the codebook. Additionally, trying to scroll through the codebook to look for a potential actor took an immense amount of time. Finally, because not all our team members were as familiar with coding software, we opted for a more streamlined and basic approach. As a result, we manually and inductively coded the planning documents in an Excel sheet. As we reviewed each document, excerpts of text were pasted into the Excel sheet. Text excerpts included at least two social actors (organizations) that were planning to take some action to manage Lake Erie. We coded these excerpts for the type of action being proposed/planned (e.g., harmful algal bloom-related or not, such as biodiversity). We also tracked whether the excerpt explicitly stated *where* the action was going to take place or whether the coder implied the location based on the surrounding text in the document. Table S12 describes the fields that were coded in each document.

Table S12. Planning documents were read and text excerpts containing two or more social actors (organizations) were entered into an Excel sheet. Excerpts were inductively coded.

Category of Data	**Brief Description**
Document Title	The title of the planning document being coded
Document Year	The year that the document was finalized
Excerpt	An excerpt of text that contained at least two social actors, a relationship between the social actors.
Social Actor 1	A person or organization mentioned in the excerpt
Social Actor 2	A person or organization mentioned in the excerpt
Social Relationship	A word or phrase describing the relationship between Social Actor 1 and Social Actor 2
HAB Indicator	Which of a list of HAB-related terms (if any) the excerpt pertained to (e.g., Phosphorus control)
Non-HAB Indicator	A description of any non-HAB terms the excerpt pertained to (e.g., Cadmium control)
Ecological Actor	A description of where the excerpt and Social Actors were functioning (e.g., a Watershed, a Tributary, a State)
Ecological Actor - Embedded or Not	An indicator of whether the ecological actor was explicitly stated in the excerpt or if the coder deduced it from context surrounding the excerpt (e.g., an excerpt in the St. Joseph's Watershed Plan that does not indicate where restoration work is happening may be coded as St. Joseph's Watershed)

The way our excel coding sheet was developed, each row indicated a single relationship between two social actors. In cases where two social actors were engaged in more than one relationship type within a single excerpt, the row was copied and each relationship type was entered. A similar approach was taken when more than two social actors were involved in a single excerpt. As an example, the *Maumee River Watershed Plan* (2016) has an excerpt that reads, "With funding support and technical assistance from the U.S. Environmental Protection Agency, Ohio Department of Natural Resources and Ohio State Department of Agriculture will collaborate to implement the existing Phosphorus reduction program." Using our coding schema above, the coding excel sheet would consist of 5 rows. The first row would relate the U.S. Environmental Protection Agency to the Ohio Department of Natural Resources (funding); the second row would relate the same social actors for technical assistance; the third and fourth rows would relate the U.S. Environmental Protection Agency to the Ohio State Department of Agriculture for funding and technical assistance, respectively; and the fifth row would relate the Ohio Department of Natural Resources to the Ohio State Department of Agriculture (collaboration). Building off this, each row was coded with the Ecological Actor, "Maumee River Watershed" (based on contextual evidence), and the Ecological Indicator “Phosphorus”. By taking this approach, we can capture the breadth of relationships captured in the planning documents.

Social Actor Attribute Data

We collected several attribute variable data as shown and defined in Table S13. Ultimately, we used both organization type and governance level in this paper to test hypotheses on homophily.

Table S13. Social relationships were aggregated into six categories based on a combination of matrix correlation comparisons and literature review on social networks and transaction costs. Grey rows identify the attributes used in this particular paper.

Portion of Network Data	**Attribute**	**Definition**
Social Actors	Single (binary)	Is the organization a single, stand-alone organization or is it several organizations functioning together
Social Actors	Specific (binary)	Is the organization a formal organization or is it a general grouping of actors (e.g., U.S. EPA vs. governments)
Social Actors	OrgType (categorical)	What type of organization is it? Options: agriculture, not-for-profit, research, academic, government, citizen group, unspecified
Social Actors	GovLevel (categorical)	What governance level is the organization function at? Options: local (sub-state), state, regional, national, unspecified
Social Actors	Diversity (categorical)	If the organization is several organizations functioning together, how many different types of organizations are involved?
Social Actors	Size (categorical)	If the organization is several organizations functioning together, how many organizations make up the overarching organization?
Social Actors	Geo (categorical)	Where is the headquarters of the organization located?
Social Actors	Nation (categorical)	What is the Nation that the organization is in?

