UNIVERSITY OF OKLAHOMA

GRADUATE COLLEGE

INFORMATIONAL AND SOCIAL DRIVERS OF CONSERVATION PRACTICE ADOPTION: EXAMINING SPATIAL DATA NEEDS AND SOCIAL NETWORK DYNAMICS

A DISSERTATION
SUBMITTED TO THE GRADUATE FACULTY
in partial fulfillment of the requirements for the
Degree of
DOCTOR OF PHILOSOPHY

By

REBECCA ANN VEIGA NASCIMENTO
Norman, Oklahoma
2025

INFORMATIONAL AND SOCIAL DRIVERS OF CONSERVATION PRACTICE ADOPTION: EXAMINING SPATIAL DATA NEEDS AND SOCIAL NETWORK DYNAMICS

A DISSERTATION APPROVED FOR THE
DEPARTMENT OF GEOGRAPHY AND ENVIRONMENTAL SUSTAINABILITY

BY THE COMMITTEE CONSISTING OF

Dr. Thomas Neeson, Chair

Dr. Chengbin Deng

Dr. Charles Nicholson

Dr. Caryn Vaughn

Dr. Anni Yang

© Copyright by REBECCA ANN VEIGA NASCIMENTO 2025
All Rights Reserved.

Acknowledgements

First, I would like to thank my advisor, Dr. Thomas Neeson, for being a generous and patient mentor. Tom provided me with a strong foundation that fostered both creativity and rigor in my research. He is an exceptional teacher, researcher, and collaborator and I am deeply grateful for his guidance and support.

I would also like to thank my committee members. Dr. Charles Nicholson is a fantastic teacher whose courses equipped me with technical skills needed to pursue my research. Dr. Anni Yang offered thoughtful early feedback that encouraged me to think more deeply about governance frameworks. Dr. Caryn Vaughn shared thoughtful perspectives and steady encouragement, and Dr. Chengbin Deng brought genuine investment in student success. I am grateful to each of you for the time and effort you devoted to serving on my committee.

I am grateful to all members of the Neeson Lab, past and present. Your engaged discussions, constructive feedback, and wide-ranging interests made the lab an inspiring and intellectually generous community. Each of you contributed in meaningful ways to my growth as a researcher and collaborator.

Finally, to my dearest family and friends—your love and support have sustained me over the last five years. Kyle Mattingly, thank you for inspiring me to take the leap into a Ph.D. and for introducing me to the Department of Geography and Environmental Sustainability. Jade Jones, your friendship has been a generous source of encouragement and valuable perspective time and time again; thank you. Megan Malish, we began this journey together, and it has been a true blessing to share it with you through challenging classes, key milestones, and countless office talks. I could not have asked for a better partner and friend. Amir Ahiq, thank you for your encouragement and belief that this was possible, even amidst the many challenges of life. And to my parents, Terry and Barbara, thank you for your unwavering support and for imparting to me a lifelong love of learning.

Table of Contents

List of Tables

List of Figures

Abstract

Conservation outcomes are fundamentally shaped by the social and political systems that guide data collection, analysis, management decisions, and project implementation. This dissertation examines how data, social networks, and governance structures influence the adoption of conservation practices. Across three studies, I analyzed how the availability of actionable information, the structure of relationships among conservation actors, and the dynamics of governance interact to support or constrain conservation actions. The first study evaluated how U.S. water resource managers use spatial data to assess watershed condition and prioritize actions. Survey results reveal that while spatial data were widely used, available datasets were not well aligned with practitioner needs. Gaps in economic and socio-political information such as project costs, incentives, and organizational responsibilities pose greater challenges to decision-making than deficiencies in biophysical data. These findings highlight opportunities to develop integrated data products that combine economic and institutional information to better support effective, coordinated watershed management. In a second study, I used social network analysis to investigate how relationship-building among conservation actors might influence the spread of conservation initiatives. Using the independent cascade and linear threshold information diffusion models, I show that adding new social connections can sometimes enhance and sometimes hinder practice adoption. Increased connectivity generally promoted broader adoption under the independent cascade model, but additional ties often reduced diffusion under the linear threshold model. In a third study, I again used social network analysis to examine how governance approach (i.e., top-down vs. bottom-up) and organization type shape conservation adoption. Simulations show that bottom-up communication initiated by nongovernmental organizations and local governments consistently produced higher adoption levels than top-down communication from state or federal agencies. Together, these three studies

illustrate how information, social networks, and governance processes jointly shape conservation effectiveness and offer practical guidance for designing data products, outreach strategies, and collaborative frameworks to strengthen environmental management.

Introduction

Conservation efforts worldwide are increasingly challenged by accelerating pressures from climate change, biodiversity loss, and water scarcity (Leclère et al., 2020; Rilov et al., 2020; Tickner et al., 2020). At the heart of addressing these challenges lies the recognition that conservation is both an ecological and a social endeavor. While ecological conditions shape opportunities and constraints for implementing conservation practices, socio-political factors (e.g., human decision-making, organizational relationships, and governance frameworks) ultimately determine whether conservation actions are implemented, scaled, and sustained (Ban et al., 2013; Bennett et al., 2017; Neeson et al., 2022; Niemiec et al., 2021). The interplay between ecological science and social processes has become central to conservation research, as practitioners and scholars alike seek to understand how best to design, target, and spread conservation practices across diverse social and ecological landscapes. The overarching goal of this dissertation is to examine how data needs, conservation social networks, and governance structure influence the promotion or limitation of conservation actions and to generate actionable insights that help practitioners improve program effectiveness.

Spatial data use and barriers in watershed management

Conservation of freshwater systems is functionally implemented by the decisions of resource managers, planners, and practitioners. These actors engage in diverse conservation efforts that range from improving soil health to implementing large-scale riparian restoration, all with the goal of supporting interrelated watershed functions (Daily et al., 2009; Flotemersch et al., 2016). Decision making and conservation actions are also complicated by the need to act across multiple spatial scales, from site-specific projects to basin-wide planning (Mu et al., 2023;

Park & Lee, 2020). This complexity means that conservation is not only ecological but also deeply social, requiring extensive collaboration among agencies, regulated parties, and other stakeholders. Many of these conservation efforts rely on spatial data to inform planning, monitoring, and project selection. Biophysical data such as hydrology, soils, and species occurrence help characterize watershed condition, while socio-economic data such as demographics and land ownership provide critical context for management decisions (Sun et al., 2022; Webb et al., 2013). Advances in GIS, data platforms, and remote sensing have expanded access to biophysical datasets (Budhathoki et al., 2008; Krishnamurthy & Awazu, 2016; Wulder et al., 2012), and indices that integrate multiple variables are increasingly used to assess ecosystem condition, stressors, and management outcomes (Allan et al., 2013; Mazor et al., 2016; Ode et al., 2005; Rothrock et al., 2008). Recent work also highlights the importance of integrating socio-economic information with ecological assessments, yet it remains unclear to what extent managers apply both types of data in practice and whether available data align with the needs of resource managers (Curtis et al., 2005; Koundouri et al., 2016; Scown et al., 2017; Webb et al., 2013).

At the same time, global change is reshaping watershed conditions, placing added demands on water resource managers and decision-support tools. Changes in hydrology, temperature, and water quality interact with land use pressures, creating a mismatch between global-scale drivers and local-scale responses (Allan, 2004; Christian-Smith & Merenlender, 2010; Grimm et al., 2016; Isaak et al., 2015; Kaushal et al., 2018; Paukert et al., 2011; Tsvetkova & Randhir, 2019). While continued investments in biophysical spatial data remain valuable, refinement of these datasets alone may not address the full scope of management needs. Effectiveness in watershed management is also shaped by social, political, and organizational context that can constrain or empower conservation programs (Arai et al., 2021; Floress et al., 2009, 2018; Frame et al., 2004; Mancilla García et al., 2019; Pierre et al., 2017; Shifflett et al., 2019; Shunglu et al., 2022; Weston & Conrad, 2015; White et al., 2022). These factors can be as influential as technical data in determining conservation outcomes and the feasibility of management actions.

Relationship building to promote conservation adoption

Conservation programs often take decades to gain traction, with success linked to local actor support and the structure of social relationships (Botts et al., 2019; Farwig et al., 2024; Maxwell et al., 2020; Mills et al., 2019; Nesbitt et al., 2024). Research shows that social networks are central to effective collaboration across diverse stakeholders, with network structure shaping how information flows and behaviors spread (Alix-Garcia et al., 2018; Bodin & Crona, 2009; Bodin & Prell, 2011; Cunningham et al., 2016; Kaweesa et al., 2018; Olsson et al., 2008; Valente & Pumpuang, 2007). Conservation actors frequently attempt to strengthen these networks through workshops, training seminars, and field demonstrations, which can foster broader adoption of practices (Baird et al., 2016) . Yet some social relationships exert far greater influence than others, with certain connections playing particularly important roles in advancing conservation initiatives (Cunningham et al., 2016; Mbaru & Barnes, 2017).

Since the spread of information in social networks is influenced by structural properties, the question of how to intervene within networks to accelerate conservation practice adoption has applied importance (de Lange et al., 2019, 2021; Lubell et al., 2017). Network science offers useful modeling approaches, such as the independent cascade (IC) and linear threshold (LT) models to simulate how information or practices propagate through a network (Azaouzi et al., 2021; Shakarian et al., 2015). The IC model conceptualizes adoption as a function of individual activation probabilities, while the LT model emphasizes peer influence and thresholds of adoption. Both frameworks provide tools for investigating real-world conservation scenarios, from practices that spread readily under favorable social and economic conditions to those that face resistance due to high costs, limited legitimacy, or established norms. Simulating how conservation practices diffuse under different network conditions generates evidence to inform outreach strategies and relationship building efforts.

Linking social networks and governance

Conservation governance operates within a landscape of both top-down policy/program frameworks and bottom-up, community driven initiatives. Across ecosystems and governance systems worldwide, debates continue over the relative effectiveness of centralized, hierarchical approaches compared to locally driven, grassroots efforts (Ballarini et al., 2021; Fraser et al., 2006; Koontz & Newig, 2014). Top-down approaches provide regulatory authority, resources, and coordination across large scales, while bottom-up approaches bring local knowledge, trust, and social legitimacy that are essential for long-term adoption (Enqvist et al., 2020; Mc Culloch-Jones et al., 2021). Aligning these governance approaches often improves implementation success, as linking formal directives with local action can strengthen conservation outcomes (Ding et al., 2019; Eicken et al., 2021).

Despite these insights, uncertainty remains about the conditions under which each approach is most effective in spreading conservation practices. Practitioners working under real-world constraints (limited time, funding, and institutional capacity) face challenges in deciding how best to balance top-down and bottom-up strategies. Social network analysis provides a useful means to investigate these dynamics, offering a way to evaluate under what conditions do top-down or bottom-up approaches most effectively initiate and spread conservation practices across environmental governance groups. Examining this question is especially critical as conservation challenges intensify, requiring approaches that combine institutional authority with grassroots engagement to ensure broad adoption and durable success.

Dissertation overview

The goal of this dissertation is to examine how spatial data needs, conservation actor social networks, and governance approaches influence the promotion or limitation of conservation actions. This dissertation combines empirical surveys, social network analysis, and information diffusion modeling to evaluate how data, relationships, and institutional contexts influence conservation adoption.

In Chapter One, I assess how U.S. water resource managers use spatial data, examine alignment with decision making needs, and potential socio-political and organizational barriers to improving watershed condition. In Chapter Two, I use information diffusion models to test how structural modifications in conservation networks may influence the spread of conservation practices. In Chapter Three, I use the information diffusion models to examine how organizational type and governance approaches affect the spread of conservation practices. Together, these chapters provide a systematic examination of the connections between spatial data, social networks, and governance structures in shaping conservation practice adoption. By addressing these dimensions, this dissertation seeks to generate actionable insights for conservation practitioners seeking to navigate complex environmental and social contexts.

All three of these research chapters were carried out with my advisor and co-author Thomas Neeson.

References

Alix-Garcia, J. M., Sims, K. R. E., Orozco-Olvera, V. H., Costica, L. E., Fernández Medina, J. D., & Romo Monroy, S. (2018). Payments for environmental services supported social capital while increasing land management. Proceedings of the National Academy of Sciences, 115(27), 7016–7021. https://doi.org/10.1073/pnas.1720873115

Allan, J. D. (2004). Landscapes and Riverscapes: The Influence of Land Use on Stream Ecosystems. Annual Review of Ecology, Evolution, and Systematics, 35(1), 257–284. https://doi.org/10.1146/annurev.ecolsys.35.120202.110122

Allan, J. D., McIntyre, P. B., Smith, S. D. P., Halpern, B. S., Boyer, G. L., Buchsbaum, A., Burton, G. A., Campbell, L. M., Chadderton, W. L., Ciborowski, J. J. H., Doran, P. J., Eder, T., Infante, D. M., Johnson, L. B., Joseph, C. A., Marino, A. L., Prusevich, A., Read, J. G., Rose, J. B., … Steinman, A. D. (2013). Joint analysis of stressors and ecosystem services to enhance restoration effectiveness. Proceedings of the National Academy of Sciences, 110(1), 372–377. https://doi.org/10.1073/pnas.1213841110

Arai, Y., Maswadi, M., Oktoriana, S., Suharyani, A., Didik, D., & Inoue, M. (2021). How Can We Mitigate Power Imbalances in Collaborative Environmental Governance? Examining the Role of the Village Facilitation Team Approach Observed in West Kalimantan, Indonesia. Sustainability, 13(7), 3972. https://doi.org/10.3390/su13073972

Azaouzi, M., Mnasri, W., & Ben Romdhane, L. (2021). New trends in influence maximization models. Computer Science Review, 40, 100393. https://doi.org/10.1016/j.cosrev.2021.100393

Baird, J., Jollineau, M., Plummer, R., & Valenti, J. (2016). Exploring agricultural advice networks, beneficial management practices and water quality on the landscape: A geospatial social-ecological systems analysis. Land Use Policy, 51, 236–243. https://doi.org/10.1016/j.landusepol.2015.11.017

Ballarini, E., D'Adamo, R., Pazienza, G., Zaggia, L., & Vafeidis, A. (2021). Assessing the applicability of a bottom-up or top-down approach for effective management of a coastal lagoon area. Ocean & Coastal Management, 200, 105417. https://doi.org/10.1016/j.ocecoaman.2020.105417

Ban, N. C., Mills, M., Tam, J., Hicks, C. C., Klain, S., Stoeckl, N., Bottrill, M. C., Levine, J., Pressey, R. L., Satterfield, T., & Chan, K. M. (2013). A social–ecological approach to conservation planning: Embedding social considerations. Frontiers in Ecology and the Environment, 11(4), 194–202. https://doi.org/10.1890/110205

Bennett, N. J., Roth, R., Klain, S. C., Chan, K., Christie, P., Clark, D. A., Cullman, G., Curran, D., Durbin, T. J., Epstein, G., Greenberg, A., Nelson, M. P., Sandlos, J., Stedman, R., Teel, T. L., Thomas, R., Veríssimo, D., & Wyborn, C. (2017). Conservation social science: Understanding and integrating human dimensions to improve conservation. Biological Conservation, 205, 93–108. https://doi.org/10.1016/j.biocon.2016.10.006

Bodin, Ö., & Crona, B. I. (2009). The role of social networks in natural resource governance: What relational patterns make a difference? Global Environmental Change, 19(3), 366–374. https://doi.org/10.1016/j.gloenvcha.2009.05.002

Bodin, Ö., & Prell, C. (Eds.). (2011). Social Networks and Natural Resource Management: Uncovering the Social Fabric of Environmental Governance. Cambridge University Press; Cambridge Core. https://doi.org/10.1017/CBO9780511894985

Botts, E. A., Pence, G., Holness, S., Sink, K., Skowno, A., Driver, A., Harris, L. R., Desmet, P., Escott, B., Lötter, M., Nel, J., Smith, T., Daniels, F., Sinclair, S., Stewart, W., & Manuel, J. (2019). Practical actions for applied systematic conservation planning. Conservation Biology, 33(6), 1235–1246. https://doi.org/10.1111/cobi.13321

Budhathoki, N. R., Bruce, B. (Chip), & Nedovic-Budic, Z. (2008). Reconceptualizing the role of the user of spatial data infrastructure. GeoJournal, 72(3–4), 149–160. https://doi.org/10.1007/s10708-008-9189-x

Christian-Smith, J., & Merenlender, A. M. (2010). The Disconnect Between Restoration Goals and Practices: A Case Study of Watershed Restoration in the Russian River Basin, California. Restoration Ecology, 18(1), 95–102. https://doi.org/10.1111/j.1526-100X.2008.00428.x

Cunningham, R., Cvitanovic, C., Measham, T., Jacobs, B., Dowd, A.-M., & Harman, B. (2016). Engaging communities in climate adaptation: The potential of social networks. Climate Policy, 16(7), 894–908. https://doi.org/10.1080/14693062.2015.1052955

Curtis, A., Byron, I., & MacKay, J. (2005). INTEGRATING SOCIO-ECONOMIC AND BIOPHYSICAL DATA TO UNDERPIN COLLABORATIVE WATERSHED MANAGEMENT. Journal of the American Water Resources Association, 41(3), 549–563. https://doi.org/10.1111/j.1752-1688.2005.tb03754.x

Daily, G. C., Polasky, S., Goldstein, J., Kareiva, P. M., Mooney, H. A., Pejchar, L., Ricketts, T. H., Salzman, J., & Shallenberger, R. (2009). Ecosystem services in decision making: Time to deliver. Frontiers in Ecology and the Environment, 7(1), 21–28. https://doi.org/10.1890/080025

de Lange, E., Dobson, A. D. M., Milner-Gulland, E. J., & Keane, A. (2021). Combining simulation and empirical data to explore the scope for social network interventions in conservation. Biological Conservation, 261, 109292. https://doi.org/10.1016/j.biocon.2021.109292

de Lange, E., Milner-Gulland, E. J., & Keane, A. (2019). Improving Environmental Interventions by Understanding Information Flows. Trends in Ecology & Evolution, 34(11), 1034–1047. https://doi.org/10.1016/j.tree.2019.06.007

Ding, L., Chen, L., Ding, C., & Tao, J. (2019). Global Trends in Dam Removal and Related Research: A Systematic Review Based on Associated Datasets and Bibliometric Analysis. Chinese Geographical Science, 29(1), 1–12. https://doi.org/10.1007/s11769-018-1009-8

Eicken, H., Danielsen, F., Sam, J.-M., Fidel, M., Johnson, N., Poulsen, M. K., Lee, O. A., Spellman, K. V., Iversen, L., Pulsifer, P., & Enghoff, M. (2021). Connecting Top-Down and Bottom-Up Approaches in Environmental Observing. BioScience, 71(5), 467–483. https://doi.org/10.1093/biosci/biab018

Enqvist, J. P., Tengö, M., & Bodin, Ö. (2020). Are bottom-up approaches good for promoting social–ecological fit in urban landscapes? Ambio, 49(1), 49–61. https://doi.org/10.1007/s13280-019-01163-4

Farwig, N., Sprenger, P. P., Baur, B., Böhning-Gaese, K., Brandt, A., Eisenhauer, N., Ellwanger, G., Hochkirch, A., Karamanlidis, A. A., Mehring, M., Pusch, M., Rehling, F., Sommerwerk, N., Spatz, T., Svenning, J.-C., Tischew, S., Tockner, K., Tscharntke, T., Vadrot, A. B. M., … Mosbrugger, V. (2024). Identifying Major Factors for Success and Failure of Conservation Programs in Europe. Environmental Management. https://doi.org/10.1007/s00267-024-02086-x

Floress, K., Connolly, S., Halvorsen, K. E., Egan, A., Schuler, T., Hill, A., DeSenze, P., Fenimore, S., & Karriker, K. (2018). Implementing Landscape Scale Conservation across Organizational Boundaries: Lessons from the Central Appalachian Region, United States. Environmental Management, 62(5), 845–857. https://doi.org/10.1007/s00267-018-1081-y

Floress, K., Mangun, J. C., Davenport, M. A., & Williard, K. W. J. (2009). Constraints to Watershed Planning: Group Structure and Process 1: C onstraints to W atershed P lanning : G roup S tructure and P rocess. JAWRA Journal of the American Water Resources Association, 45(6), 1352–1360. https://doi.org/10.1111/j.1752-1688.2009.00368.x

Flotemersch, J. E., Leibowitz, S. G., Hill, R. A., Stoddard, J. L., Thoms, M. C., & Tharme, R. E. (2016). A Watershed Integrity Definition and Assessment Approach to Support Strategic Management of Watersheds. River Research and Applications, 32(7), 1654–1671. https://doi.org/10.1002/rra.2978

Frame, T. M., Gunton, T., & Day, J. C. (2004). The role of collaboration in environmental management: An evaluation of land and resource planning in British Columbia. Journal of Environmental Planning and Management, 47(1), 59–82. https://doi.org/10.1080/0964056042000189808

Fraser, E. D. G., Dougill, A. J., Mabee, W. E., Reed, M., & McAlpine, P. (2006). Bottom up and top down: Analysis of participatory processes for sustainability indicator identification as a pathway to community empowerment and sustainable environmental management. Journal of Environmental Management, 78(2), 114–127. https://doi.org/10.1016/j.jenvman.2005.04.009

Grimm, N. B., Groffman, P., Staudinger, M., & Tallis, H. (2016). Climate change impacts on ecosystems and ecosystem services in the United States: Process and prospects for sustained assessment. Climatic Change, 135(1), 97–109. https://doi.org/10.1007/s10584-015-1547-3

Isaak, D. J., Young, M. K., Nagel, D. E., Horan, D. L., & Groce, M. C. (2015). The cold-water climate shield: Delineating refugia for preserving salmonid fishes through the 21st century. Global Change Biology, 21(7), 2540–2553. https://doi.org/10.1111/gcb.12879

Kaushal, S. S., Likens, G. E., Pace, M. L., Utz, R. M., Haq, S., Gorman, J., & Grese, M. (2018). Freshwater salinization syndrome on a continental scale. Proceedings of the National Academy of Sciences, 115(4). https://doi.org/10.1073/pnas.1711234115

Kaweesa, S., Mkomwa, S., & Loiskandl, W. (2018). Adoption of Conservation Agriculture in Uganda: A Case Study of the Lango Subregion. Sustainability, 10(10), 3375. https://doi.org/10.3390/su10103375

Koontz, T. M., & Newig, J. (2014). From Planning to Implementation: Top-Down and Bottom-Up Approaches for Collaborative Watershed Management: Implementing Collaborative Watershed Plans. Policy Studies Journal, 42(3), 416–442. https://doi.org/10.1111/psj.12067

Koundouri, P., Ker Rault, P., Pergamalis, V., Skianis, V., & Souliotis, I. (2016). Development of an integrated methodology for the sustainable environmental and socio-economic management of river ecosystems. Science of The Total Environment, 540, 90–100. https://doi.org/10.1016/j.scitotenv.2015.07.082

Krishnamurthy, R., & Awazu, Y. (2016). Liberating data for public value: The case of Data.gov. International Journal of Information Management, 36(4), 668–672. https://doi.org/10.1016/j.ijinfomgt.2016.03.002

Leclère, D., Obersteiner, M., Barrett, M., Butchart, S. H. M., Chaudhary, A., De Palma, A., DeClerck, F. A. J., Di Marco, M., Doelman, J. C., Dürauer, M., Freeman, R., Harfoot, M., Hasegawa, T., Hellweg, S., Hilbers, J. P., Hill, S. L. L., Humpenöder, F., Jennings, N., Krisztin, T., … Young, L. (2020). Bending the curve of terrestrial biodiversity needs an integrated strategy. Nature, 585(7826), 551–556. https://doi.org/10.1038/s41586-020-2705-y

Lubell, M., Jasny, L., & Hastings, A. (2017). Network Governance for Invasive Species Management. Conservation Letters, 10(6), 699–707. https://doi.org/10.1111/conl.12311

Mancilla García, M., Hileman, J., Bodin, Ö., Nilsson, A., & Jacobi, P. R. (2019). The unique role of municipalities in integrated watershed governance arrangements: A new research frontier. Ecology and Society, 24(1), art28. https://doi.org/10.5751/ES-10793-240128

Maxwell, S. L., Cazalis, V., Dudley, N., Hoffmann, M., Rodrigues, A. S. L., Stolton, S., Visconti, P., Woodley, S., Kingston, N., Lewis, E., Maron, M., Strassburg, B. B. N., Wenger, A., Jonas, H. D., Venter, O., & Watson, J. E. M. (2020). Area-based conservation in the twenty-first century. Nature, 586(7828), 217–227. https://doi.org/10.1038/s41586-020-2773-z

Mazor, R. D., Rehn, A. C., Ode, P. R., Engeln, M., Schiff, K. C., Stein, E. D., Gillett, D. J., Herbst, D. B., & Hawkins, C. P. (2016). Bioassessment in complex environments: Designing an index for consistent meaning in different settings. Freshwater Science, 35(1), 249–271. https://doi.org/10.1086/684130

Mbaru, E. K., & Barnes, M. L. (2017). Key players in conservation diffusion: Using social network analysis to identify critical injection points. Biological Conservation, 210, 222–232. https://doi.org/10.1016/j.biocon.2017.03.031

Mc Culloch-Jones, S., Novellie, P., Roux, D. J., & Currie, B. (2021). Exploring the alignment between the bottom-up and top-down objectives of a landscape-scale conservation initiative. Environmental Conservation, 48(4), 255–263. https://doi.org/10.1017/S0376892921000321

Mills, M., Bode, M., Mascia, M. B., Weeks, R., Gelcich, S., Dudley, N., Govan, H., Archibald, C. L., Romero-de-Diego, C., Holden, M., Biggs, D., Glew, L., Naidoo, R., & Possingham, H. P. (2019). How conservation initiatives go to scale. Nature Sustainability, 2(10), 935–940. https://doi.org/10.1038/s41893-019-0384-1

Mu, M., Gao, L., Zhang, H., Ge, J., Zhang, Z., Qiu, Y., & Zhao, X. (2023). Effects of land use on water quality at different spatial scales in the middle reaches of Huaihe River. Journal of Freshwater Ecology, 38(1), 2176373. https://doi.org/10.1080/02705060.2023.2176373

Neeson, T. M., Wineland, S. M., Phillips, E., & McFadden, J. (2022). The dynamics of mature and emerging freshwater conservation programs. Frontiers in Environmental Science, 10, 888521. https://doi.org/10.3389/fenvs.2022.888521

Nesbitt, H. K., Metcalf, A. L., Floyd, T. M., Uden, D. R., Chaffin, B. C., Gulab, S., Banerjee, S., Vallury, S., Hamlin, S. L., Metcalf, E. C., Fogarty, D. T., Twidwell, D., & Allen, C. R. (2024). Social networks and transformative behaviours in a grassland social-ecological system. People and Nature, 6(5), 1877–1892. https://doi.org/10.1002/pan3.10695

Niemiec, R. M., Gruby, R., Quartuch, M., Cavaliere, C. T., Teel, T. L., Crooks, K., Salerno, J., Solomon, J. N., Jones, K. W., Gavin, M., Lavoie, A., Stronza, A., Meth, L., Enrici, A., Lanter, K., Browne, C., Proctor, J., & Manfredo, M. (2021). Integrating social science into conservation planning. Biological Conservation, 262, 109298. https://doi.org/10.1016/j.biocon.2021.109298

Ode, P. R., Rehn, A. C., & May, J. T. (2005). A Quantitative Tool for Assessing the Integrity of Southern Coastal California Streams. Environmental Management, 35(4), 493–504. https://doi.org/10.1007/s00267-004-0035-8

Olsson, P., Folke, C., & Hughes, T. P. (2008). Navigating the transition to ecosystem-based management of the Great Barrier Reef, Australia. Proceedings of the National Academy of Sciences, 105(28), 9489–9494. https://doi.org/10.1073/pnas.0706905105

Park, S.-R., & Lee, S.-W. (2020). Spatially Varying and Scale-Dependent Relationships of Land Use Types with Stream Water Quality. International Journal of Environmental Research and Public Health, 17(5), 1673. https://doi.org/10.3390/ijerph17051673

Paukert, C. P., Pitts, K. L., Whittier, J. B., & Olden, J. D. (2011). Development and assessment of a landscape-scale ecological threat index for the Lower Colorado River Basin. Ecological Indicators, 11(2), 304–310. https://doi.org/10.1016/j.ecolind.2010.05.008

Pierre, J., Røiseland, A., Peters, B. G., & Gustavsen, A. (2017). Comparing local politicians' and bureaucrats' assessments of democratic participation: The cases of Norway and Sweden. International Review of Administrative Sciences, 83(4), 658–675. https://doi.org/10.1177/0020852315598214

Rilov, G., Fraschetti, S., Gissi, E., Pipitone, C., Badalamenti, F., Tamburello, L., Menini, E., Goriup, P., Mazaris, A. D., Garrabou, J., Benedetti-Cecchi, L., Danovaro, R., Loiseau, C., Claudet, J., & Katsanevakis, S. (2020). A fast-moving target: Achieving marine conservation goals under shifting climate and policies. Ecological Applications, 30(1), e02009. https://doi.org/10.1002/eap.2009

Rothrock, P. E., Simon, T. P., & Stewart, P. M. (2008). Development, calibration, and validation of a littoral zone plant index of biotic integrity (PIBI) for lacustrine wetlands. Ecological Indicators, 8(1), 79–88. https://doi.org/10.1016/j.ecolind.2007.01.002

Scown, M. W., Flotemersch, J. E., Spanbauer, T. L., Eason, T., Garmestani, A., & Chaffin, B. C. (2017). People and water: Exploring the social-ecological condition of watersheds of the United States. Elementa: Science of the Anthropocene, 5, 64. https://doi.org/10.1525/elementa.189

Shakarian, P., Bhatnagar, A., Aleali, A., Shaabani, E., & Guo, R. (2015). Diffusion in social networks. Springer.

Shifflett, Newcomer-Johnson, Yess, & Jacobs. (2019). Interdisciplinary Collaboration on Green Infrastructure for Urban Watershed Management: An Ohio Case Study. Water, 11(4), 738. https://doi.org/10.3390/w11040738

Shunglu, R., Köpke, S., Kanoi, L., Nissanka, T. S., Withanachchi, C. R., Gamage, D. U., Dissanayake, H. R., Kibaroglu, A., Ünver, O., & Withanachchi, S. S. (2022). Barriers in Participative Water Governance: A Critical Analysis of Community Development Approaches. Water, 14(5), 762. https://doi.org/10.3390/w14050762

Sun, Y., Li, Y., Ma, R., Gao, C., & Wu, Y. (2022). Mapping urban socio-economic vulnerability related to heat risk: A grid-based assessment framework by combing the geospatial big data. Urban Climate, 43, 101169. https://doi.org/10.1016/j.uclim.2022.101169

Tickner, D., Opperman, J. J., Abell, R., Acreman, M., Arthington, A. H., Bunn, S. E., Cooke, S. J., Dalton, J., Darwall, W., Edwards, G., Harrison, I., Hughes, K., Jones, T., Leclère, D., Lynch, A. J., Leonard, P., McClain, M. E., Muruven, D., Olden, J. D., … Young, L. (2020). Bending the Curve of Global Freshwater Biodiversity Loss: An Emergency Recovery Plan. BioScience, 70(4), 330–342. https://doi.org/10.1093/biosci/biaa002

Tsvetkova, O., & Randhir, T. O. (2019). Spatial and temporal uncertainty in climatic impacts on watershed systems. Science of The Total Environment, 687, 618–633. https://doi.org/10.1016/j.scitotenv.2019.06.141

Valente, T. W., & Pumpuang, P. (2007). Identifying Opinion Leaders to Promote Behavior Change. Health Educ Behav, 34(6), 881–896. https://doi.org/10.1177/1090198106297855

Webb, N. P., Stokes, C. J., & Marshall, N. A. (2013). Integrating biophysical and socio-economic evaluations to improve the efficacy of adaptation assessments for agriculture. Global Environmental Change, 23(5), 1164–1177. https://doi.org/10.1016/j.gloenvcha.2013.04.007

Weston, S., & Conrad, C. (2015). Community-Based Water Monitoring in Nova Scotia: Solutions for Sustainable Watershed Management. Environment and Natural Resources Research, 5(2), p1. https://doi.org/10.5539/enrr.v5n2p1

White, T. B., Petrovan, S. O., Booth, H., Correa, R. J., Gatt, Y., Martin, P. A., Newell, H., Worthington, T. A., & Sutherland, W. J. (2022). Determining the economic costs and benefits of conservation actions: A decision support framework. Conservation Science and Practice, 4(12), e12840. https://doi.org/10.1111/csp2.12840

Wulder, M. A., Masek, J. G., Cohen, W. B., Loveland, T. R., & Woodcock, C. E. (2012). Opening the archive: How free data has enabled the science and monitoring promise of Landsat. Remote Sensing of Environment, 122, 2–10. https://doi.org/10.1016/j.rse.2012.01.010

Chapter One

SPATIAL DATA AND WATERSHED MANAGEMENT IN THE UNITED STATES: PRACTITIONER PERSPECTIVES ON DATA NEEDS AND DECISION-MAKING BARRIERS

Keywords:

Conservation decision-making, socio-economic data, spatial data, water manger survey, watershed planning

Abstract

Water resource managers use a range of spatial data products to assess watershed condition, prioritize sites for restoration or preservation, and identify future research needs. Many data products exist, but there is not a clear understanding regarding their relative usefulness and what improvements would be helpful to managers. We surveyed 103 water quality managers across the United States to understand their 1) perceptions of watershed condition and approaches to watershed assessment, 2) use of and need for spatial data products (e.g., watershed health index) on watershed condition, and 3) perceived barriers to improving watershed condition. We find that spatial data sets are commonly used in watershed assessments, but available spatial data are not well aligned with water resource managers' needs. Notable gaps exist around socio-economic data. Managers reported that estimates of the projected costs of management actions would be very useful for guiding conservation investments, and the lack of reliable economic data was identified as a significant barrier to improving watershed condition. In contrast, only about half (46%) of respondents said that the availability of biophysical data was a barrier to improving watershed condition. Therefore, investments in improving data on the social and economic costs of proposed projects may be more useful than improvements in biophysical data describing watershed condition and function. This study reveals the ready use of spatial data by water resource managers and opportunities for researchers to create the multidisciplinary spatial data products desired by managers to address a wide variety of watershed management decisions. Practical Implication. Our findings suggest that future investments in spatial data should prioritize economic and implementation-focused information, such as project cost estimates and cross-agency activity tracking, over further refinement of biophysical data alone. Addressing socio-political and organizational barriers, alongside

technical improvements, will enhance the practical utility of spatial tools and better support decision-makers in implementing effective, coordinated watershed management strategies.

Introduction

Watershed managers, planners, and conservation actors engage in many types of decisions that affect conservation efforts and the protections afforded to rivers, lakes, and their surrounding landscape. Initiatives that aim to maintain or restore watershed functions may range from community flood mitigation programs focused on the benefits of riparian wetland restoration to agriculture advisors promoting soil health for crops. Although conservation actions differ in approach and objective, they all support improving and sustaining interrelated watershed functions and services (Daily et al., 2009; Flotemersch et al., 2016). Likewise, conservation decisions and actions are often targeted at different spatial scales, ranging from watershed wide planning to site specific projects (Mu et al., 2023; Park & Lee, 2020). There are also a multitude of organizations and agencies that exemplify the role of watershed management actors. This includes federal, state, and local agencies that often have defined regulatory responsibilities and national or local environmental organizations with a conservation mission. Altogether there is a broad group of people, programs, and projects that comprise the field of watershed conservation.

Given the many types of conservation actions undertaken to support healthy watersheds, decision-makers rely on equally diverse spatial data to inform planning, monitoring, project selection and investments. Broadly defined, spatial data are georeferenced information that map environmental or social variables across the landscape. Some spatial data sets describe biophysical systems (e.g., topography, hydrology, precipitation, soils, land cover, and species occurrence), while others describe socio-economic systems (e.g., human demographics, land ownership, economic information, and political boundaries). Both biophysical and socio-economic spatial data are critical for understanding the biophysical condition of watersheds and the social context in which management occurs (Sánchez et al., 2010; Sun et al., 2022; Webb et al., 2013).

In recent decades investments in spatial data have increased and been supported by advances in GIS technologies, data platforms, and remote sensing (Budhathoki et al., 2008; Krishnamurthy & Awazu, 2016; Wulder et al., 2012). In the United States many foundational single layer data sets (e.g., topography, stream hydrology, precipitation, soils, landcover, species occurrence, demographics) are locally and nationally available. These diverse data sets are often synthesized into metrics or indices that characterize ecosystem condition or stress; for example, an aquatic ecosystem health index may be composed of hydrology, habitat, water quality, and biological metrics (Mazor et al., 2016; Ode et al., 2005; Rothrock et al., 2008). Similarly, managing multiple stressors often requires combined indices that can quantify overall condition, set management goals, and evaluate progress. Allan et al., (2013) demonstrated that quantifying cumulative stress in relationship to ecosystem services can support effectively directing restoration investments. At the same time, there is growing recognition of the important role of socio-economic factors in watershed management (Curtis et al., 2005; Koundouri et al., 2016; Webb et al., 2013). Scown et al. (2017) examined the spatial patterns in social-ecological conditions across U.S. watersheds and identified "win-win" areas where high watershed integrity coincides with high human well-being, and "lose-win" areas where watershed integrity is low and human well-being is high. While there has been increased academic focus on integrating biophysical and socio-economic dimension in watershed assessments (Scown et al., 2017) it remains unclear to what extent water resource managers are applying both types of spatial data in practice. Identifying patterns of use and potential gaps in spatial data is critical as managers confront increasing demands to address complex watershed challenges.

The generation and circulation of spatial data by researchers and use by resource managers demonstrates the central role of spatial analysis in navigating challenging and evolving watershed conditions. Among the most urgent environmental challenges, global climate change intensifies the urgency and complexity of watershed management by altering hydrologic regimes, increasing stream temperatures, and exacerbating the effects of land use change and water quality impairments (Grimm et al., 2016; Isaak et al., 2015; Kaushal et al., 2018). These changes occur at different spatial and temporal scales across the landscape, which can make it difficult for local managers to respond to site specific impacts of global processes (Allan, 2004; Christian-Smith & Merenlender, 2010; Paukert et al., 2011). For example, water supply planning is conducted at the local level and depends upon watershed processes such as runoff, infiltration, and water yield, all of which are influenced by global-scale changes in precipitation and temperature (Tsvetkova & Randhir, 2019). This dual pressure of responding to local watershed conditions while also considering global climate driven impacts results in increasing demand on spatial data and associated decision support tools used by water resource managers (Brown et al., 2013). Despite investments in and growing reliance on spatial data, questions remain about how spatial data are applied in watershed management and whether available data align with the needs of decision-makers (McIntosh et al., 2007; Quinn et al., 2022; Wang et al., 2016).

Although spatial data on ecosystem condition, stressors, and services are widely used to support conservation decisions, it is not necessarily true that continued investment in refining and expanding these biophysical data sets will generate proportional benefits. In many settings, decision-makers lack even basic information about the potential social-political and economic costs of proposed conservation actions (Lubchenco, 1998; Niemiec et al., 2021; White, Petrovan, Booth, et al., 2022), and spatial variation in project costs and feasibility, rather than variation in environmental benefits, may determine the cost-effectiveness of a proposed project (Moilanen et al., 2011; Van Deynze et al., 2022). Biophysical spatial data are valuable, yet continued investment in building and refining these data sets may not yield dividends if other barriers constrain resource managers. Technical information and scientific expertise are essential to policy initiatives and conservation program implementation; however, social, political, and economic factors also influence decision-making. Barriers to effective watershed management can include discord over competing or ambiguous organization authority or roles, and organizational structural difficulties (Floress et al., 2009; Mancilla García et al., 2019). Likewise, power imbalances between dominant groups and marginalized stakeholders are known to influence decision-making processes and can hinder adoption of equitable social and environmental actions (Arai et al., 2021; Frame et al., 2004; Shunglu et al., 2022). Secure long-term funding has also been identified as a crucial need for various watershed management measures (Floress et al., 2018; Shifflett et al., 2019; Weston & Conrad, 2015; Wineland, Fovargue, York, et al., 2021). Furthermore, public administration research indicates that there can be both convergence and divergence in attitudes and knowledge on various topics between civil servants and politicians (Pierre et al., 2017). Because non-technical factors such as these also motivate environmental outcomes it is important to reckon with their influence when determining how to best direct resources.

Here, we surveyed water resource managers across the United States and asked how they use spatial data, what data gaps exist, and what barriers constrain watershed management. We focused on water resource managers in state government agencies who collectively oversee a wide range of conservation and restoration programs. Our goal was to assess whether currently available spatial data align with their needs, and to evaluate the relative importance of further investment in biophysical spatial data sets versus socio-economic dataset. The responses offer insight into the status and trends of spatial data use and highlight the technical and practical needs of water resource managers engaged in watershed management across the United States. We focused on four research questions. First, what tools are used to evaluate watershed function or condition? Second, how do watershed managers expect changes in watershed functions? Third, what types of spatial data (biophysical and/or socio-economic) and associated data products would be most useful to support various tasks or planning? Fourth, what socio-political, organizational, and data availability barriers hinder efforts to improve in watershed condition? Systematically, we know little about how socio-political circumstances influence or constrain potential actions by water resource managers; therefore, gaining insight into how managers perceive the relative importance of technical data needs versus the socio-political atmosphere and organizational cooperation is valuable for directing resources and designing strategies to improve watershed conditions, especially in the context of global climate change.