Social-Ecological Network Descriptives

We analyzed 69 planning documents. While we initially coded six relationship types, we ultimately limited, defined, and analyzed three relationships for this paper: Information Sharing, Collaboration, and Institution Building. These three relationships were chosen because they represent the different levels (low, medium, and high) of probable transaction cost relationships. Table S14 shows the count of social actors (organizations) and ecological actors (watersheds) for each of the selected relationships. Row color represents either the Central (white) or Western (gray) Basin.

Table S14. The count of social actors and ecological actors (treated as nodes in this paper) for each type of relationship. We coded a total of 69 planning documents that yielded 1,080 social actors and 27 ecological actors.

Relationship Type	Basin	Count of Social Actors	Count of Ecological Actors
Collaboration	Central	360	5
Collaboration	Western	569*	20
Information Sharing/Engagement	Central	71	7
Information Sharing/Engagement	Western	426	20
Institution Building	Central	18	7
Institution Building	Western	59	20

*569 represents actors from planning documents as well as partners listed on webpages of conglomerate organizations. For example, the Cooperative Institute for Great Lakes Research (CIGRL) is composed of 17 partner organizations.

Social Networks

These social networks are presented below in Figure S11–Figure S16 by relationship type and basin (Central is low environmental risk; Western is high environmental risk). Nodes represent social actors *only.* Green nodes represent government actors and red nodes represent all other actors.

Figure S11. Social network for information sharing in the Central Basin (low environmental risk)

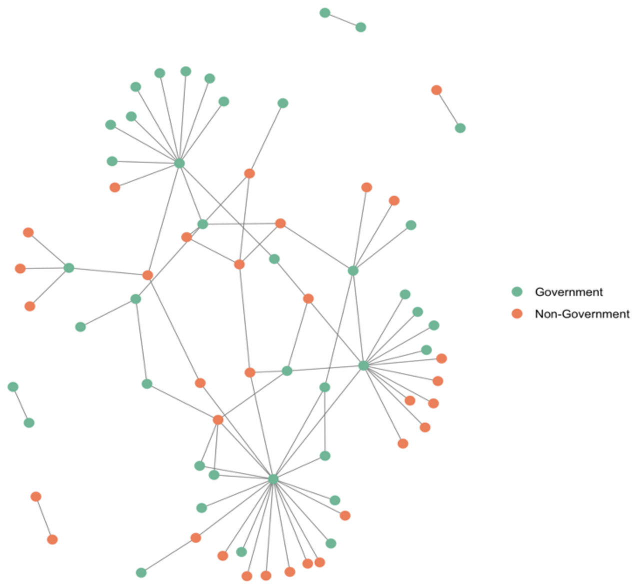


Figure S12. Social network for information sharing in the Western Basin (high environmental risk)

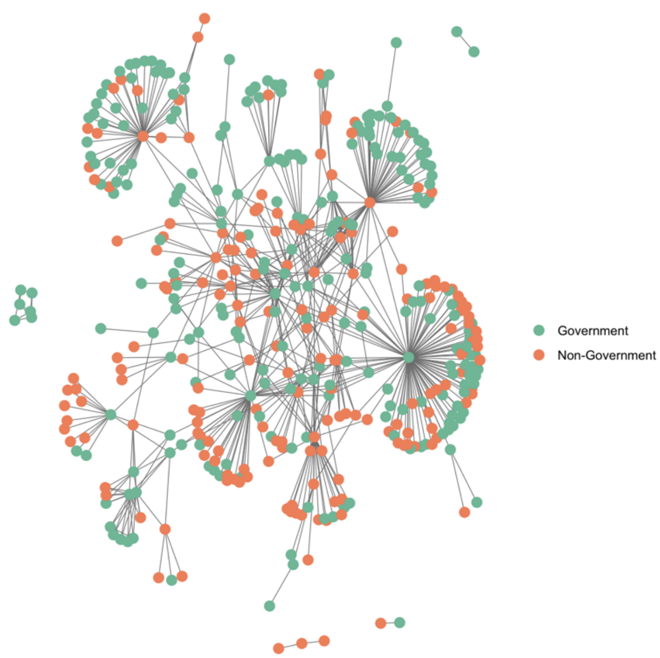


Figure S13. Social network for collaboration in the Central Basin (low environmental risk)