Methods

We designed and implemented a twenty-six-question online survey to inquire about watershed assessment methods, tools, and spatial data (biophysical and/or socio-economic) and associated products from water resource managers. Here, we focus on a subset of these questions directly related to our three research questions. Table 1-1 presents the research questions and corresponding survey questions.

A number of survey questions focused on anticipated changes in watershed functions and approaches to watershed assessment, which related to our first research question: how do watershed managers expect watershed functions to change in the future and what tools are used to evaluate watershed function or condition? The aim of these questions was to capture respondents' outlook on improving or worsening watershed functions and the extent that assessment tools are employed to measure watershed changes. Next, we inquired about the usefulness of different spatial data for watershed management tasks or decision making (questions 17, 18). This supported our third research question: what spatial data and/or associated products would be most useful for water resource managers? This question serves to reveal if currently available spatial data products are aligned with what practitioners identify as useful or is there a need for researchers to generate new products. Finally, question 24 was used to discover what water resource managers perceive as barriers to improving watershed conditions.

The participants targeted for this research survey were water resource managers from environmental agencies or non-governmental organizations with watershed and/or surface water quality management authorities. Survey respondents were recruited from state environmental agencies across the United States through the Association of Clean Water Administrators (ACWA). ACWA is a professional organization primarily comprised of state agency officials responsible for the implementation of surface water quality protection programs. Additionally, participation was invited through a national committee of state and federal agency water quality professionals coordinated by U.S. Environmental Protection Agency (EPA). Persons within these two primary recruitment groups were encouraged to share the survey with colleagues associated with local government or nongovernmental organizations to further expand the pool of participants. The final group of participants represented a diverse population of water resource managers with a range of expertise and experience.

The survey software Qualtrics (Qualtrics, Provo, UT) was used to host the survey and a web link to the survey was distributed directly to potential participants via email. Prior to beginning the survey, participants were presented with an informed consent form outlining that the study was voluntary, and all responses were anonymous. Participants were required to provide affirmative consent before proceeding. The consent form also included contact information for the researchers and the university's Institutional Review Board, in case participants had questions or concerns about their rights or the study procedures. The survey included multiple choice, Likert scale, and rank order questions. We used a snowball sampling approach in which directly contacted individuals were encouraged to further distribute the survey to other colleagues. This approach proved practical and facilitated targeted recruitment among the professional networks of the two initial recruitment groups. A reminder email was sent to directly contacted individuals two weeks after the original survey distribution requesting completion of the survey. In total one hundred and three people responded to the survey, with forty-eight complete responses included in final analysis (useable response rate = 47%).

The target audience consisted of professional water resource managers, for whom the survey language and topics were presumably familiar; however, we did not conduct a formal comprehension assessment. The survey was beta-tested and refined with out-of-sample water resources managers prior to distribution. Snowball sampling, while effective for reaching our intended participant group, may have introduced sampling bias by excluding professionals that are less well connected to the initial professional networks where the survey was distributed. This is a limitation that may have affected the representativeness of the sample population. The study also relied on self-reported data, which may be subject to biases such as confirmation bias or selective recall. Finally, the focus on a single national context may constrain the generalizability of the findings, particularly for countries with very different policies, programs, or watershed governance structures.

Results

Respondent characteristics

The majority (87%) of respondents were affiliated with state agencies responsible for implementing federal Clean Water Act programs. This strong response from a key participant group was important because the Clean Water Act includes both regulatory and nonregulatory water quality management programs that often work together across the watershed-waterbody spatial scale. The remaining respondents (13%) were staff from federal agencies, local government, and non-governmental organizations; these responses are valuable to broaden perspective of the survey results. The respondents self-identified their positions, with most working in mid-level management (44%) or technical staff (43%) positions; the remaining 13% identified themselves as senior management, field staff, or policy advisors. Professional experience was well distributed among respondents with 33% having more than 20 years of experience and 36% with 10 to 20 years. Only 8% reported 5 to 9 years and 23% had less than 5 years of professional experience. Collectively, this was an experienced group of water resource managers, able to offer insights into the application of spatial data to watershed management practices and what non-technical factors may hinder improvements in watershed condition.

Watershed assessment

To understand how watershed function or condition is currently evaluated and characterized, we assessed the frequency, type, and content of watershed assessment tools used by participants (research question one). When asked about their familiarity with watershed assessment, defined as "a holistic characterization of watershed function or impairment using a suite of physical, chemical, and biological variables within the watershed," a large majority (85%) of respondents reported being very familiar with these approaches, and most indicated they have used a watershed assessment tool in their work (Fig. 1-1A). For respondents that currently use a watershed assessment tool, 62% apply the tool on an annual or less frequent basis; although,34% of respondents reported they do not use a standardized watershed assessment tool at all. The incorporation of some type of geographic information, such as web-based maps or other visualizations was a common element of many assessment tools (Fig. 1-1B). Overall, 69% of assessment tools had some type of geographic component, while spreadsheet tools were used by about half (49%) of respondents either as a standalone analysis format or in combination with GIS. A smaller group (14%) reported the use of “other” tools not categorized as GIS or spreadsheets and a single respondent stated the tool was not electronic (Fig. 1-1B).

Watershed assessment tools currently in use are diverse and characterize either condition, function, or both. Most (39%) respondents reported using single index watershed assessment tools to characterize integrated watershed condition (Fig. 1-1C). In contrast, 18% of tools are a single index that describes integrated watershed function or ecosystem service. Tools based on multiple indices were also reported, with 18% based on multiple condition metrics, 11% describing multiple watershed functions and 14% using multiple indices that assess both watershed condition and function (Fig. 1-1C). Output formats also varied, with 47% producing static products (i.e., final report, map, spreadsheet results) and 35% identified the output as an interactive map.

Although spatial data is commonly included in watershed assessment tools (Fig. 1-1B), we find that data layers in current tools are not aligned with practitioner needs (research question 3). For example, all respondents reported that a spatial data layer incorporating information on best management practice (BMP) effectiveness and associated cost would be useful, and approximately 45% identified this layer as very useful (Fig. 1-2). However, data on the potential costs and effectiveness of candidate projects are rarely available in existing tools (Fig. 1-1C).

Likewise, spatial data layers that synthesize the implementation actions of a respondent's own agency and other agencies were very desirable but typically unavailable. Seventy-six percent of respondents identified an implementation action layer for their own agency to be useful or very useful and 83% identified a layer of this type with another agency's information to be useful or very useful. Regarding layers that characterize watershed stressors and/or the condition of functions there was greater desire for layers focused on a single stressor or function with 86% and 81% identifying these as useful or very useful, respectively. Comparatively, combined function or cumulative stressor layers were considered 65% and 66% useful or very useful, respectively.

When asked about future conditions, respondents predicted that all six of the key watershed functions will be impacted more by climate change than by other human activities (Fig. 1-3) (research question 2). Greater than 70% of respondents predicted that all six functions will slightly or considerably worsen in the future. For all six watershed functions, at most one-third of respondents predicted that watershed functions would stay the same in response to climate change (Fig. 1-3A). Seven percent of people expect slight improvements in chemistry regulation and no respondents identified considerable improvement for any function. When asked about likely changes to watershed function due to other human activities, respondents generally expect watershed function to worsen slightly (Fig. 1-3B). The functions of hydrology, sediment and temperature regulation are expected to slightly worsen by 45 – 48 percent of respondents. Whereas chemistry regulation (61%) and hydrologic connectivity (51%) are viewed more likely to stay the same or improve slightly.

Although elements of current watershed assessment tools are not well aligned with practitioners' needs, most respondents ranked funding and organizational challenges, not data needs, as the most serious barriers to improving watershed conditions (Fig. 1-4) (research question 4). All barriers categorized as organizational challenges were believed to be a moderate to serious barrier by more than 55% of respondents. Lack of funding was near the top of respondent concerns with 81% finding it to be a moderate or serious barrier. When considering barriers related to data the need for economic data was of the greatest concern with almost 75% of respondents identifying it as a moderate to significant barrier. Forty-four percent of respondents reported the lack of a watershed analysis tool as a moderate or serious barrier. Other data needs, such as stressor data or additional awareness on ecosystem services, were reported to be moderate or serious barriers by about 40 to 50 percent of respondents.

Discussion

There is widespread knowledge of watershed functions and prevalent use of assessment methodologies by water resource managers. This is important as both communities and ecosystems depend on sustained watershed integrity to deliver a variety of ecosystem services (Flotemersch et al., 2016; Scown et al., 2017) and a major threat to freshwater systems are anthropogenic changes to the surrounding watershed (Tickner et al., 2020; Vörösmarty et al., 2010; Davis, et al 2015). However, an ongoing challenge is achieving management actions that include the fundamental linkages between watershed landscapes, downstream waterbodies, and potential conflicts between conservation and other human activities (Hermoso et al., 2016; Howard et al., 2018; Lin et al., 2017). While watershed assessment tools are widely used, their content and functionality fall short of meeting the multifaceted needs of water resource managers. Notably water resource managers identified spatial data layers that are multi-disciplinary and synthesize information as the most useful. A BMP spatial data layer that includes information on both BMP effectiveness and implementation cost was identified as the most desired spatial data layer. Likewise, resource managers were keen on spatial data that would synthesize project or activity information across agencies with different responsibilities. A data layer of this nature is particularly relevant given that more than half of respondents found lack of agency coordination to be a moderate to significant barrier to improving watershed conditions. Developing these datasets would provide additional context for existing biophysical spatial data and support more effective inter-agency decision making (Neeson et al., 2018).

Beyond the need for multi-disciplinary and synthesized biophysical spatial data resources, managers also identified specific data gaps, most notably in economic information. Economic data was identified as the most pressing data need; the lack of economic data was considered a barrier to improving watershed condition by approximately 75% of respondents. Watershed planning and management increasingly require consideration of monetary cost and social economic benefits that arise from conservation or restoration (Naidoo et al., 2006; White, Petrovan, Christie, et al., 2022). Federal and state agencies are often required to conduct economic analysis as part of rule adoption and implementation (Carey, 2022; Office of Management and Budget, 2003). Therefore, the lack of economic data not only represents a technical shortfall but highlights a broader misalignment between the types of spatial data generated by researchers and the needs of practitioners tasked with justifying and implementing projects. One way to address this gap could be through environmental and natural resources valuation studies, which can be extrapolated to similar sites or situations using benefit transfer methods (Polasky et al., 2011; Richardson et al., 2015). For example, findings such as increased water clarity linked to increased waterfront home values or household willingness to pay amounts to reduce nutrient pollution, can inform decisions and actions across different watersheds (Guignet et al., 2021; Nelson et al., 2015). Improving access to economic information and incorporating it into spatial data sets could provide resource managers critical insights into the economic value of non-market watershed goods and services.

The emphasis on economic data as the most critical spatial data gap highlights a need for decision-making frameworks that account for both ecological and fiscal outcomes (Chen et al., 2025; Naidoo et al., 2006, 2006; Tallis et al., 2008; Wineland et al., 2023). In many settings, watershed managers are required to demonstrate cost-effectiveness or provide economic justifications for proposed conservation actions (Carey, 2022; Office of Management and Budget, 2003). Without access to spatially explicit estimates of costs or benefits, managers may struggle to prioritize projects or secure funding, especially when competing with other infrastructure or development priorities. This lack of readily available economic data limits the ability to communicate the broader value of watershed services to stakeholders and political decision-makers, ultimately limiting the adoption and implementation of conservation measures.

Similarly, the lack of standardized watershed assessment methods presents another critical information gap and one that limits the ability to comprehensively interpret existing data at the watershed scale. Approximately one third of respondents do not have or use a standardized watershed assessment method and 44% identified lack of an analysis tool as a moderate to serious barrier to watershed improvement. This represents a considerable gap where data collected on individual watershed stressors or functions (e.g. water chemistry, habitat) are not systematically applied and interpreted to comprehensively characterize watershed condition. While site specific data provide valuable detail, they often fail to capture watershed wide interactions that drive overall condition. As a result, management actions may be localized to individual waterbodies and decoupled from the larger watershed spatial context. For practitioners currently using a watershed assessment method, most are composed of individual condition or stressor indices. Identification and response to individual local watershed impacts or stressors may overlook the cumulative or synergistic impact from multiple stressors (Dubé et al., 2013; Halpern & Fujita, 2013). Moreover, management actions taken at larger spatial scales can be considerably more cost effective as compared with local site-specific actions (Neeson et al., 2015). The interest in spatial data layers that would provide combined or synthesized information could be leveraged to shift focus to cumulative condition/stressor analysis (Neeson et al., 2016). This presents an opportunity to develop or evolve watershed assessment methods to evaluate cumulative effects and center management decision making on integrated watershed function.

Respondents were pessimistic about the future impacts of climate change on watershed functions and by extension will need resources to address both near and far term impacts. It is expected that survey participants would have a working knowledge about interactive effects between watershed land use and climate that directly impacts downstream water quality (Ervinia et al., 2019; Serpa et al., 2017). Yet, knowledge regarding if or how climate change may influence traditional best management practice performance and the favored composition of practices is likely less widespread (Dudula & Randhir, 2016; Jeon et al., 2018; Qiu et al., 2019). This general concern for changing climate conditions could be combined with the desire for multi-disciplinary synthesized information to introduce climate change mitigation considerations into manager decision making (Fovargue et al., 2021; Wineland, Fovargue, Gill, et al., 2021). For example, spatial layers that combine stream temperature with land cover data could help managers identify cold-water refugia for protection or prioritize riparian restoration where it would provide the greatest thermal benefit under future climate conditions. Incorporating future climate condition information into familiar spatial data resources or expanding current assessment methods to include climate factors would provide resource managers with desired synthesized multi-disciplinary data and integrate climate change considerations into practitioner decision making.

However, not all challenges to improving watershed conditions were technical in nature. Respondents emphasized the critical role of organizational and institutional dynamics. These dynamics can include systemic challenges such as lack of socio-political urgency, limited funding, and competing priorities, all of which can hinder the development, integration, and maintenance of comprehensive spatial datasets. The survey findings highlight that water resource managers experience socio-political constraints to improving watershed conditions. A majority of respondents identified organizational or socio-political barriers as a moderate to serious impediments. When funding is unreliable or agency coordination limited, it becomes difficult to maintain current spatial datasets, collaborate across jurisdictions, or implement watershed wide actions. These challenges can prevent collaborative development of interdisciplinary spatial data products even when the need among practitioners is clearly identified. Furthermore, decision-making within agencies is affected by the broader socio-political context. Political, legal, and economic factors can have influence over environmental priorities and decision (Pahl-Wostl, 2007; Smith et al., 2011; Wise et al., 2014). It can be scientifically challenging and politically precarious to expose these intangible or implicit underlying decision-making dynamics. However, collaborative efforts to build trust and legitimacy in scientific data can improve buy-in and motivate decisions for better environmental outcomes (Cash & Belloy, 2020; Cravens, 2016; Goldsmith et al., 2016). Recognizing the relationship between socio-political and biophysical processes is valuable for evaluating when and where resources may be best directed toward addressing technical improvements or socio-political governance challenges (Colloff & Pittock, 2019; Eakin et al., 2017).

Conclusion

Watershed management opportunities and challenges are embedded within the broader economic and socio-political atmosphere and strict focus on data driven and technical issues does not engage with overall conditions to promote change or better outcomes for watershed integrity. Research should prioritize developing integrated spatial data products that combine biophysical, economic, and social information. This type of synthesized spatial data could facilitate progress and support improved watershed conditions that traditional data alone may not accomplish. While this study has limitations, including the focus on a single national context and reliance on self-reported data, the views presented reflect the perspectives of an experienced group of water resource managers. These insights offer valuable guidance on how best to support practitioners with spatial data and tools as they plan, implement, and advocate for watershed conservation.

References

Allan, J. D. (2004). Landscapes and Riverscapes: The Influence of Land Use on Stream Ecosystems. *Annual Review of Ecology, Evolution, and Systematics*, *35*(1), 257–284. https://doi.org/10.1146/annurev.ecolsys.35.120202.110122

Allan, J. D., McIntyre, P. B., Smith, S. D. P., Halpern, B. S., Boyer, G. L., Buchsbaum, A., Burton, G. A., Campbell, L. M., Chadderton, W. L., Ciborowski, J. J. H., Doran, P. J., Eder, T., Infante, D. M., Johnson, L. B., Joseph, C. A., Marino, A. L., Prusevich, A., Read, J. G., Rose, J. B., … Steinman, A. D. (2013). Joint analysis of stressors and ecosystem services to enhance restoration effectiveness. *Proceedings of the National Academy of Sciences*, *110*(1), 372–377. https://doi.org/10.1073/pnas.1213841110

Arai, Y., Maswadi, M., Oktoriana, S., Suharyani, A., Didik, D., & Inoue, M. (2021). How Can We Mitigate Power Imbalances in Collaborative Environmental Governance? Examining the Role of the Village Facilitation Team Approach Observed in West Kalimantan, Indonesia. *Sustainability*, *13*(7), 3972. https://doi.org/10.3390/su13073972

Brown, C. J., Saunders, M. I., Possingham, H. P., & Richardson, A. J. (2013). Managing for Interactions between Local and Global Stressors of Ecosystems. *PLoS ONE*, *8*(6), e65765. https://doi.org/10.1371/journal.pone.0065765

Budhathoki, N. R., Bruce, B. (Chip), & Nedovic-Budic, Z. (2008). Reconceptualizing the role of the user of spatial data infrastructure. *GeoJournal*, *72*(3–4), 149–160. https://doi.org/10.1007/s10708-008-9189-x

Carey, M. (2022, March 8). *Cost-Benefit Analysis in Federal Agency Rulemaking (IF12058)*.

Cash, D. W., & Belloy, P. G. (2020). Salience, Credibility and Legitimacy in a Rapidly Shifting World of Knowledge and Action. *Sustainability*, *12*(18), 7376. https://doi.org/10.3390/su12187376

Chen, M., Adam, N. A., Gulzar, F., Li, X., Azlarova, M., & Roos, B. (2025). Integrating ecological indicators into economic and financial decision-making management. *Ecological Indicators*, *174*, 113482. https://doi.org/10.1016/j.ecolind.2025.113482

Christian-Smith, J., & Merenlender, A. M. (2010). The Disconnect Between Restoration Goals and Practices: A Case Study of Watershed Restoration in the Russian River Basin, California. *Restoration Ecology*, *18*(1), 95–102. https://doi.org/10.1111/j.1526-100X.2008.00428.x

Colloff, M. J., & Pittock, J. (2019). Why we disagree about the Murray–Darling Basin Plan: Water reform, environmental knowledge and the science-policy decision context. *Australasian Journal of Water Resources*, *23*(2), 88–98. https://doi.org/10.1080/13241583.2019.1664878

Cravens, A. E. (2016). Negotiation and Decision Making with Collaborative Software: How MarineMap 'Changed the Game' in California's Marine Life Protected Act Initiative. *Environmental Management*, *57*(2), 474–497. https://doi.org/10.1007/s00267-015-0615-9

Curtis, A., Byron, I., & MacKay, J. (2005). INTEGRATING SOCIO-ECONOMIC AND BIOPHYSICAL DATA TO UNDERPIN COLLABORATIVE WATERSHED

MANAGEMENT. *Journal of the American Water Resources Association*, *41*(3), 549–563. https://doi.org/10.1111/j.1752-1688.2005.tb03754.x

Daily, G. C., Polasky, S., Goldstein, J., Kareiva, P. M., Mooney, H. A., Pejchar, L., Ricketts, T. H., Salzman, J., & Shallenberger, R. (2009). Ecosystem services in decision making: Time to deliver. *Frontiers in Ecology and the Environment*, *7*(1), 21–28. https://doi.org/10.1890/080025

Dubé, M. G., Duinker, P., Greig, L., Carver, M., Servos, M., McMaster, M., Noble, B., Schreier, H., Jackson, L., & Munkittrick, K. R. (2013). A framework for assessing cumulative effects in watersheds: An introduction to Canadian case studies: Watershed CEA Framework. *Integrated Environmental Assessment and Management*, *9*(3), 363–369. https://doi.org/10.1002/ieam.1418

Dudula, J., & Randhir, T. O. (2016). Modeling the influence of climate change on watershed systems: Adaptation through targeted practices. *Journal of Hydrology*, *541*, 703–713. https://doi.org/10.1016/j.jhydrol.2016.07.020

Eakin, H., Bojórquez-Tapia, L. A., Janssen, M. A., Georgescu, M., Manuel-Navarrete, D., Vivoni, E. R., Escalante, A. E., Baeza-Castro, A., Mazari-Hiriart, M., & Lerner, A. M. (2017). Urban resilience efforts must consider social and political forces. *Proceedings of the National Academy of Sciences*, *114*(2), 186–189. https://doi.org/10.1073/pnas.1620081114

Ervinia, A., Huang, J., Huang, Y., & Lin, J. (2019). Coupled effects of climate variability and land use pattern on surface water quality: An elasticity perspective and watershed health indicators. *Science of The Total Environment*, *693*, 133592. https://doi.org/10.1016/j.scitotenv.2019.133592

Floress, K., Connolly, S., Halvorsen, K. E., Egan, A., Schuler, T., Hill, A., DeSenze, P., Fenimore, S., & Karriker, K. (2018). Implementing Landscape Scale Conservation across Organizational Boundaries: Lessons from the Central Appalachian Region, United States. *Environmental Management*, *62*(5), 845–857. https://doi.org/10.1007/s00267-018-1081-y

Floress, K., Mangun, J. C., Davenport, M. A., & Williard, K. W. J. (2009). Constraints to Watershed Planning: Group Structure and Process [1]: C ONSTRAINTS TO W ATERSHED P LANNING : G ROUP S TRUCTURE AND P ROCESS. *JAWRA Journal of the American Water Resources Association*, *45*(6), 1352–1360. https://doi.org/10.1111/j.1752-1688.2009.00368.x

Flotemersch, J. E., Leibowitz, S. G., Hill, R. A., Stoddard, J. L., Thoms, M. C., & Tharme, R. E. (2016). A Watershed Integrity Definition and Assessment Approach to Support Strategic Management of Watersheds. *River Research and Applications*, *32*(7), 1654–1671. https://doi.org/10.1002/rra.2978

Fovargue, R. E., Rezapour, S., Rosendahl, D., Wootten, A. M., Sabzi, H. Z., Moreno, H. A., & Neeson, T. M. (2021). Spatial planning for water sustainability projects under climate uncertainty: Balancing human and environmental water needs. *Environmental Research Letters*, *16*(3), 034050. https://doi.org/10.1088/1748-9326/abdd58

Frame, T. M., Gunton, T., & Day, J. C. (2004). The role of collaboration in environmental management: An evaluation of land and resource planning in British Columbia. *Journal of*

Environmental Planning and Management, *47*(1), 59–82. https://doi.org/10.1080/0964056042000189808

Goldsmith, K., Granek, E., Lubitow, A., & Papenfus, M. (2016). Bridge over troubled waters: A synthesis session to connect scientific and decision making sectors. *Marine Policy*, *70*, 30–39. https://doi.org/10.1016/j.marpol.2016.04.015

Grimm, N. B., Groffman, P., Staudinger, M., & Tallis, H. (2016). Climate change impacts on ecosystems and ecosystem services in the United States: Process and prospects for sustained assessment. *Climatic Change*, *135*(1), 97–109. https://doi.org/10.1007/s10584-015-1547-3

Guignet, D., Heberling, M. T., Papenfus, M., & Griot, O. (2021). Property values, water quality, and benefit transfer: A nationwide meta-analysis. *Land Economics*, 050120-0062R1. https://doi.org/10.3368/le.98.2.050120-0062R1

Halpern, B. S., & Fujita, R. (2013). Assumptions, challenges, and future directions in cumulative impact analysis. *Ecosphere*, *4*(10), art131. https://doi.org/10.1890/ES13-00181.1

Hermoso, V., Filipe, A. F., Segurado, P., & Beja, P. (2016). Catchment zoning to unlock freshwater conservation opportunities in the Iberian Peninsula. *Diversity and Distributions*, *22*(9), 960–969. https://doi.org/10.1111/ddi.12454

Howard, J. K., Fesenmyer, K. A., Grantham, T. E., Viers, J. H., Ode, P. R., Moyle, P. B., Kupferburg, S. J., Furnish, J. L., Rehn, A., Slusark, J., Mazor, R. D., Santos, N. R., Peek, R. A., & Wright, A. N. (2018). A freshwater conservation blueprint for California: Prioritizing watersheds for freshwater biodiversity. *Freshwater Science*, *37*(2), 417–431. https://doi.org/10.1086/697996

Isaak, D. J., Young, M. K., Nagel, D. E., Horan, D. L., & Groce, M. C. (2015). The cold-water climate shield: Delineating refugia for preserving salmonid fishes through the 21st century. *Global Change Biology*, *21*(7), 2540–2553. https://doi.org/10.1111/gcb.12879

Jeon, D. J., Ki, S. J., Cha, Y., Park, Y., & Kim, J. H. (2018). New methodology of evaluation of best management practices performances for an agricultural watershed according to the climate change scenarios: A hybrid use of deterministic and decision support models. *Ecological Engineering*, *119*, 73–83. https://doi.org/10.1016/j.ecoleng.2018.05.006

Kaushal, S. S., Likens, G. E., Pace, M. L., Utz, R. M., Haq, S., Gorman, J., & Grese, M. (2018). Freshwater salinization syndrome on a continental scale. *Proceedings of the National Academy of Sciences*, *115*(4). https://doi.org/10.1073/pnas.1711234115

Koundouri, P., Ker Rault, P., Pergamalis, V., Skianis, V., & Souliotis, I. (2016). Development of an integrated methodology for the sustainable environmental and socio-economic management of river ecosystems. *Science of The Total Environment*, *540*, 90–100. https://doi.org/10.1016/j.scitotenv.2015.07.082

Krishnamurthy, R., & Awazu, Y. (2016). Liberating data for public value: The case of Data.gov. *International Journal of Information Management*, *36*(4), 668–672. https://doi.org/10.1016/j.ijinfomgt.2016.03.002

Kuehne, L. M., Strecker, A. L., & Olden, J. D. (2020). Knowledge Exchange and Social Capital for Freshwater Ecosystem Assessments. *BioScience*, *70*(2), 174–183. https://doi.org/10.1093/biosci/biz142

Lin, Y.-P., Lin, W.-C., Li, H.-Y., Wang, Y.-C., Hsu, C.-C., Lien, W.-Y., Anthony, J., & Petway, J. R. (2017). Integrating Social Values and Ecosystem Services in Systematic Conservation Planning: A Case Study in Datuan Watershed. *Sustainability*, *9*(5), 718. https://doi.org/10.3390/su9050718

Lubchenco, J. (1998). Entering the Century of the Environment: A New Social Contract for Science. *Science*, *279*(5350), 491–497. https://doi.org/10.1126/science.279.5350.491

Mancilla García, M., Hileman, J., Bodin, Ö., Nilsson, A., & Jacobi, P. R. (2019). The unique role of municipalities in integrated watershed governance arrangements: A new research frontier. *Ecology and Society*, *24*(1), art28. https://doi.org/10.5751/ES-10793-240128

Mazor, R. D., Rehn, A. C., Ode, P. R., Engeln, M., Schiff, K. C., Stein, E. D., Gillett, D. J., Herbst, D. B., & Hawkins, C. P. (2016). Bioassessment in complex environments: Designing an index for consistent meaning in different settings. *Freshwater Science*, *35*(1), 249–271. https://doi.org/10.1086/684130

McIntosh, B. S., Seaton, R. A. F., & Jeffrey, P. (2007). Tools to think with? Towards understanding the use of computer-based support tools in policy relevant research. *Environmental Modelling & Software*, *22*(5), 640–648. https://doi.org/10.1016/j.envsoft.2005.12.015

Moilanen, A., Leathwick, J. R., & Quinn, J. M. (2011). Spatial prioritization of conservation management: Spatial prioritization of conservation management. *Conservation Letters*, *4*(5), 383–393. https://doi.org/10.1111/j.1755-263X.2011.00190.x

Mu, M., Gao, L., Zhang, H., Ge, J., Zhang, Z., Qiu, Y., & Zhao, X. (2023). Effects of land use on water quality at different spatial scales in the middle reaches of Huaihe River. *Journal of Freshwater Ecology*, *38*(1), 2176373. https://doi.org/10.1080/02705060.2023.2176373

Naidoo, R., Balmford, A., Ferraro, P., Polasky, S., Ricketts, T., & Rouget, M. (2006). Integrating economic costs into conservation planning. *Trends in Ecology & Evolution*, *21*(12), 681–687. https://doi.org/10.1016/j.tree.2006.10.003

Neeson, T. M., Ferris, M. C., Diebel, M. W., Doran, P. J., O'Hanley, J. R., & McIntyre, P. B. (2015). Enhancing ecosystem restoration efficiency through spatial and temporal coordination. *Proceedings of the National Academy of Sciences*, *112*(19), 6236–6241. https://doi.org/10.1073/pnas.1423812112

Neeson, T. M., Moody, A. T., O'Hanley, J. R., Diebel, M., Doran, P. J., Ferris, M. C., Colling, T., & McIntyre, P. B. (2018). Aging infrastructure creates opportunities for cost-efficient restoration of aquatic ecosystem connectivity. *Ecological Applications*, *28*(6), 1494–1502. https://doi.org/10.1002/eap.1750

Neeson, T. M., Smith, S. D. P., Allan, J. D., & McIntyre, P. B. (2016). Prioritizing ecological restoration among sites in multi-stressor landscapes. *Ecological Applications*, *26*(6), 1785–1796. https://doi.org/10.1890/15-0948.1

Niemiec, R. M., Gruby, R., Quartuch, M., Cavaliere, C. T., Teel, T. L., Crooks, K., Salerno, J., Solomon, J. N., Jones, K. W., Gavin, M., Lavoie, A., Stronza, A., Meth, L., Enrici, A., Lanter, K., Browne, C., Proctor, J., & Manfredo, M. (2021). Integrating social science into conservation planning. *Biological Conservation*, *262*, 109298. https://doi.org/10.1016/j.biocon.2021.109298

Ode, P. R., Rehn, A. C., & May, J. T. (2005). A Quantitative Tool for Assessing the Integrity of Southern Coastal California Streams. *Environmental Management*, *35*(4), 493–504. https://doi.org/10.1007/s00267-004-0035-8

Office of Management and Budget. (2003, September 17). *Regulatory Analysis*. https://www.whitehouse.gov/wp-content/uploads/2023/11/CircularA-4.pdf

Pahl-Wostl, C. (2007). The implications of complexity for integrated resources management. *Environmental Modelling & Software*, *22*(5), 561–569. https://doi.org/10.1016/j.envsoft.2005.12.024

Park, S.-R., & Lee, S.-W. (2020). Spatially Varying and Scale-Dependent Relationships of Land Use Types with Stream Water Quality. *International Journal of Environmental Research and Public Health*, *17*(5), 1673. https://doi.org/10.3390/ijerph17051673

Paukert, C. P., Pitts, K. L., Whittier, J. B., & Olden, J. D. (2011). Development and assessment of a landscape-scale ecological threat index for the Lower Colorado River Basin. *Ecological Indicators*, *11*(2), 304–310. https://doi.org/10.1016/j.ecolind.2010.05.008

Pierre, J., Røiseland, A., Peters, B. G., & Gustavsen, A. (2017). Comparing local politicians' and bureaucrats' assessments of democratic participation: The cases of Norway and Sweden. *International Review of Administrative Sciences*, *83*(4), 658–675. https://doi.org/10.1177/0020852315598214

Polasky, S., Nelson, E., Pennington, D., & Johnson, K. A. (2011). The Impact of Land-Use Change on Ecosystem Services, Biodiversity and Returns to Landowners: A Case Study in the State of Minnesota. *Environmental and Resource Economics*, *48*(2), 219–242. https://doi.org/10.1007/s10640-010-9407-0

Qiu, J., Shen, Z., Leng, G., Xie, H., Hou, X., & Wei, G. (2019). Impacts of climate change on watershed systems and potential adaptation through BMPs in a drinking water source area. *Journal of Hydrology*, *573*, 123–135. https://doi.org/10.1016/j.jhydrol.2019.03.074

Quinn, N. W. T., Sridharan, V., Ramirez-Avila, J., Imen, S., Gao, H., Talchabhadel, R., Kumar, S., & McDonald, W. (2022). Applications of GIS and remote sensing in public participation and stakeholder engagement for watershed management. *Socio-Environmental Systems Modelling*, *4*, 18149. https://doi.org/10.18174/sesmo.18149

Richardson, L., Loomis, J., Kroeger, T., & Casey, F. (2015). The role of benefit transfer in ecosystem service valuation. *Ecological Economics*, *115*, 51–58. https://doi.org/10.1016/j.ecolecon.2014.02.018

Rothrock, P. E., Simon, T. P., & Stewart, P. M. (2008). Development, calibration, and validation of a littoral zone plant index of biotic integrity (PIBI) for lacustrine wetlands. *Ecological Indicators*, *8*(1), 79–88. https://doi.org/10.1016/j.ecolind.2007.01.002

Sánchez, M. C., Montes, A. V., Verdinelli, G. B., Juncà, M. B., & Priego-Santander, Á. G. (2010). Defining environmental management units based upon integrated socio-economicand biophysical indicators at the Pacific coast OF Mexico. *Interciencia*, *35*, 33–40.

Scown, M. W., Flotemersch, J. E., Spanbauer, T. L., Eason, T., Garmestani, A., & Chaffin, B. C. (2017). People and water: Exploring the social-ecological condition of watersheds of the United States. *Elementa: Science of the Anthropocene*, *5*, 64. https://doi.org/10.1525/elementa.189

Serpa, D., Nunes, J. P., Keizer, J. J., & Abrantes, N. (2017). Impacts of climate and land use changes on the water quality of a small Mediterranean catchment with intensive viticulture. *Environmental Pollution*, *224*, 454–465. https://doi.org/10.1016/j.envpol.2017.02.026

Shifflett, Newcomer-Johnson, Yess, & Jacobs. (2019). Interdisciplinary Collaboration on Green Infrastructure for Urban Watershed Management: An Ohio Case Study. *Water*, *11*(4), 738. https://doi.org/10.3390/w11040738

Shunglu, R., Köpke, S., Kanoi, L., Nissanka, T. S., Withanachchi, C. R., Gamage, D. U., Dissanayake, H. R., Kibaroglu, A., Ünver, O., & Withanachchi, S. S. (2022). Barriers in Participative Water Governance: A Critical Analysis of Community Development Approaches. *Water*, *14*(5), 762. https://doi.org/10.3390/w14050762

Smith, M. S., Horrocks, L., Harvey, A., & Hamilton, C. (2011). Rethinking adaptation for a 4 ˚ C world. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *369*(1934), 196–216. https://doi.org/10.1098/rsta.2010.0277

Sun, Y., Li, Y., Ma, R., Gao, C., & Wu, Y. (2022). Mapping urban socio-economic vulnerability related to heat risk: A grid-based assessment framework by combing the geospatial big data. *Urban Climate*, *43*, 101169. https://doi.org/10.1016/j.uclim.2022.101169

Tallis, H., Kareiva, P., Marvier, M., & Chang, A. (2008). An ecosystem services framework to support both practical conservation and economic development. *Proceedings of the National Academy of Sciences*, *105*(28), 9457–9464. https://doi.org/10.1073/pnas.0705797105

Tickner, D., Opperman, J. J., Abell, R., Acreman, M., Arthington, A. H., Bunn, S. E., Cooke, S. J., Dalton, J., Darwall, W., Edwards, G., Harrison, I., Hughes, K., Jones, T., Leclère, D., Lynch, A. J., Leonard, P., McClain, M. E., Muruven, D., Olden, J. D., … Young, L. (2020). Bending the Curve of Global Freshwater Biodiversity Loss: An Emergency Recovery Plan. *BioScience*, *70*(4), 330–342. https://doi.org/10.1093/biosci/biaa002

Tsvetkova, O., & Randhir, T. O. (2019). Spatial and temporal uncertainty in climatic impacts on watershed systems. *Science of The Total Environment*, *687*, 618–633. https://doi.org/10.1016/j.scitotenv.2019.06.141

Van Deynze, B., Fonner, R., Feist, B. E., Jardine, S. L., & Holland, D. S. (2022). What influences spatial variability in restoration costs? Econometric cost models for inference and prediction in restoration planning. *Biological Conservation*, *274*, 109710. https://doi.org/10.1016/j.biocon.2022.109710

Vörösmarty, C. J., McIntyre, P. B., Gessner, M. O., Dudgeon, D., Prusevich, A., Green, P., Glidden, S., Bunn, S. E., Sullivan, C. A., Liermann, C. R., & Davies, P. M. (2010). Global threats to human water security and river biodiversity. *Nature*, *467*(7315), 555–561. https://doi.org/10.1038/nature09440

Wang, G., Mang, S., Cai, H., Liu, S., Zhang, Z., Wang, L., & Innes, J. L. (2016). Integrated watershed management: Evolution, development and emerging trends. *Journal of Forestry Research*, *27*(5), 967–994. https://doi.org/10.1007/s11676-016-0293-3

Webb, N. P., Stokes, C. J., & Marshall, N. A. (2013). Integrating biophysical and socio-economic evaluations to improve the efficacy of adaptation assessments for agriculture. *Global Environmental Change*, *23*(5), 1164–1177. https://doi.org/10.1016/j.gloenvcha.2013.04.007

Weston, S., & Conrad, C. (2015). Community-Based Water Monitoring in Nova Scotia: Solutions for Sustainable Watershed Management. *Environment and Natural Resources Research*, *5*(2), p1. https://doi.org/10.5539/enrr.v5n2p1

White, T. B., Petrovan, S. O., Booth, H., Correa, R. J., Gatt, Y., Martin, P. A., Newell, H., Worthington, T. A., & Sutherland, W. J. (2022). Determining the economic costs and benefits of conservation actions: A decision support framework. *Conservation Science and Practice*, *4*(12), e12840. https://doi.org/10.1111/csp2.12840

White, T. B., Petrovan, S. O., Christie, A. P., Martin, P. A., & Sutherland, W. J. (2022). What is the Price of Conservation? A Review of the Status Quo and Recommendations for Improving Cost Reporting. *BioScience*, *72*(5), 461–471. https://doi.org/10.1093/biosci/biac007

Wineland, S. M., Fovargue, R., Gill, K. C., Rezapour, S., & Neeson, T. M. (2021). Conservation planning in an uncertain climate: Identifying projects that remain valuable and feasible across future scenarios. *People and Nature*, *3*(1), 221–235. https://doi.org/10.1002/pan3.10169

Wineland, S. M., Fovargue, R., York, B., Lynch, A. J., Paukert, C. P., & Neeson, T. M. (2021). Is there enough water? How bearish and bullish outlooks are linked to decision maker perspectives on environmental flows. *Journal of Environmental Management*, *280*, 111694. https://doi.org/10.1016/j.jenvman.2020.111694

Wineland, S. M., Rezapour, S., & Neeson, T. M. (2023). Small tradeoffs between social equity and conservation outcomes in a freshwater payment for ecosystem services scheme. *Ecological Applications*, *33*(4), e2829. https://doi.org/10.1002/eap.2829

Wise, R. M., Fazey, I., Stafford Smith, M., Park, S. E., Eakin, H. C., Archer Van Garderen, E. R. M., & Campbell, B. (2014). Reconceptualising adaptation to climate change as part of pathways of change and response. *Global Environmental Change*, *28*, 325–336. https://doi.org/10.1016/j.gloenvcha.2013.12.002

Wulder, M. A., Masek, J. G., Cohen, W. B., Loveland, T. R., & Woodcock, C. E. (2012). Opening the archive: How free data has enabled the science and monitoring promise of Landsat. *Remote Sensing of Environment*, *122*, 2–10. https://doi.org/10.1016/j.rse.2012.01.010

Tables

Table 1-1 Alignment of research questions with corresponding survey questions; each research question is matched with the specific survey questions that provided data relevant to answering the research question

Research Questions		Survey Questions
1	What tools are used to evaluate watershed function/condition?	Question numbers: 10,11,12,13,14, and 15
2	How do watershed managers expect watershed functions to change in the future?	Questions 8, 9
3	What spatial data and/or associated data products would be most useful for water resource managers?	Question 17,18
4	What do water resource managers perceive as barriers to improving watershed conditions?	Question 24

Figures

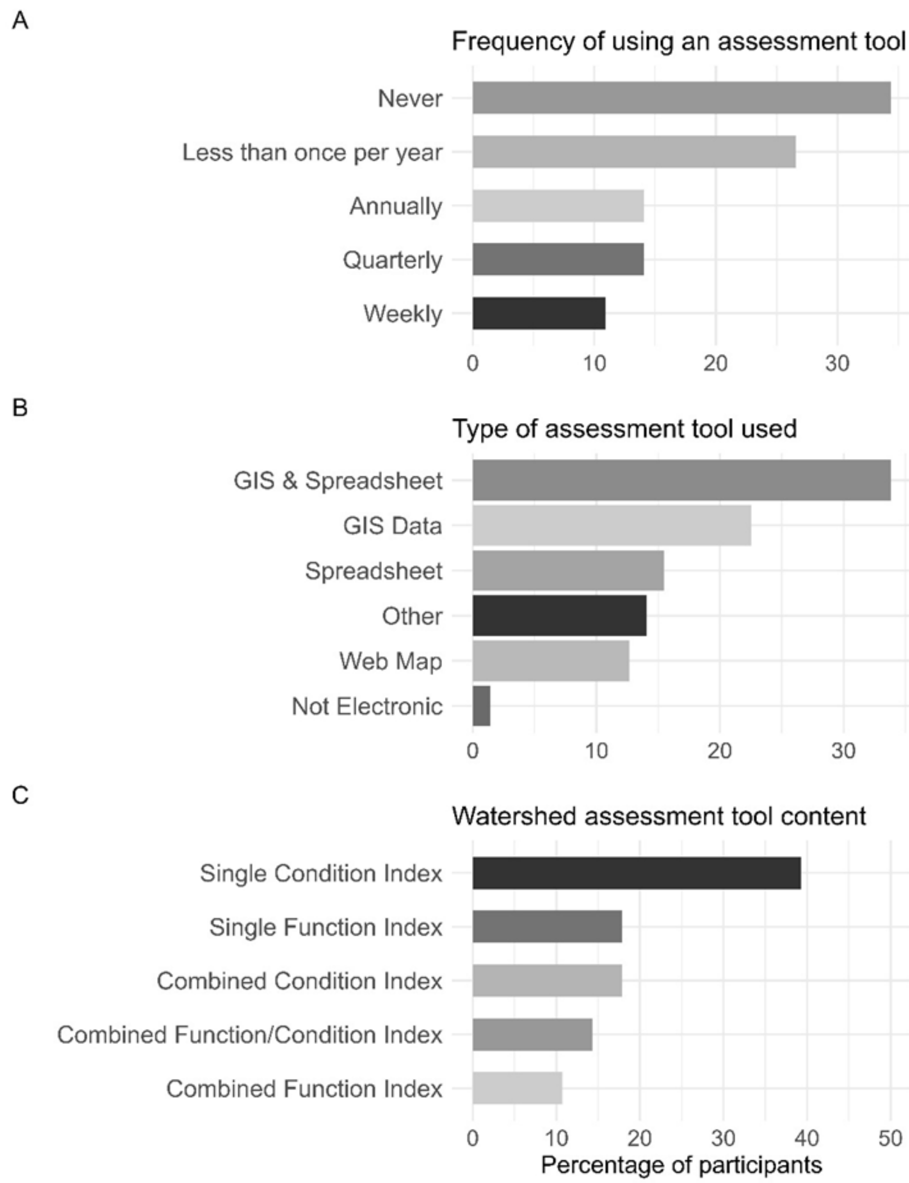

Figure 1-1 Summary of watershed assessment practices among survey participants (n=48): A) Frequency of standardized assessment tool usage for evaluating watershed condition and function; most respondents either never use tools or use them less than once per year; B) Type of assessment tool employed, with GIS & spreadsheet combinations and standalone GIS data being most common; and C) Content characteristics of the assessment tools, indicating a preference for single condition index metrics over more complex combined metrics.