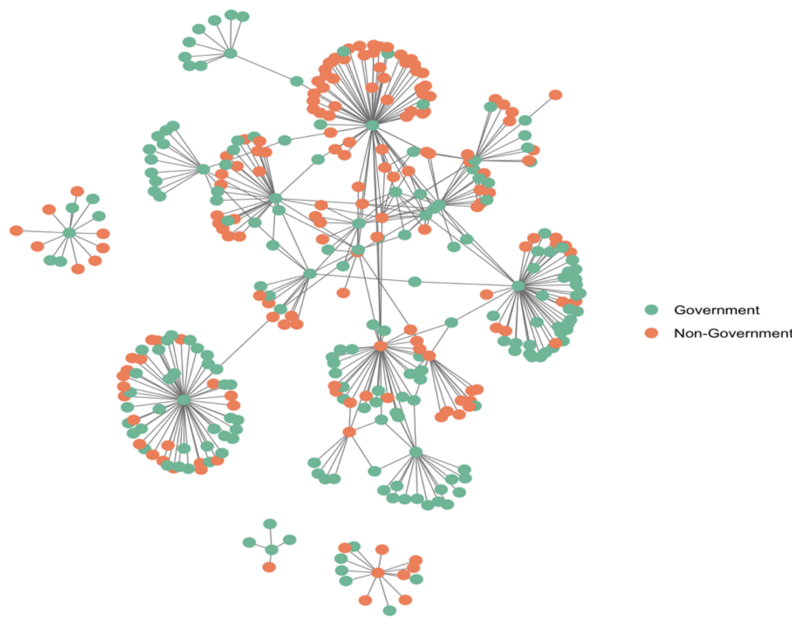


Figure S14. Social network for collaboration in the Western Basin (high environmental risk)

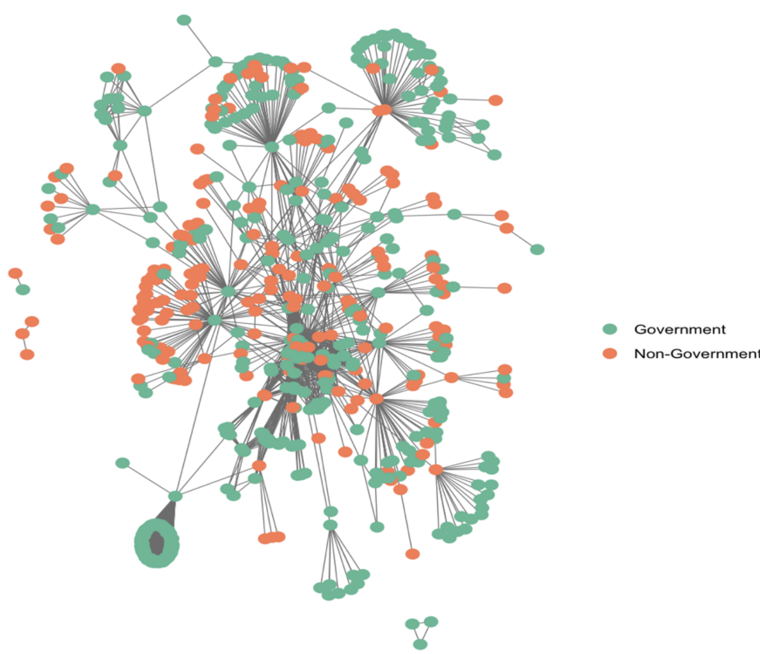


Figure S15. Social network for institution building in the Central Basin (low environmental risk)