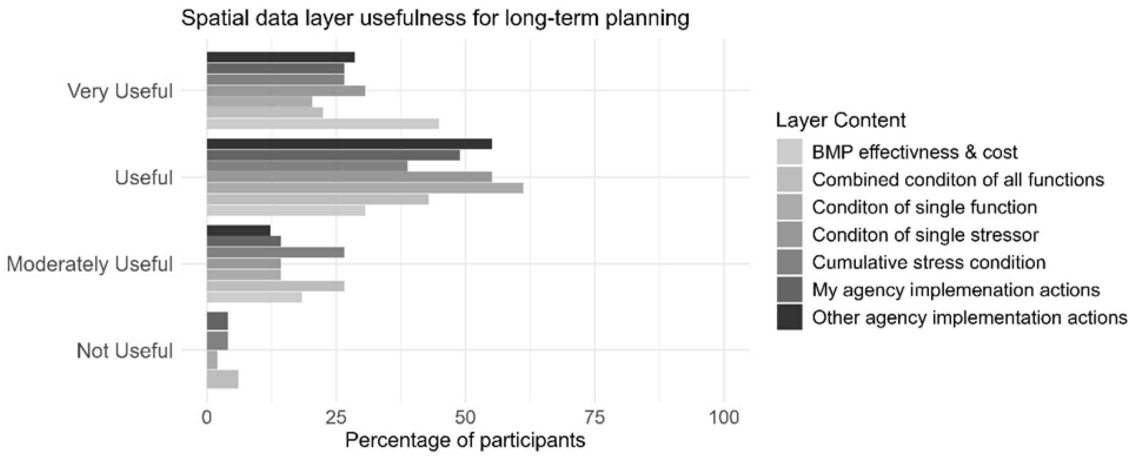

Figure 1-2 Participants' opinions on the usefulness of spatial data layers for long-term planning (n = 48). Layers focused on implementation actions and single watershed stressor or function were desired. (survey question 17).

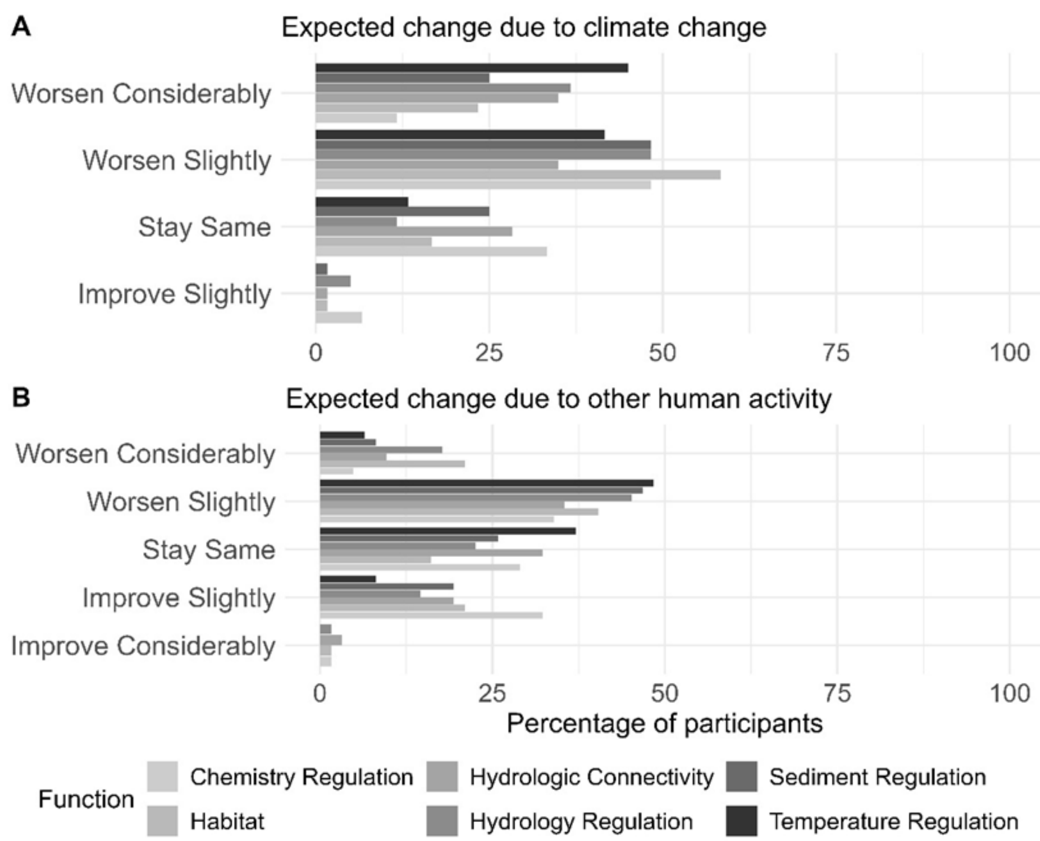

Figure 1-3 Participant (n = 48) expectations regarding future changes in watershed functions due to two major drivers: A) climate change and B) other human activities. Responses reflect participants' expectations about six watershed functions: chemistry regulation hydrologic connectivity, sediment regulation, habitat, hydrology regulation, and temperature regulation (survey questions 8 and 9).

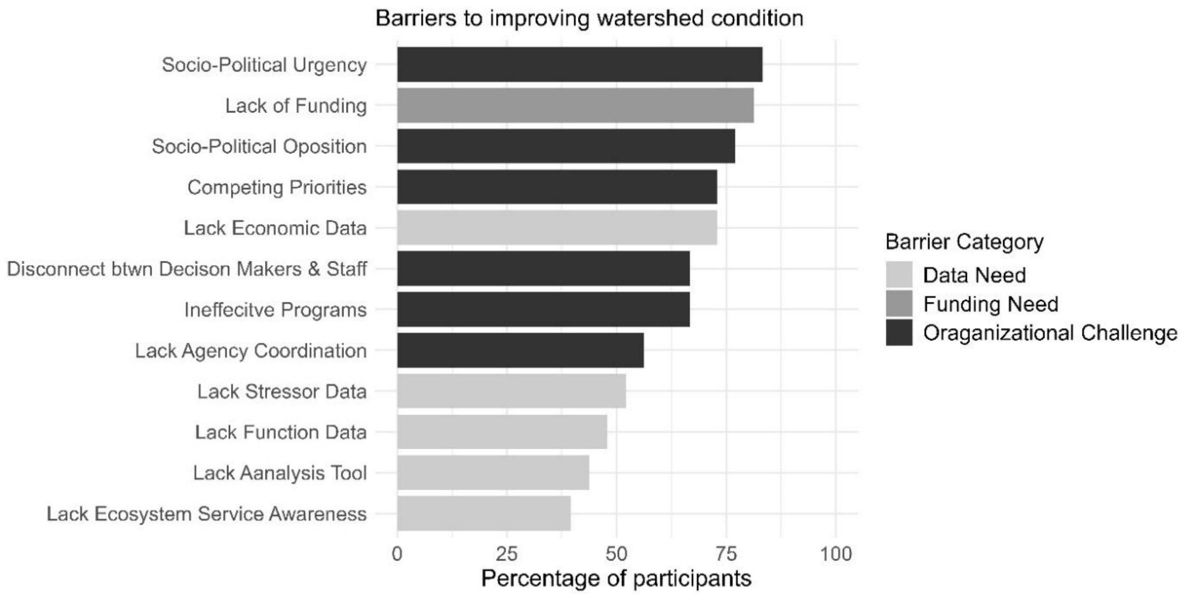

Figure 1-4 Participants' opinions on perceived barriers to improving watershed conditions, showing the combined percentage of responses rated as either a "serious barrier" or "moderate barrier" (n=48). Socio-political factors and funding limitations were identified as the most significant barriers.

Chapter Two

RELATIONSHIP-BUILDING SOMETIMES HELPS AND SOMETIMES HINDERS THE SPREAD OF CONSERVATION INITIATIVES

Keywords:

conservation program, information diffusion models, network interventions, network structure, relationship-building, social networks

Abstract

The spread of conservation initiatives often depends on patterns of social interactions among conservation actors. With this in mind, conservation practitioners often invest in social networking and outreach, under the assumption that the creation of new relationships will enhance the spread of conservation programs. Here, we test this assumption by modeling the diffusion of a conservation practice across two social networks of conservation actors. For two common models of information spread (the independent cascade and linear threshold models), we investigated whether and how the addition of new social relationships (i.e., network edges) altered the spread of conservation initiatives across the networks. Our results show that adding network connections is sometimes beneficial and sometimes counterproductive. Under the independent cascade model, increased connectivity generally facilitated broader adoption, particularly when actors were receptive to new practices. In some cases, adoption grew by more than 25% simply through the addition of new social relationships among actors. In contrast, under the linear threshold model, additional connections often hindered information diffusion. Given the dramatic differences in outcomes between linear threshold and independent cascade models, future work should determine which of these models better describes conservation networks. A key practical insight for conservation practitioners is that establishing a core group of early adopters (i.e., a larger number of initially active nodes) promotes overall adoption rates. Our results overall underscore the need for strategies to effectively allocate resources, design outreach strategies, and foster collaborative relationships that maximize the adoption of conservation initiatives.

Introduction

Conservation is fundamentally a social endeavor. Conservation practitioners work collaboratively to advance many different initiatives; yet some programs take off and others fail to spread widely (Mills et al., 2019). Many conservation programs take decades to gain meaningful levels of adoption, prompting continued proposals for conservation success in the 21st century (Botts et al., 2019; Maxwell et al., 2020; Mills et al., 2019). Post hoc reviews of successful programs have found social factors central to favorable outcomes. A recent assessment of government conservation programs in Europe found that local actor support is critical for achieving conservation goals (Farwig et al., 2024). It has also been found that the social network of a local actor is more predictive of an actor engaging in transformative behaviors than ecological changes on the landscape (Nesbitt et al., 2024). The presence of social networks has been identified as an essential element of cases in which diverse stakeholder groups have successfully addressed a natural resource problem (Alix-Garcia et al., 2018; Kaweesa et al., 2018; Olsson et al., 2008). At a time when there is an urgent need for effective practices across ecosystems (Leclère et al., 2020; Rilov et al., 2020; Tickner et al., 2020) leveraging social network science is a promising strategy for scaling up conservation efforts.

In cases in and beyond conservation, the structure of a social network itself affects the flow of information and behavior across the network. Broadly defined, the structure of a social network refers to quantitative measures of who interacts with whom, and how frequently (Bodin & Prell, 2011). The structure of a social network is known to affect how actors share information and actually behave (Bodin & Crona, 2009; Cowan & Jonard, 2004; Valente & Pumpuang, 2007). For example, the propagation of rumors was found to depend on the network topological structure (Potterat et al. 1999), network size and structure drive the spread of videos on YouTube (Yoganarasimhan, 2012), and network cohesion was associated with infectious disease transmission patterns (Zhou et al., 2007). These examples illustrate how broad information sharing and the transfer of critical material within tightly connected groups are influenced via network structural properties. These same network mechanisms that shape how people share knowledge and are responsive to popular information may also be key ingredients needed to address contemporary environmental crises including biodiversity loss and global climate change, where collaboration and knowledge exchange are expected to be essential components for successful conservation programs.

Given that the structure of a social network influences how information and behavior spread through the network, an important question is: how might network structure be modified to boost the spread of conservation initiatives and ideas? Towards this goal, conservation actors commonly modify their own social networks by hosting or participating in management practice workshops, communities of practice, training seminars, or field demonstrations of best practices. These outreach and networking actions do indeed foster the spread of conservation initiatives (Baird et al., 2016), but it is also true that some social relationships have more influence than others on the spread of behaviors and ideas (Wineland and Neeson 2022). Empirical network analysis has found that a core network of central brokers can engage new actors and coordinate peripheral actor actions to successfully address a collective action problem like invasive species eradication (Lubell et al., 2017). Likewise, transformational adopters of new agricultural practices are those that have formed strong informational links, bridging across groups, allowing decisive changes (Dowd et al., 2014). However, knowledge gaps limit efforts to identify which new relationships might have the greatest impact on the spread of conservation initiatives. Collecting sociometric data and achieving these structural changes is often expensive because time and effort is required to build social relationships and in the case of transformational adopters there is risk of lost social capital (Dowd et al., 2014; Eckles et al., 2022). For these reasons, our goal is to identify cost-effective approaches to structurally intervene within the network.

Network science provides important tools for exploring how modifications of network structure might influence the spread of conservation initiatives. In particular, there are two primary models of how information or behavior propagates through a network. In the first model, termed independent cascade (IC), an individual's likelihood of adopting a new behavior depends on their own intrinsic characteristics (e.g., resistance to change). In the second model, termed linear threshold (LT), an individual's likelihood of adoption depends on the behavior of all of their peers. Both models are typically represented as directed graphs G (V, E), where V is a set of nodes that represents an organization or actor that can be in an active or inactive state and E is a set of edges that connect nodes in the graph (Azaouzi et al., 2021). In the independent cascade model, an active node (v1) may activate a presently inactive neighboring node (v2) according to its activation probability Pv1, v2, which denotes the probability of v1 activating v2. Thus, the model enables us to explore real-world scenarios ranging from those in which individuals readily adopt new conservation initiatives (i.e., activation probability is high) to those in which individuals are resistant to change or conservation initiatives entail high economic, social or political costs (i.e., the probability of adoption is low). In the linear threshold model, an inactive node (v1) evaluates the active or inactive state of all its neighboring nodes (e.g., v2, v3, v4) and if the proportion of active neighboring nodes exceeds a predetermined threshold, node v1 will activate (Saito et al., 2016; Shakarian et al., 2015). The LT and IC information diffusion models both require a seed set of active nodes to initiate the diffusion process. The set of initially active nodes can be chosen randomly or strategically depending on the modeling objective. Finally, the number of activated nodes, representing information spread, is used to evaluate model results.

Here we investigate how relationship-building (i.e., the addition of new edges to networks of conservation actors) might help or hinder the spread of conservation initiatives in two social networks. The networks are 1) a regional network of water program decision-makers (n = 24 individuals) from the Oklahoma and Texas portions of the Red River Basin and 2) a national network of workshop participants (n = 426) from the Sustainable Rivers Program organized by The Nature Conservancy and U.S. Army Corps of Engineers (USACE) (Wineland & Neeson, 2022). These networks are both composed of a diverse group of conservation actors with identified relationships (i.e., network connections). While both networks are focused on freshwater conservation, they include typical types of conservation actors (e.g., local, state, federal agencies, NGOs, private landowners, academics) and serve as representative networks and provide information applicable to other ecosystems. Also, these two networks characterize the spatial scales (i.e., local, regional, national) at which conservation programs are implemented. We used these two networks to investigate two research questions: 1) how does the addition of new network connections boost the spread of a conservation practice, and 2) where in the network would new edges have the greatest effect on the spread of a conservation practice? Addressing these questions can provide practical evidence to conservation practitioners on how to advantageously engage conservation actors and utilize resources when launching conservation management campaigns.

Methods

Network descriptions

Two empirical networks of freshwater conservation actors were used for these analyses. The first is an interstate network (n = 24) composed of water resources decision-makers from the Oklahoma and Texas portions of the Red River Basin (RRB) (Fig. 2-1a). This network was constructed from a survey, which asked participants how frequently they communicated and actors (i.e. nodes) were only connected if both participants respond that they do in fact communicate with one another (Wineland et al., 2021). The final RRB network was weighted, based on communication frequency, and undirected (Wineland et al., 2021). In this paper, we used the unweighted Red River Basin network to isolate the influence of changes to network structure. The second network is a national network (n = 426) of workshop attendees from the U.S. Army Corps of Engineers' and the Nature Conservancy Sustainable Rivers Program (SRP) (Wineland & Neeson, 2022) (Fig. 2-1b). This network was constructed from participants (water managers, scientists, stakeholders) at national environmental flow workshops. Wineland and Neeson (2022) constructed the network from workshop participant lists and assumed that participants had unweighted, undirected ties and that each individual workshop was a complete network, meaning two nodes were connected if they participated in the same workshop. Additional information on typology and structural features of the RRB and SRP networks can be found in Wineland and Neeson (2022). The Red River Basin social network data were collected by Wineland et al. (2021, 2022) following protocols approved by the Institutional Review Board (IRB permit no. 10670). The Sustainable Rivers Program social network was derived from publicly available workshop participant lists.

Simulation experiments

We used the independent cascade (IC) and linear threshold (LT) models to simulate the diffusion of a hypothetical conservation practice across the RRB and SRP networks and quantify how new network connections (i.e. structural changes to the network) boosted the spread of the conservation practice (Research Question 1). In both the IC and LT models, nodes (i.e., individuals) are Boolean and may be either active or inactive. For our simulations, we used the activation of a node to represent the adoption of the hypothetical conservation practice by that individual. Thus, we quantified the level of adoption of a conservation practice as the proportion of nodes that were active at the end of a simulation.

Recall a distinction between the IC and LT models is the mode of activation. The IC model is a simple information diffusion where activation only requires interaction with a single neighboring node. The LT model simulates a complex diffusion, which requires assessing the state of all neighboring nodes (Shakarian et al., 2015, pp. 35-38). We designed a series of simulations to systematically explore the full range of the parameter space for both models and reveal when the addition of new edges to the network would influence the final number of activated nodes (Table 2-1). The IC and LT models both require an initial seed set of active nodes to initiate the models. The seed set size for a given simulation was pre-determined; however, which nodes acted as the seeds were randomly selected in the simulation. The seed set sizes were previously found to encompass the minimum and maximum extent of possible node activation (Wineland and Neeson, 2022).

Our algorithm for adding new edges was to randomly select two nodes and test if those nodes were already connected in the network. If they were not connected, the model would connect them by adding an edge to the network. The model would continue randomly selecting nodes and adding edges until the edge budget was satisfied. A new edge between two previously unconnected nodes represents a new social connection between two conservation actors.

Finally, the IC model requires node activation probabilities, and the LT model requires node activation thresholds. We tested each seed set size and each edge budget across a range (0.01, 0.05, 0.1-0.9) of activation probabilities (IC) and thresholds (LT). The aim with the range of possible activation probabilities/thresholds was to characterize possible real-world challenges or achievements possible when working with conservation actors. For example, a very low activation probability (or high activation threshold) is a model condition that reflects actors resistant to practice adoption for any reason. This analysis does not characterize or explore motive behind an actor's resistance; however, one can imagine it to be a range of factors such as costly practice implementation or social prerogatives. A high activation probability (or low activation threshold) reflects a model condition where actors are very receptive to practice adoption. Again, this analysis does not characterize motives, but it could be supposed as low cost easily adopted practices or low social barriers to adoption. The information diffusion models were implemented using the influence.mining package in R version 4.2.2 (Hussain, 2021; R Core Team, 2023).

Identifying strategies for high-impact edge additions

After conducting the simulation experiments summarized in Table 2-1, we performed a post-hoc analysis to identify how the location of new edges within the network affected the final level of adoption of the conservation practice (Research Question 2). To do this, we selected the lowest-performing (in terms of final number of activated nodes) and highest-performing deciles of networks. We then quantified the relationship between the final number of activated nodes in each modified network and three measures of network structure: 1) clustering coefficient, 2) number of clusters, and 3) network modularity. The clustering coefficient is a measure of how tightly connected the neighbors of a node are to each other (Barabasi, 2016; Watts & Strogatz, 1998). The calculation of clustering coefficient returns a value between zero and one, where one means the network is composed of tightly connected communities and a zero means that a node's neighbors are loosely connected to each other (Barabasi, 2016). We used the global clustering coefficient as an overall measure of the networks' tendency to form cohesive groups. The number of clusters reflects the number of distinct subgroups of nodes that are more densely connected to each other than to the rest of the network (Fortunato, 2010). Identifying clusters is useful to understand network community structure; for example, a network may be composed of tightly connected groups (e.g., 2-3 clusters) or a network may be divided into many smaller groups (e.g., 6 -10 clusters). Modularity serves to quantify the strength of network community structure; it reflects how much stronger the connections are within communities than between communities (Luke, 2015). Modularity scores close to zero would indicate a random network without strong community division and a score of one would indicate well separated community structure within the network. All metrics were calculated using the igraph package in R version 4.2.2 (Csardi & Nepusz, 2006).

Results

Independent cascade model

Under the independent cascade (IC) model, the addition of new edges to the social networks typically increased the spread of conservation initiatives (Fig. 2-2a, 2-2b). In the RRB network (Fig. 2-2a), this trend was strongest when a modest number of nodes were initially active (i.e., at seed set sizes of two, three and four). For a seed set size of two, for example, the mean number of final activated nodes rose from 14.8 (in the original, unmodified network) to 18.9 (when 100 new edges were added to the network). This represents a 27% increase in node activation resulting from a 78% increase in the number of edges. A similar trend was also observed in the national SRP network (Fig. 2-2b). Examining seed set five, the mean number of activated nodes was 302 with zero new edges added to the network and after the addition of 45,000 new edges the mean number of active nodes was 377: a 24.8% increase. In this model scenario the addition of network connections steadily benefited the number of final activated nodes.

While the addition of new edges typically increased the spread of conservation initiatives, this pattern did not hold when the conservation initiative was initially very rare (i.e., the seed set size was very small; Fig 2-2a and 2-2b). When only a single node in the network was initially active, the addition of new edges to the network did not always enhance the spread of conservation initiatives. In the Red River Basin network, the range of nodes activated when 100 edges are added to the network was within the range of possible node activation when zero edges were added to the network (Fig. 2-2a). Similarly, in the national Sustainable River Program network, with a seed set size of one, the addition of 45,000 new edges to the network worked to greatly reduced node activation; the mean number of activated nodes dropped from 300 to less than 250 (Fig. 2-2b).

When the probability of node activation was low (i.e., in cases where individuals are resistant to change, either due to interpersonal factors or the cost of adopting the initiative), the addition of new edges to the social network did not enhance the spread of the conservation initiative. In both the RRB and SRP networks, the addition of new edges had little effect on node activation when the activation probability was below 0.5 (Fig. 2-3a and 2-3b). For activation probabilities of 0.5 and above, the benefit of new edges increased with increasing activation probability. Note, activation probabilities below 0.1 (i.e., 0.05 and 0.01) produced similar results.

Linear threshold

In contrast to the independent cascade model, the addition of new edges to a network under a linear threshold model generally decreased the spread of conservation initiatives (Fig. 2-4a and 2-4b). In the LT model for the RRB with a seed set size of five, a mean of 3.4 nodes were activated when zero new edges were added to the network and after adding 100 additional network edges the mean dropped to less than 1 activated node. For this simulation, the maximum number of activated nodes occurred with zero new edges and the information spread relied upon the initial seed set. The national SRP network (seed set 15) displayed a similar pattern with the maximum mean number of activated nodes (92.2) occurring when zero edges were added and diminishing returns continued as the edge budget continued to increase (Fig 2-4b). After adding 45,000 new edges to the network the mean number of activated nodes decreased to 4.7, which is a 95% decrease in node activation.

Similar to the independent cascade model, when activation thresholds were high (i.e., individuals were resistant to change) in the linear threshold model, the addition of new edges to the social network did not enhance the spread of the conservation initiative (Fig. 2-5a, 2-5b). In the RRB network, the addition of new relationships (i.e., network edges) increased the number of final adopters only for activation thresholds of 0.01 and 0.05. At higher activation thresholds, the addition of new relationships decreased the number of final adopters. In the SRP network, the addition of new edges was not beneficial for activation thresholds greater than 0.01.

Drivers of variability in model outcomes

Across a range of model parameterizations, we observed high variability in the number of final activated nodes even when model parameters were held constant (i.e., error bars were large in Figs. 2-3 - 2-6). Nevertheless, we did not find any relationships between structural measures of the modified networks (e.g., the locations of new edges) and the final number of activated nodes. The majority of both the low and high preforming networks for the RRB had clustering coefficients of approximately 0.6 (Fig.2-6a), which means on average 60% of the possible edges between a node's neighbors were actually present in the network. Thus, a node's neighbors were generally interconnected, but some distant connections were also present across the network. The SRP network had a slightly lower clustering coefficient of 0.4, which suggests a moderate level of clustering (Fig. 2-7a). The number of clusters was also not markedly different between low and high preforming networks. The RRB both low and high preforming networks had three to four clusters (Fig. 2-6b). The national SRP network generally formed five to eight clusters across both low and high performing networks (Fig. 2-7b). The relatively low modularity values for both networks highlighted dense inter-community connections. The RRB networks had modularity scores of 0.1, indicating an evenly connected network (Fig. 2-6c). The modularity metric for the SRP networks was approximately 0.3 implying a moderate tendency to form communities, but the division between communities was not very strong (Fig. 2-7c). There was little difference between the modularity scores for low versus high performing networks for the RRB or SRP networks (Fig. 2-6c, 2-7c).

Discussion

Our results overall show that the addition of new social relationships to a network can sometimes benefit and sometimes impair the spread of conservation initiatives, programs, and behavior. The choice of information diffusion model has a crucial role in shaping outcomes; we observed clear differences between the independent cascade model, when information diffusion is based on intrinsic node properties (e.g., resistance to change), and the linear threshold model, which simulates information diffusion based on the activity of all peer nodes. For both models, the benefits of new relationships depend on individuals' resistance to change (i.e., activation probability and activation threshold in the IC and LT models, respectively). We also found that the final number of activated nodes was positively correlated with the number of initially active nodes, but this relationship was mediated by other parameters in complex ways.

These simulation results provide valuable insights for conservation practitioners. Across both the regional Red River Basin network and the national Sustainable Rivers Program network, the number of initially active nodes (i.e., seed set size) played a critical role in determining node activation outcomes under both the IC and LT models. In general, larger seed sets led to greater overall node activation, reinforcing the importance of establishing a core group of early adopters to drive the spread of a conservation practice. This finding aligns with research demonstrating that larger initial active seed sets enhance information diffusion more efficiently by increasing information spread within a shorter time frame (Nöldeke et al., 2020). Additionally, Akbarpour et al. (2017) found that increasing the number of randomly activated seeds resulted in broader diffusion compared to optimizing seed selection based on network structure. Similarly, Wineland and Neeson (2022) showed that larger seed sets result in greater overall node activation, independent of the seed selection method used. These results underscore the importance of establishing a foundational group of early conservation practice adopters to amplify adoption across the network.

The IC model simulations showed that when actors are receptive to the conservation practice, for instance if it is a required practice and/or monetary or social costs to adoption are low, and the initial active actors are few, then modifying network structure through the addition of new network connections is beneficial. Under these conditions, time and resources invested in organizing a large outreach event are likely to generate returns in terms of increasing practice adoption. As an example, consider a workshop for construction stormwater permitees. Typically, the actors have a regulatory requirement to meet (making them receptive to adoption), practices often have low capital cost (e.g., silt fencing) and technical experts are providing information. This example scenario aligns with model conditions that produced increased practice adoption. These findings are reflected in the ideas that increased connectivity or dense connections between actors facilitates knowledge sharing (Reagans & McEvily, 2003; Valente & Pumpuang, 2007). Networks with a small number of initial actors can be effective for the dissemination of general information (Crona & Bodin, 2006). Likewise, knowledge sharing nodes can be highly connected across the entire network (Cunningham et al., 2016). However, at higher seed sets limited returns were observed as edge budgets increased, implying that strategically introducing conservation initiative information via particular actors (i.e., seeds) can be equally effective to broadly increasing network density through new network connections.

In contrast, under the LT model, adding edges tended to hinder the spread of conservation initiatives. In the LT model, a node's probability of activation depends on the active or inactive state of all neighboring nodes. The addition of new relationships (i.e., edges) to a network increases the average number of neighbors (i.e., degree) of each node, such that a greater number of active neighbors is necessary to overcome the activation threshold. As a result, the prospect for node activation can be diluted and the overall success of information diffusion decreases as network density increases (Centola, 2018, p. 37). We hypothesize that the small seed set sizes, relative to network size, are not large enough to stimulate node activation across the network;

thus, subsequent edge addition does not overcome the lack of initial activation (Fig. 2-4b). Seed sets of moderate size (10, 15, 20) are large enough to kick off initial activation and the mean number of activated nodes increases with a larger seed set. Yet, node activation diminishes as additional edges increase network complexity and a greater number of active neighbors are needed to overcome the activation threshold. As the seed set size increases from 20 to 25 a tipping point is observed where the initial seed launches node activation within the network and node activation continues to increase as more connections are added to the network (Fig. 2-4b). A synergistic interaction occurred between the original seed set size and additional connections added to the network. Similar results have also been found empirically where providing actors with new information was negatively correlated to conservation outcomes (Stern et al., 2017). Moreover, the approach of conducting targeted outreach was shown to be effective for invasive species detection (Mazzotti et al., 2024); this is opposed to indiscriminate outreach, which would be similar to non-selective new edge addition in our simulations. Other studies highlighted the importance of network structure and that overly dense networks can hinder effective information diffusion (Crona & Bodin, 2006; Dowd et al., 2014). These dynamics highlight the importance of balancing initial seed set size and network structure to optimize diffusions and suggests that well-designed interventions can exploit these synergies to enhance network-wide adoption (Valente, 2012).

Beyond network structure, activation probability/threshold values are crucial in determining information diffusion success. However, a persistent challenge remains: how to accurately determine real-world values for these simulation parameters? While the characteristics of conservation initiatives can theoretically be mapped onto simulation conditions - such as, whether a practice is widely used or novel (large vs. small seed set), whether barriers to adoption are low or high (activation probabilities/thresholds), and whether outreach efforts are widespread or targeted (edge budget) - translating these theoretical frameworks into reliable measurable actor parameters is difficult. For example, how do we determine whether an individual actor has an activation probability of 0.2 or 0.6, or whether a decision is simple or complex? Social-psychology scholarship counsels that behavioral intent alone is often an unreliable predictor of actual behavior (Heberlein, 2012, pp. 64-68) and the best predictor of future behavior is past behavior (Heberlein, 2012, p. 61). Similarly, status quo bias can prevent individuals from acting even when they recognize the benefits of doing so (Cinner, 2018). Delaroche (2020) synthesized findings from studies on agricultural conservation practices, showing that factors such as attitude and perceived behavioral control can significantly influence adoption intentions and, in some cases, be the strongest predictor of actual practice adoption. Since precisely and consistently quantifying an individual's activation probability/threshold may be challenging, fostering network wide relationship-building strategies can enhance network resilience and informational redundancy (Dowd et al., 2014; Singh, 2005), potentially mitigating uncertainties in individual actor activation parameters.

The simulation results presented here highlight several important directions for future research. The dramatic differences between the independent cascade and linear threshold model outcomes underscore the need for a deeper examination of which model more accurately represents networks of conservation actors and the spread of specific practices. Because real-world networks are rarely static, understanding how these models perform as networks evolve is critical. Exploring whether strategies such as adding new connections or emphasizing key actors remain effective over time could provide valuable insights into network resilience and adaptability. Furthermore, the observed trade-offs between seed set size and edge additions warrant further investigation. Incorporating temporal dynamics into diffusion simulations could uncover the relative advantages of allowing information to spread organically versus implementing targeted interventions to accelerate adoption. These two approaches (progressive diffusion and strategic network interventions) likely proceed on different timescales, influencing how quickly network activation reaches saturation. However, our study did not explicitly consider time as a variable. Future research on the temporal aspects of information diffusion could help optimize intervention strategies, particularly for large and dynamic networks.

Future research might also explore the relationships among alternative metrics of conservation success. We measured success as the number of activated nodes, i.e., the final level of adoption of a conservation practice across the network. This definition of success is intuitive and has been used in previous syntheses of the spread of conservation initiatives (Mills et al. 2019) but does not directly address issues of justice and fairness in program design. There is increasing recognition that conservation programs that are socially equitable are more likely to succeed (Bennett & Dearden, 2014; Klein et al., 2015). A core element of this fairness is procedural justice, i.e., the "equitable involvement of all stakeholder groups in rule making and decisions" (Law et al., 2018). Thus, the number of new network edges may itself be a measure of success insofar as it increases procedural justice for individuals in the network. Notably, our simulation results reveal that these two measures of success, adoption and inclusivity, can be in tension with one another, particularly in the LT model, where increasing network connectivity through new edges unexpectedly reduced overall node activation.

When setting out to launch conservation initiatives the observed differences between simulations with the IC and LT models underscores the importance of tailoring network interventions to the specific characteristics of conservation initiatives and the target audience.

For example, initiatives with a monetary or perceived sociopolitical cost (adoption resistance) may benefit from fostering smaller tightly knit groups of early adopters and demonstrations of initiative success to lower activation thresholds and at the same time these groups benefit from bridging ties to provide needed external information or resources (Bodin and Corona 2009). Conversely, conservation practices that are more readily adopted can achieve broader diffusion through the overall expansion of the network and increase inter-group connections. In practical terms, our findings highlight that conservation practitioners should carefully weigh potential tradeoffs associated with different network interventions. Further research on this topic could extend this work by exploring temporal dynamics of information diffusion and considering the quality of interaction between actors. The demand to address contemporary environmental challenges is increasing and applying insights from social network information diffusion modeling to conservation efforts can support practitioners to design strategies that overcome barriers to adoption and achieve meaningful scalable impacts.

References

Alix-Garcia, J. M., Sims, K. R. E., Orozco-Olvera, V. H., Costica, L. E., Fernández Medina, J. D., & Romo Monroy, S. (2018). Payments for environmental services supported social capital while increasing land management. Proceedings of the National Academy of Sciences, 115(27), 7016–7021. https://doi.org/10.1073/pnas.1720873115

Azaouzi, M., Mnasri, W., & Ben Romdhane, L. (2021). New trends in influence maximization models. Computer Science Review, 40, 100393. https://doi.org/10.1016/j.cosrev.2021.100393

Baird, J., Jollineau, M., Plummer, R., & Valenti, J. (2016). Exploring agricultural advice networks, beneficial management practices and water quality on the landscape: A geospatial social-ecological systems analysis. Land Use Policy, 51, 236–243. https://doi.org/10.1016/j.landusepol.2015.11.017

Barabasi, A.-L. (2016). Network Science. In Network Science. Cambridge University Press, Cambridge, United Kingdom.

Bennett, N. J., & Dearden, P. (2014). Why local people do not support conservation: Community perceptions of marine protected area livelihood impacts, governance and management in Thailand. Marine Policy, 44, 107–116. https://doi.org/10.1016/j.marpol.2013.08.017

Bodin, Ö., & Crona, B. I. (2009). The role of social networks in natural resource governance: What relational patterns make a difference? Global Environmental Change, 19(3), 366–374. https://doi.org/10.1016/j.gloenvcha.2009.05.002

Bodin, Ö., & Prell, C. (Eds.). (2011). Social Networks and Natural Resource Management: Uncovering the Social Fabric of Environmental Governance. Cambridge University Press; Cambridge Core. https://doi.org/10.1017/CBO9780511894985

Botts, E. A., Pence, G., Holness, S., Sink, K., Skowno, A., Driver, A., Harris, L. R., Desmet, P., Escott, B., Lötter, M., Nel, J., Smith, T., Daniels, F., Sinclair, S., Stewart, W., & Manuel, J. (2019). Practical actions for applied systematic conservation planning. Conservation Biology, 33(6), 1235–1246. https://doi.org/10.1111/cobi.13321

Centola, D. (2018). How behavior spreads: The science of complex contagions. Princeton University Press.

Cowan, R., & Jonard, N. (2004). Network structure and the diffusion of knowledge. Journal of Economic Dynamics and Control, 28(8), 1557–1575. https://doi.org/10.1016/j.jedc.2003.04.002

Crona, B., & Bodin, Ö. (2006). What You Know is Who You Know? Communication Patterns Among Resource Users as a Prerequisite for Co-management. Ecology and Society, 11(2), art7. https://doi.org/10.5751/ES-01793-110207

Csardi, G., & Nepusz, T. (2006). The igraph software package for complex network research. InterJournal, Complex Systems, 1695. https://igraph.org

Cunningham, R., Cvitanovic, C., Measham, T., Jacobs, B., Dowd, A.-M., & Harman, B. (2016). Engaging communities in climate adaptation: The potential of social networks. Climate Policy, 16(7), 894–908. https://doi.org/10.1080/14693062.2015.1052955

Dowd, A.-M., Marshall, N., Fleming, A., Jakku, E., Gaillard, E., & Howden, M. (2014). The role of networks in transforming Australian agriculture. Nature Climate Change, 4(7), 558–563. https://doi.org/10.1038/nclimate2275

Eckles, D., Esfandiari, H., Mossel, E., & Rahimian, M. A. (2022). Seeding with Costly Network Information. Operations Research, 70(4), 2318–2348. https://doi.org/10.1287/opre.2022.2290

Farwig, N., Sprenger, P. P., Baur, B., Böhning-Gaese, K., Brandt, A., Eisenhauer, N., Ellwanger, G., Hochkirch, A., Karamanlidis, A. A., Mehring, M., Pusch, M., Rehling, F., Sommerwerk, N., Spatz, T., Svenning, J.-C., Tischew, S., Tockner, K., Tscharntke, T., Vadrot, A. B. M., … Mosbrugger, V. (2024). Identifying Major Factors for Success and Failure of Conservation Programs in Europe. Environmental Management. https://doi.org/10.1007/s00267-024-02086-x

Fortunato, S. (2010). Community detection in graphs. Physics Reports, 486(3–5), 75–174. https://doi.org/10.1016/j.physrep.2009.11.002

Hussain, O. (2021). Influence.mining (Version 0.2.4) [Computer software]. https://github.com/seekme94/influence.mining

Kaweesa, S., Mkomwa, S., & Loiskandl, W. (2018). Adoption of Conservation Agriculture in Uganda: A Case Study of the Lango Subregion. Sustainability, 10(10), 3375. https://doi.org/10.3390/su10103375

Klein, C., McKinnon, M. C., Wright, B. T., Possingham, H. P., & Halpern, B. S. (2015). Social equity and the probability of success of biodiversity conservation. Global Environmental Change, 35, 299–306. https://doi.org/10.1016/j.gloenvcha.2015.09.007

Law, E. A., Bennett, N. J., Ives, C. D., Friedman, R., Davis, K. J., Archibald, C., & Wilson, K. A. (2018). Equity trade-offs in conservation decision making. Conservation Biology, 32(2), 294–303. https://doi.org/10.1111/cobi.13008

Leclère, D., Obersteiner, M., Barrett, M., Butchart, S. H. M., Chaudhary, A., De Palma, A., DeClerck, F. A. J., Di Marco, M., Doelman, J. C., Dürauer, M., Freeman, R., Harfoot, M., Hasegawa, T., Hellweg, S., Hilbers, J. P., Hill, S. L. L., Humpenöder, F., Jennings, N., Krisztin, T., … Young, L. (2020). Bending the curve of terrestrial biodiversity needs an integrated strategy. Nature, 585(7826), 551–556. https://doi.org/10.1038/s41586-020-2705-y

Lubell, M., Jasny, L., & Hastings, A. (2017). Network Governance for Invasive Species Management. Conservation Letters, 10(6), 699–707. https://doi.org/10.1111/conl.12311
Luke, D. (2015). A User's Guide to Network Analysis in R (1st ed.). Springer International Publishing, Cham.