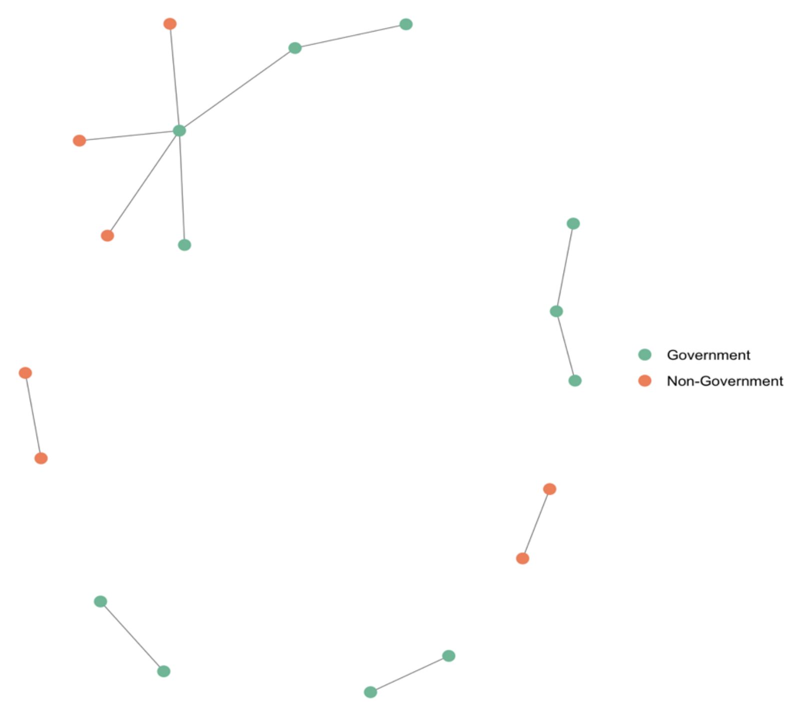
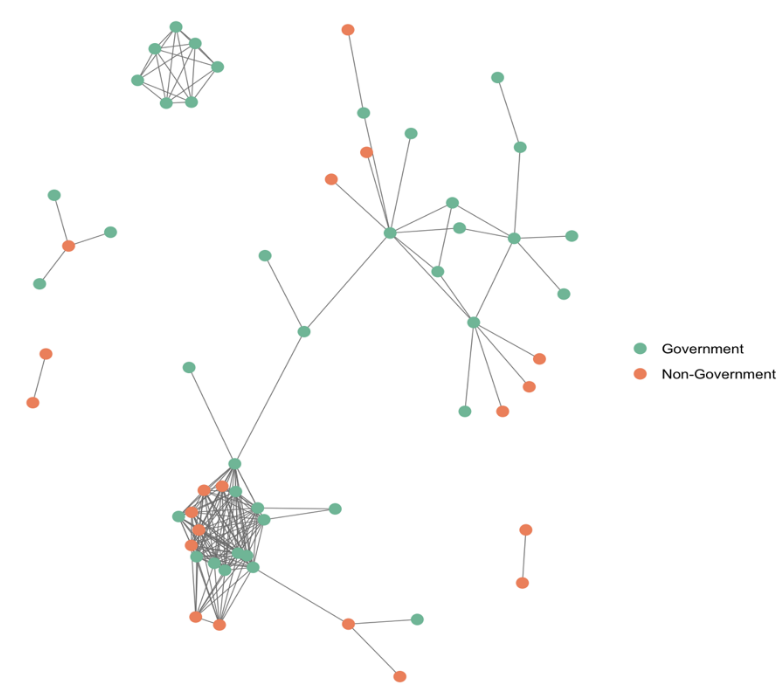


Figure S16. Social network for institution building in the Western Basin (high environmental risk)



Social-Ecological Networks

We created one social-ecological networks for each relationship in each Lake Erie Basin (Figure S17–Figure S22). These social-ecological networks are presented below by relationship type and basin (Central is low environmental risk; Western is high environmental risk). Light blue nodes represent social actors (organizations) and dark blue nodes represent ecological actors (watersheds).

Figure S17. Social-ecological network for information sharing in the Central Basin (low environmental risk)

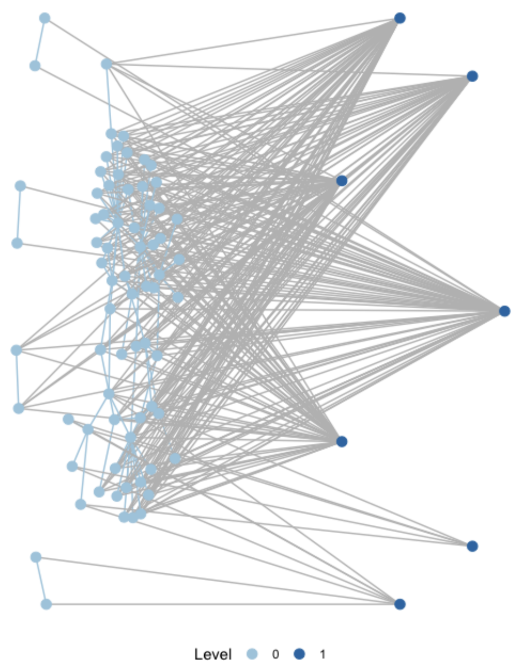


Figure S18. Social-ecological network for information sharing in the Western Basin (high environmental risk)

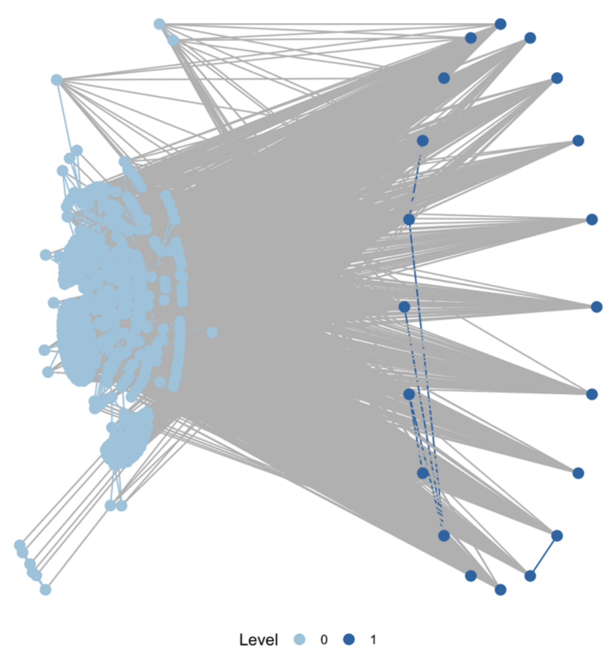


Figure S19. Social-ecological network for collaboration in the Central Basin (low environmental risk)