Maxwell, S. L., Cazalis, V., Dudley, N., Hoffmann, M., Rodrigues, A. S. L., Stolton, S., Visconti, P., Woodley, S., Kingston, N., Lewis, E., Maron, M., Strassburg, B. B. N., Wenger, A., Jonas, H. D., Venter, O., & Watson, J. E. M. (2020). Area-based conservation in the twenty-first century. Nature, 586(7828), 217–227. https://doi.org/10.1038/s41586-020-2773-z

Mills, M., Bode, M., Mascia, M. B., Weeks, R., Gelcich, S., Dudley, N., Govan, H., Archibald, C. L., Romero-de-Diego, C., Holden, M., Biggs, D., Glew, L., Naidoo, R., & Possingham, H. P. (2019). How conservation initiatives go to scale. Nature Sustainability, 2(10), 935–940. https://doi.org/10.1038/s41893-019-0384-1

Nesbitt, H. K., Metcalf, A. L., Floyd, T. M., Uden, D. R., Chaffin, B. C., Gulab, S., Banerjee, S., Vallury, S., Hamlin, S. L., Metcalf, E. C., Fogarty, D. T., Twidwell, D., & Allen, C. R. (2024). Social networks and transformative behaviours in a grassland social-ecological system. People and Nature, 6(5), 1877–1892. https://doi.org/10.1002/pan3.10695

Nöldeke, B., Winter, E., & Grote, U. (2020). Seed Selection Strategies for Information Diffusion in Social Networks: An Agent-Based Model Applied to Rural Zambia. Journal of Artificial Societies and Social Simulation, 23(4), 9. https://doi.org/10.18564/jasss.4429

Olsson, P., Folke, C., & Hughes, T. P. (2008). Navigating the transition to ecosystem-based management of the Great Barrier Reef, Australia. Proceedings of the National Academy of Sciences, 105(28), 9489–9494. https://doi.org/10.1073/pnas.0706905105

Potterat, J. J., Rothenberg, R. B., & Muth, S. Q. (1999). Network structural dynamics and infectious disease propagation. International Journal of STD & AIDS, 10(3), 182–185. https://doi.org/10.1258/0956462991913853

R Core Team. (2023). R: A language and environment for statistical computing. R Foundation for Statistical Computing. https:// www.R-project.org/

Reagans, R., & McEvily, B. (2003). Network Structure and Knowledge Transfer: The Effects of Cohesion and Range. Administrative Science Quarterly, 48(2), 240–267. https://doi.org/10.2307/3556658

Rilov, G., Fraschetti, S., Gissi, E., Pipitone, C., Badalamenti, F., Tamburello, L., Menini, E., Goriup, P., Mazaris, A. D., Garrabou, J., Benedetti-Cecchi, L., Danovaro, R., Loiseau, C., Claudet, J., & Katsanevakis, S. (2020). A fast-moving target: Achieving marine conservation goals under shifting climate and policies. Ecological Applications, 30(1), e02009. https://doi.org/10.1002/eap.2009

Saito, K., Kimura, M., Ohara, K., & Motoda, H. (2016). Super mediator – A new centrality measure of node importance for information diffusion over social network. Information Sciences, 329, 985–1000. https://doi.org/10.1016/j.ins.2015.03.034

Shakarian, P., Bhatnagar, A., Aleali, A., Shaabani, E., & Guo, R. (2015). Diffusion in social networks. Springer.

Singh, J. (2005). Collaborative Networks as Determinants of Knowledge Diffusion Patterns. Management Science, 51(5), 756–770. https://doi.org/10.1287/mnsc.1040.0349

Tickner, D., Opperman, J. J., Abell, R., Acreman, M., Arthington, A. H., Bunn, S. E., Cooke, S. J., Dalton, J., Darwall, W., Edwards, G., Harrison, I., Hughes, K., Jones, T., Leclère, D., Lynch, A. J., Leonard, P., McClain, M. E., Muruven, D., Olden, J. D., … Young, L. (2020). Bending the Curve of Global Freshwater Biodiversity Loss: An Emergency Recovery Plan. BioScience, 70(4), 330–342. https://doi.org/10.1093/biosci/biaa002

Valente, T. W., & Pumpuang, P. (2007). Identifying Opinion Leaders to Promote Behavior Change. Health Education & Behavior, 34(6), 881–896. https://doi.org/10.1177/1090198106297855

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of 'small-world' networks. 393.

Wineland, S. M., Fovargue, R., York, B., Lynch, A. J., Paukert, C. P., & Neeson, T. M. (2021). Is there enough water? How bearish and bullish outlooks are linked to decision maker perspectives on environmental flows. Journal of Environmental Management, 280, 111694. https://doi.org/10.1016/j.jenvman.2020.111694

Wineland, S. M., & Neeson, T. M. (2022). Maximizing the spread of conservation initiatives in social networks. Conservation Science and Practice. https://doi.org/10.1111/csp2.12740

Yoganarasimhan, H. (2012). Impact of social network structure on content propagation: A study using YouTube data. Quantitative Marketing and Economics, 10(1), 111–150. https://doi.org/10.1007/s11129-011-9105-4

Zhou, J., Liu, Z., & Li, B. (2007). Influence of network structure on rumor propagation. Physics Letters A, 368(6), 458–463. https://doi.org/10.1016/j.physleta.2007.01.094

Tables

Table 2-1 Original network structure characteristics (i.e., number of nodes and edges) and simulation model parameters for the Red River Basin and Sustainable River Project networks. For each network, we conducted simulation experiments to evaluate the effect of all combinations of seed set sizes (i.e., the number of initially active nodes), activation probability (for the independent cascade model) or activation threshold (for the linear threshold model), and number of new social relationships (i.e., network edges).

Network	Number of nodes	Number of edges	Seed set sizes	Activation probability/thresholds	Number of new edges
Red River Basin	24	128	1,2,3,4,5	0.01, 0.05, 0.1-0.9 interval of 0.1	0-100 interval of 10
Sustainable Rivers Project	426	12,800	1,5,10,15,20,25	0.01, 0.05, 0.1-0.9 interval of 0.1	0-45,000 interval of 15,000

Figures

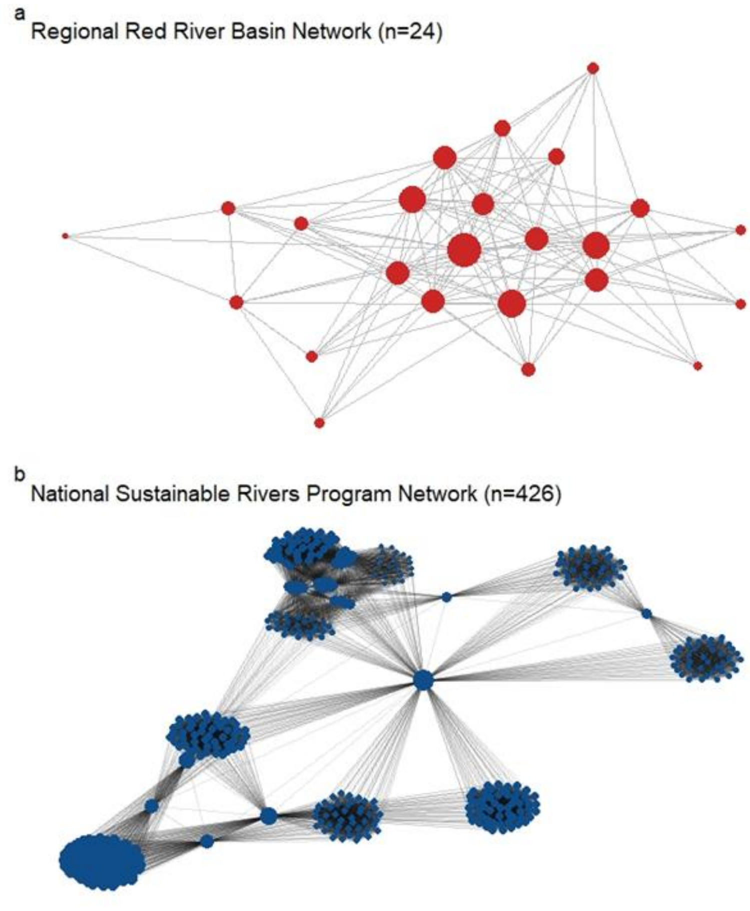

Figure 2-1 Network maps for a) the regional network of water decision-makers in the Red River Basin and b) the national Sustainable Rivers Program network. Node size is proportional to node degree.

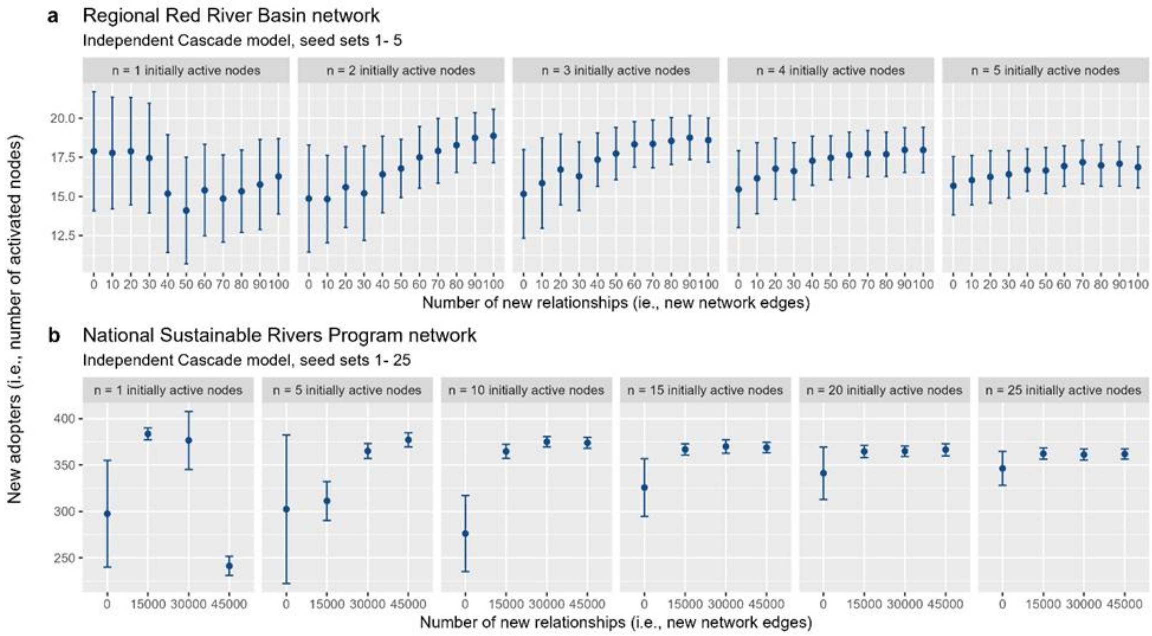

Figure 2-2 Mean (points) and standard deviation (error bars) of the final number of activated nodes for a) Red River Basin Network and b) Sustainable Rivers Program Network resulting from simulations using the independent cascade model with an activation probability of 0.9.

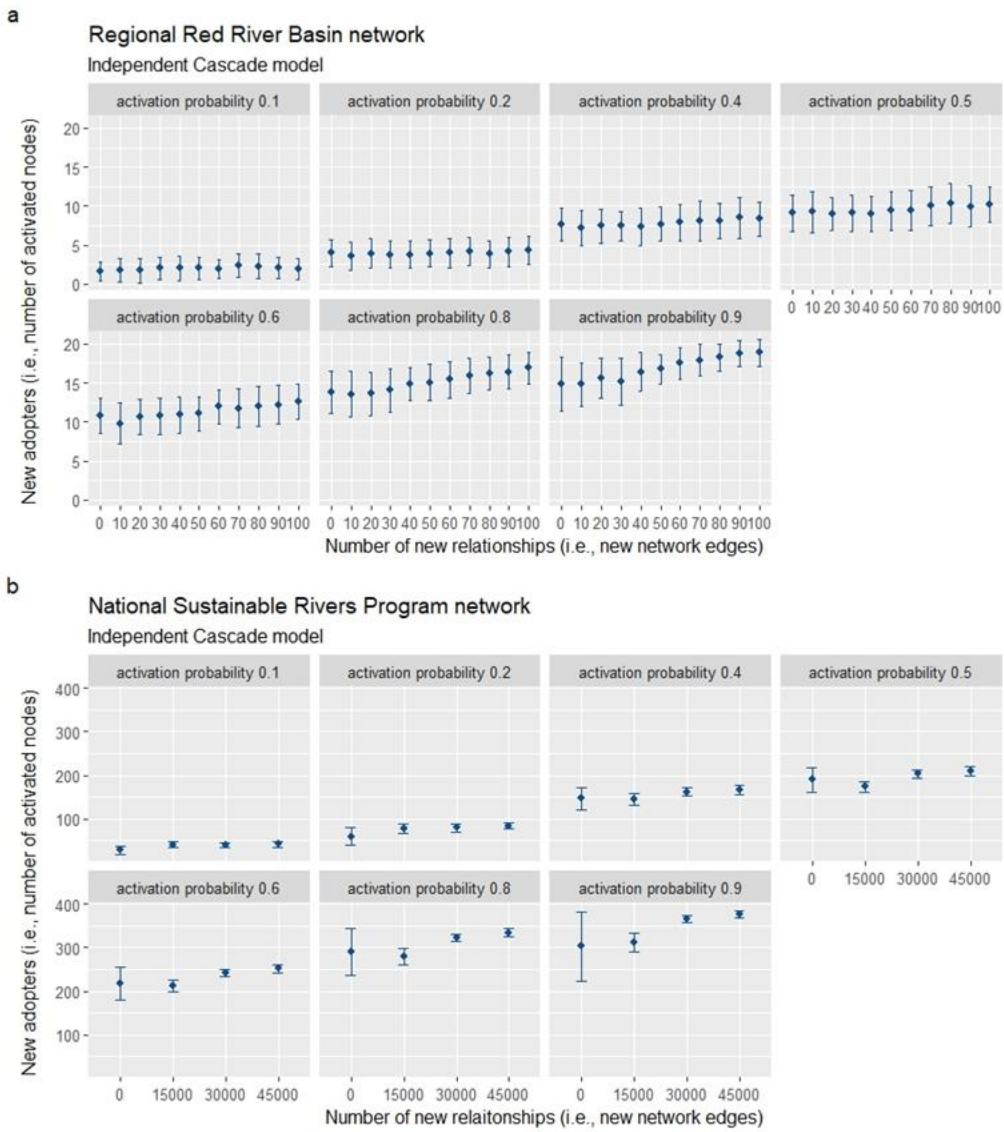

Figure 2-3 Mean (points) and standard deviation (error bars) of the final number of activated nodes for a) Red River Basin Network and b) Sustainable Rivers Program Network resulting from simulations using the independent cascade model with seed set size of two and five, respectively.

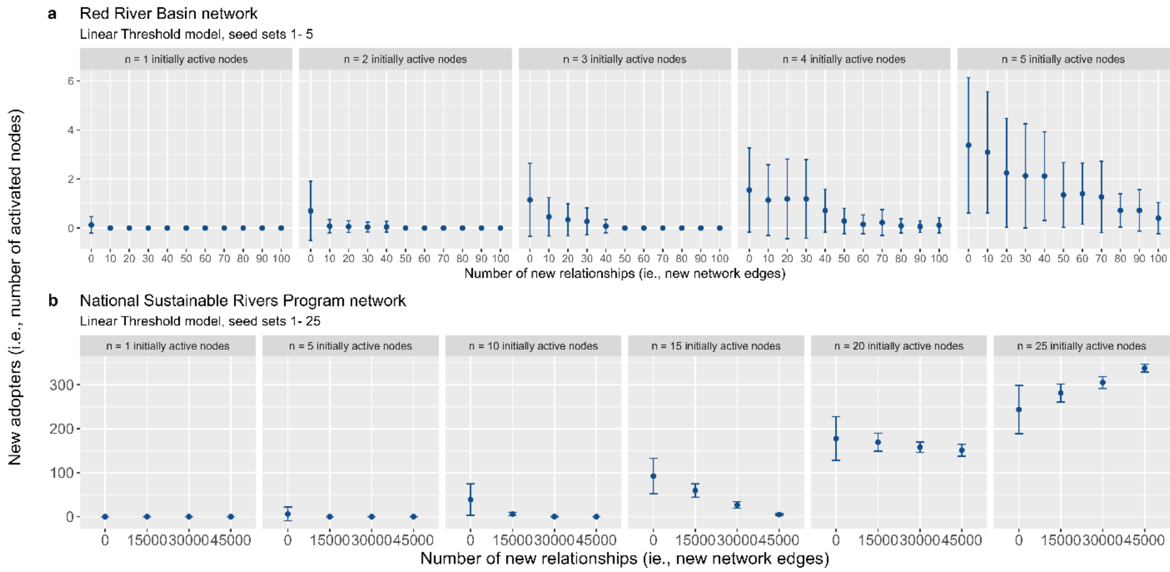

Figure 2-4 Mean (points) and standard deviation (error bars) of the final number of activated nodes for a) Red River Basin Network (activation threshold 0.3) and b) Sustainable Rivers Program Network (activation threshold 0.05) resulting from simulations using the linear threshold model.

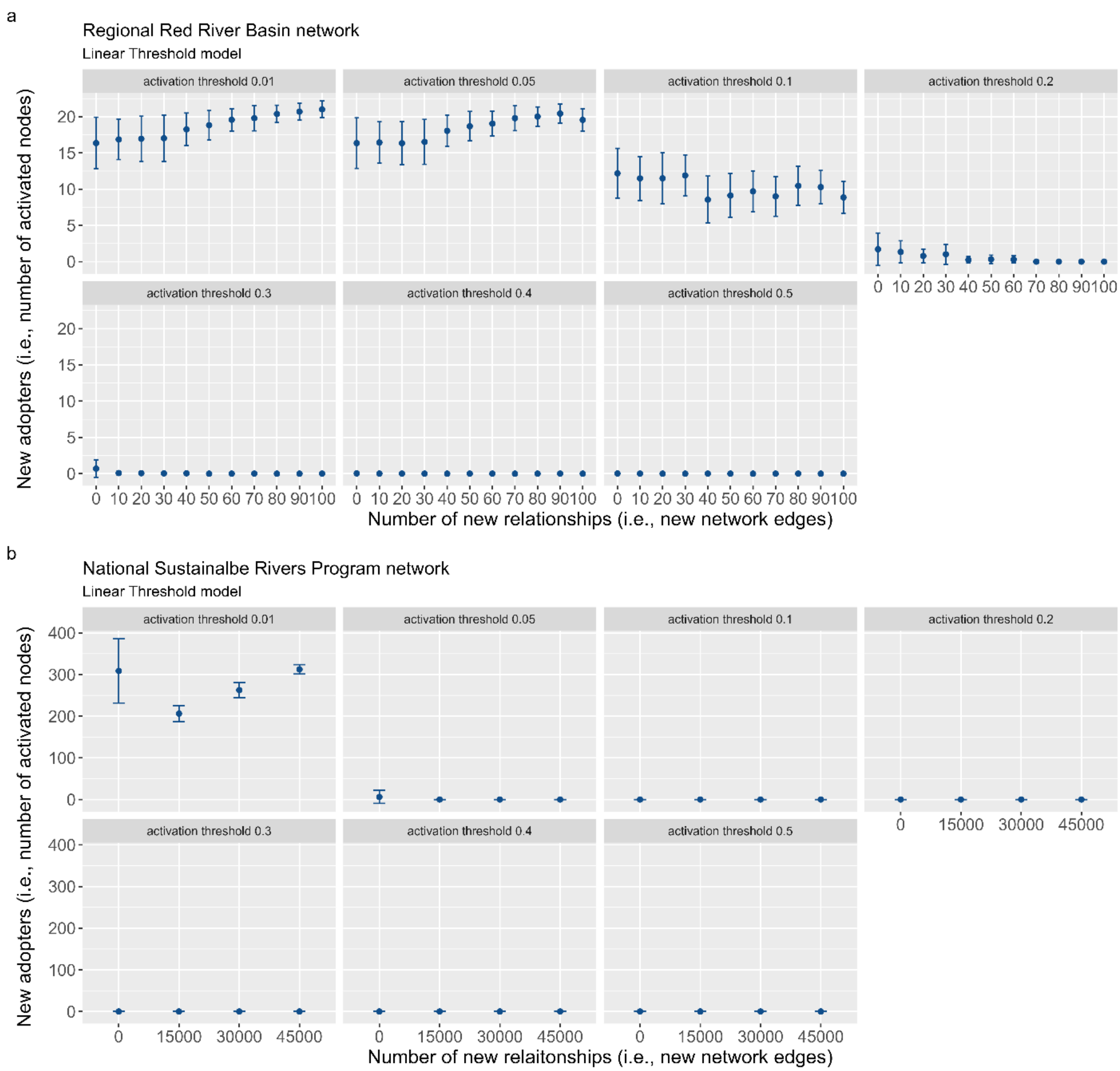

Figure 2-5 Activation threshold is a governing factor in the information diffusion models. At higher activation thresholds increasing network connections via the edge budget does not increase the mean number of activated nodes. a) Red River Basin, b) Sustainable River Program.