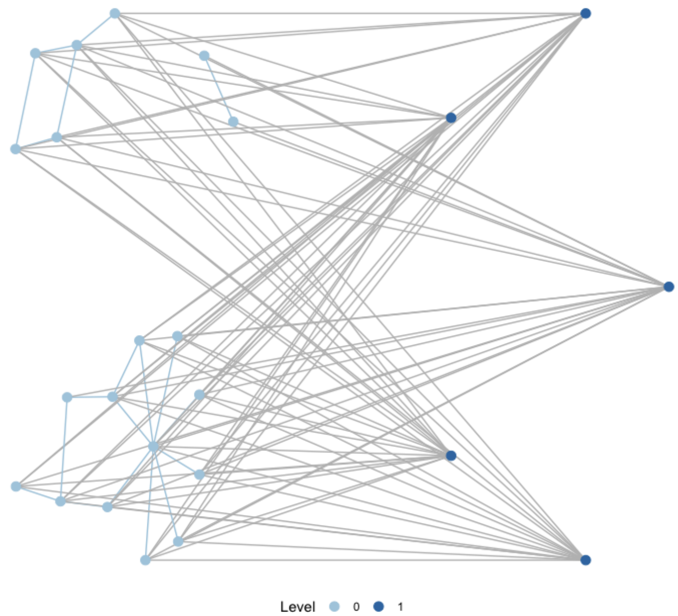


Figure S20. Social-ecological network for collaboration in the Western Basin (high environmental risk)

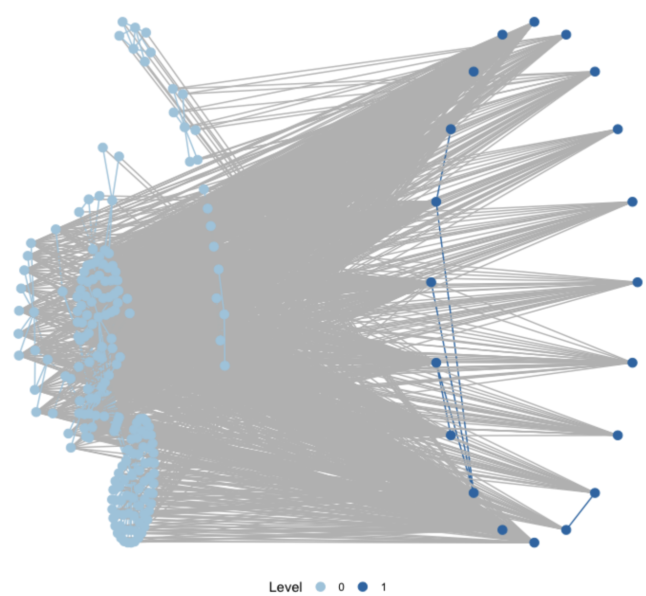


Figure S21. Social-ecological network for institution building in the Central Basin (low environmental risk)

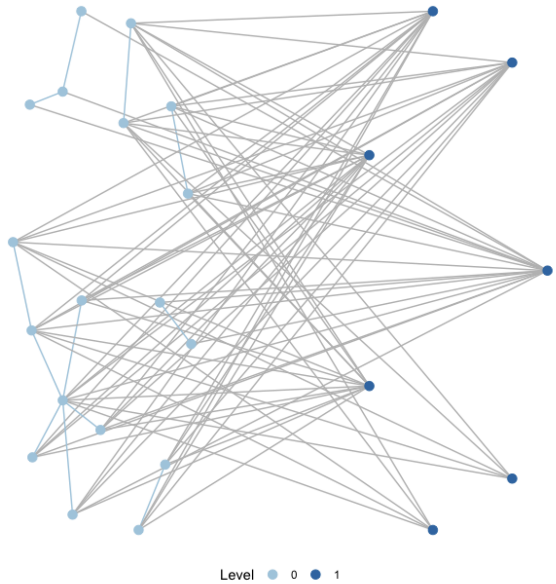


Figure S22. Social-ecological network for institution building in the Western Basin (high environmental risk)