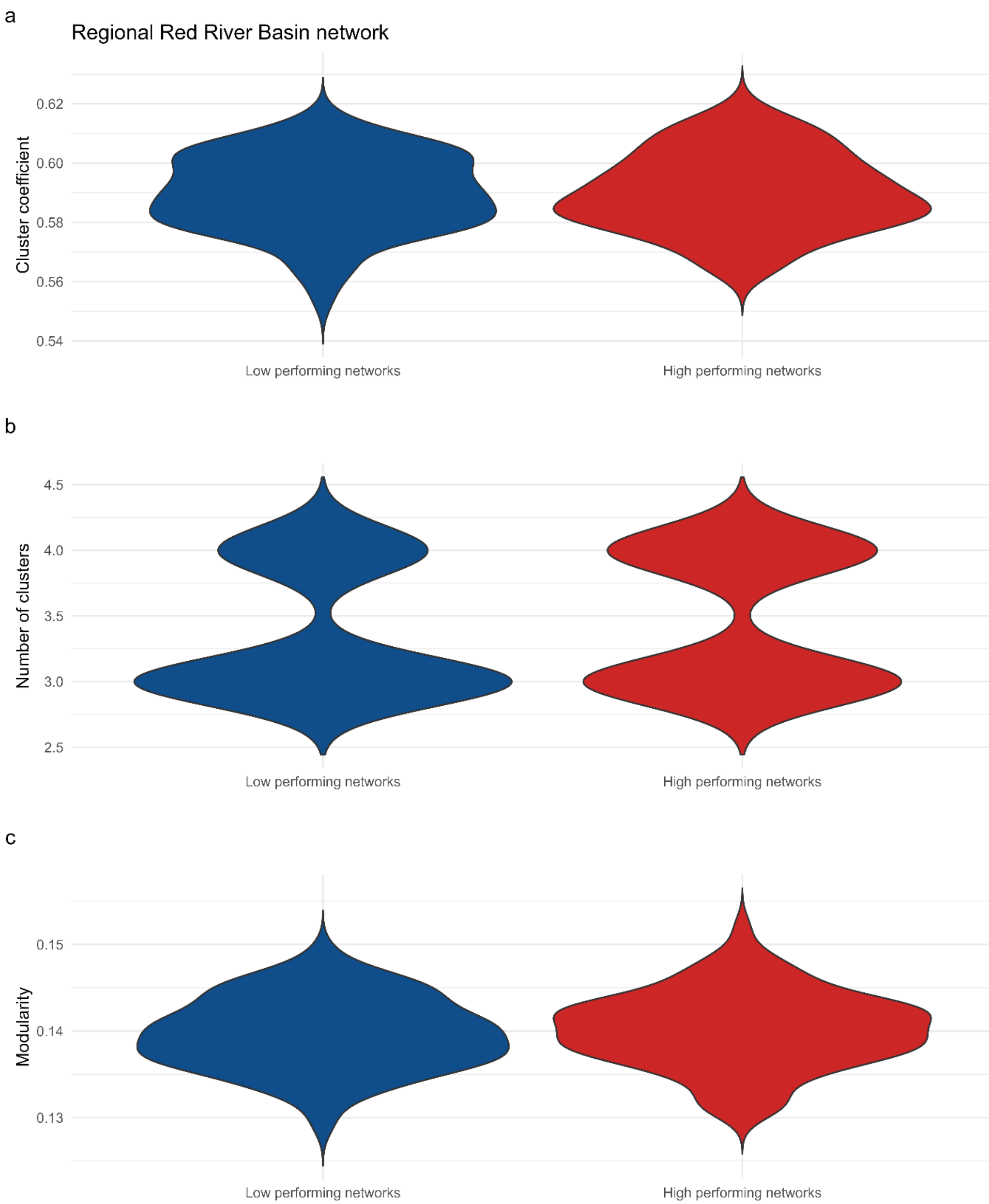

Figure 2-6 Comparison of the structures of low- and high-performing Red River basin networks. Violin plots give the frequency distribution of the a) clustering coefficient, b) number of clusters, and c) modularity for networks in the lowest (left column) or highest (right column) decile of the final number of activated nodes. Frequency distributions summarize model results from all combinations of model parameters (Table 2-2).

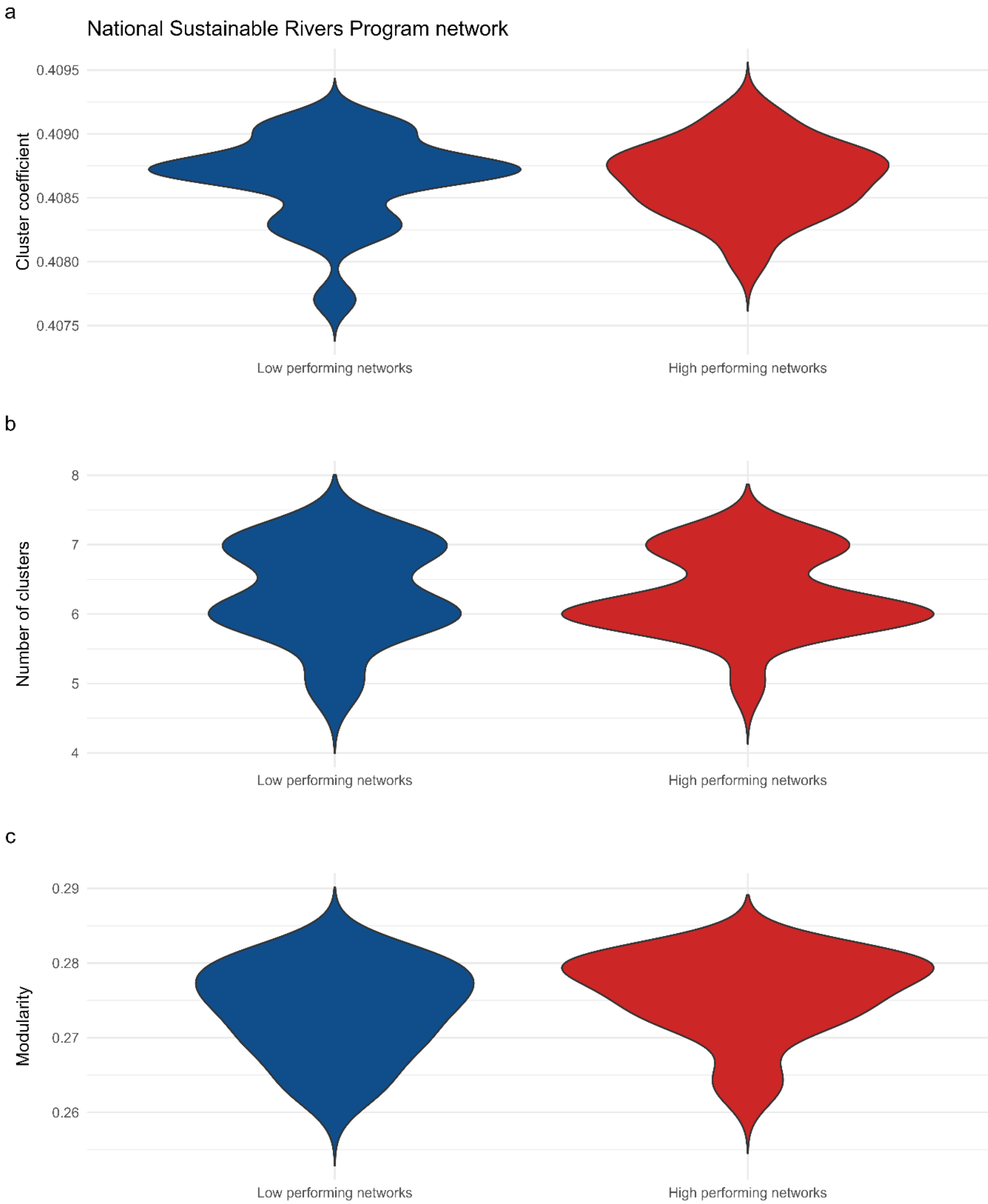

Figure 2-7 Comparison of the structures of low- and high-performing Sustainable Rivers Program networks. Violin plots give the frequency distribution of the a) clustering coefficient, b) number of clusters, and c) modularity for networks in the lowest (left column) or highest (right column) decile of the final number of activated nodes. Frequency distributions summarize model results from all combinations of model parameters (Table 2-2).

Chapter Three

INITIATING CONSERVATION PRACTICE ADOPTION: INVESTIGATING TOP-DOWN VERSUS BOTTOM-UP COMMUNICATION IN AN ENVIRONMENTAL GOVERNANCE NETWORK

Keywords:

Environmental governance, conservation practice,
top-down, bottom-up, social network

Abstract

One of the most fundamental questions in environmental governance is whether top-down or bottom-up communication is more effective. Using an empirical network of 24 conservation organizations in the Oklahoma-Texas Red River Basin, we investigated how information moves through a social network of conservation actors (non-governmental organizations (NGO), local, state, and federal agencies) and identified which actors are best positioned to initiate practice adoption. For two common information diffusion models (independent cascade and linear threshold), we simulated practice adoption under a range of conditions to test how actor organization type and communication patterns shape diffusion outcomes. Our results show that information diffusion initiated by local and NGO actors (i.e., those positioned lower in the governance hierarchy) consistently produced higher conservation practice adoption levels than initiation by state or federal organizations. The effectiveness of bottom-up communication may have been driven by the fact that individuals at NGOs were significantly more connected that those at other groups; and individuals at local government organizations communicated significantly more frequently than individuals at other types of groups. These structural and communicative advantages support the broad practice adoptions achieved by bottom-up initiation under several simulation scenarios. Results support hybrid governance approaches where organizations at higher governance levels provide policy and resource frameworks, while local and NGO actors promote adoption and network engagement. Such strategies offer practical, evidence-based guidance for advancing conservation initiatives under real-world constraints.

Introduction

Across ecosystems and governance systems worldwide, conservation success often hinges on the interaction between top-down policy frameworks and bottom-up, community-driven initiatives. From coastal lagoon systems to watershed management and forest conservation, discussions continue over whether centralized, hierarchical governance or locally driven, grassroots efforts are more effective for achieving conservation outcomes (Ballarini et al., 2021; Fraser et al., 2006; Koontz & Newig, 2014). Recent research has examined how these two governance approaches affect conservation program success (Ding et al., 2023; Enqvist et al., 2020; McCulloch-Jones et al., 2021). Findings suggest that aligning formal directives (top-down) with local initiatives (bottom-up) often improves implementation success, emphasizing the value of linking the governance approaches (Ding et al., 2023; Eicken et al., 2021). Top-down approaches offer regulatory authority and resources, while bottom-up approaches bring local knowledge, trust, and social legitimacy, factors essential for long-term adoption (Enqvist et al., 2020; McCulloch-Jones et al., 2021). Yet, the relative effectiveness of these approaches remains unclear, particularly under real-world constraints where conservation practitioners must balance time, funding, and institutional capacity. This uncertainty raises a fundamental question: under what conditions do top-down versus bottom-up approaches most effectively initiate and spread conservation practices across environmental governance groups?

Social network analysis provides a useful set of tools for investigating such questions because it links social structure to information flow and behavior outcomes. It has been applied across diverse fields, from public health to organizational learning. In health promotion, network-based interventions and information sharing have been shown to improve both short- and long-term outcomes and among adolescents, friendship networks influence the adoption or adaptation of behaviors (Hunter et al., 2019; Montgomery et al., 2020). In organizational settings, mapping knowledge-sharing networks shows that the speed and reach of learning by network actors depends on communication in both formal and informal networks (Szilágyi, 2017). Likewise, trustworthy, strong ties enable reliable knowledge exchange, while weak ties often introduce new ideas from outside an immediate group (Levin & Cross, 2004). These same dynamics (e.g., interventions, information sharing, and tie strength) are directly relevant for conservation. Whether the goal is sustainable agriculture, riparian restoration, or climate adaptation, conservation practitioners work within social networks of influence and collaboration. Applying social network analysis to conservation offers a means to translate lessons from other disciplines into strategies that may accelerate conservation innovation and adoption.

Social network analysis also examines how an actor's position within a network shapes the spread and reach of information. Actors in a position to link otherwise disconnected groups can introduce new ideas and accelerate spread, whereas tightly clustered groups may predominately circulate local information (Dowd et al., 2014; Gulati et al., 2012; Rathwell & Peterson, 2012; Uzzi & Spiro, 2005). Because both communication patterns and network position impact information diffusion dynamics, there has been growing interest in identifying which individuals or organizations to engage first when trying to spread new practices or information (Valente & Pumpuang, 2007). These starting individuals/organizations are known as seed nodes in the network and can strongly influence how widely and quickly information/practices will travel through a network. In fields such as viral marketing complex algorithms are used to identify "maximum influence" actors who can expose the marketing campaign the greatest number of people (Agha Mohammad Ali Kermani et al., 2021; Lin & Lui, 2014; Singh et al., 2019). Similar approaches have been applied to conservation networks showing that targeting maximum influence nodes can improve conservation practice adoption outcomes (Wineland & Neeson, 2022). These insights have generated an interest in identifying which individuals or organizations should be engaged first when launching or reinvigorating a conservation initiative. Yet for conservation practitioners, working with limited time and resources, sophisticated optimization methods to find influential actors are rarely feasible and coordinating across multiple governance levels can demand substantial time and effort (Bodin et al., 2016). Instead, practitioners need straightforward guidance on where to focus engagement efforts within the networks they routinely work with.

Network analysis provides tools for exploring how communication patterns and key actors may influence the spread of conservation initiatives. In particular, there are two primary models of how information or behavior propagates through a network. In the first model, independent cascade (IC), where an individual's likelihood of adopting a new behavior depends on their own intrinsic characteristics (e.g., resistance to change). In the second model, linear threshold (LT), an individual's likelihood of adoption depends on the behavior of all of their peers. Both models are typically represented as directed graphs G (V, E), where V is a set of nodes that represents an organization or actor that can be in an active or inactive state and E is a set of edges that connect nodes in the graph (Azaouzi et al., 2021). In the independent cascade model, an active node (v1) may activate a presently inactive neighboring node (v2) according to an activation probability Pv1, v2, which denotes the probability of v1 activating v2. Thus, the model enables us to explore real-world scenarios ranging from those in which individuals readily adopt new conservation initiatives (i.e., activation probability is high) to those in which individuals are resistant to change or conservation initiatives entail high economic, social or political costs (i.e., the probability of adoption is low). In the linear threshold model, an inactive node (v1) evaluates the influence all its neighboring nodes (e.g., v2, v3, v4) and if the influence of active neighboring nodes exceeds a predetermined threshold, node v1 will activate (Saito et al., 2016; Shakarian et al., 2015). The LT and IC information diffusion models both require a seed set of active nodes to initiate the diffusion process. The set of initially active nodes can be chosen randomly or strategically depending on the modeling objective. Finally, the number of activated nodes, representing information spread, is used to evaluate model results.

Here, we use an empirical conservation network to evaluate straightforward approaches to selecting initial participants for conservation initiatives and how and organization type shapes the spread of conservation initiatives. Our study focuses on a regional network of water program decision-makers (n = 24) from the Oklahoma and Texas portions of the Red River Basin (Wineland & Neeson, 2022). This network includes a diverse set of actors (local, state, and federal agencies, and NGOs) reflecting the typical organizational composition of freshwater conservation endeavors. While located in the Red River Basin, the network is representative of broader conservation governance and provides insights applicable to other ecosystems. It also captures the spatial scale (local to regional) at which conservation programs are typically initiated, implemented, and maintained. Using this network, we ask three questions: (1) which actors, based on organization type, are most effective in initiating the spread of conservation practices, (2) how are the number of social connections in the network distributed across organization type, and (3) do communication frequencies differ across organization types in the network? Addressing these questions provides practical evidence on how to strategically engage conservation actors and direct resources when launching new management campaigns.

Methods

Network description

The Red River Basin (RRB) Network is an empirical, undirected social network of freshwater conservation actors (n = 24) from the Oklahoma and Texas portions of the Red River Basin. The network was constructed using survey responses from organizational representatives, who reported how frequently they communicated with one another (Wineland et al., 2021). Individuals (nodes) were categorized into four types based on the class of agency or organization at which they worked: 1) federal, 2) state, 3) local, and 4) non-governmental organizations (NGOs; Fig. 1). Connections (edges) between nodes were retained when one or both actors indicated that they communicate with each other (Wineland et al., 2021). Further details on the network's typology and structure are provided in Wineland and Neeson (2022).

We assumed that individuals that communicate more frequently have greater influence on each other. Therefore, we determined edge weights by converting individuals' reported communication frequency (never, annually, quarterly, monthly, or weekly) into numeric weights between 0 and 1. Because we had no a priori basis for converting a particular frequency of communication (e.g., weekly) into an edge weight (e.g., 0.5), we conducted our analyses using five normalization functions that convert communication frequency into edge weights (Fig. 2). To determine whether our results were sensitive to the choice of normalization function, we performed all simulation experiments five times; once with each normalization function.

Information diffusion models

We used the independent cascade (IC) and linear threshold (LT) models to simulate the diffusion of a hypothetical conservation practice across the RRB network. In both the IC and LT models, nodes (i.e., actors) are Boolean and may be either active or inactive. For our simulations, we used the activation of a node to represent the adoption of the hypothetical conservation practice by that individual. Thus, we quantified the level of adoption of a conservation practice as the proportion of nodes that were active at the end of a simulation.

The key distinction between the IC and LT models is the mode of activation. The IC model is a simple information diffusion where activation is based on interaction with a single neighboring node. The LT model, in contrast, simulates a complex diffusion, where a node is activated when the cumulative influence of neighboring nodes exceeds a predefined threshold (Shakarian et al., 2015 pp.35-38).

The probability that a node becomes active is influenced by its activation probability (in the IC model) or its activation threshold (in the LT model). A node with a low activation probability (or high activation threshold) is resistant to the adoption of a new conservation practice. Nodes with high activation probability (or low activation thresholds) more readily adopt new practices. We applied a version of the IC model where the activation probability was the weight (normalized communication frequency) on the edge connecting the two nodes. Similarly, in the LT model the collective influence of neighboring nodes was the mean edge weight of active neighboring nodes. The information diffusion models were implemented using the influence.mining package in R version 4.2.2 (Hussain, 2021).

Simulation experiment

We parameterized the simulation experiment using the values summarized in Table 1. Empirical edge weights were obtained from reported communication frequencies based on survey data collected in Wineland et al. (2021). We designed a series of simulations to systematically explore the full range of the parameter values using both the IC and LT models (Table 1). Model parameters included seed set sizes of 1, 2, 3, 4, and 5 nodes and activation probabilities (IC) or thresholds (LT) of 0.01, 0.05, and 0.1- 0.9 in increments of 0.1. Seed set sizes were chosen based on prior work to encompass the range from minimum to maximum activation observed in the RRB network (Wineland & Neeson, 2022).

Our first research question was: Which actors are most effective at initiating the spread of conservation practices? To answer this question, we used four seed selection strategies for initiating diffusion across the network (Table 1). We modeled top-down communication by restricting initially actives nodes to only federal and state actors; thus, in top-down communication, the modeled conservation practice begins at federal and state agency governance level and propagates "down" to local and NGO actors. In bottom-up communication, we randomly selected initially active nodes from local and NGO actors; here, the conservation practice begins at local and NGO governance level and propagates "up" to federal and state actors. We compared top-down and bottom-up initiation to a baseline scenario in which initially active nodes were randomly selected without regard to governance hierarchy. We also compared all three strategies (top-down, bottom-up, and random) to the maximum possible nodes that could be activated with similar model parameters. This maximum was calculated based on the greatest number of activated nodes across 10,000 simulations. Seed selection strategy was tested across all seed set sizes, normalization functions, and both information diffusion models. For each combination of parameters, we ran 1,000 simulations to capture variation in how communication frequency, seed selection method, and model selection influence conservation practice adoption outcomes.

This analysis does not model why actors resist or adopt conservation practices. Motivations for actor adoption/non-adoption of conservation practices are often complex and can include factors like implementation costs, perceived risk, and social prerogatives. For instance, Ranjan et al. (2019, 2019) found that costs associated with adopting practices like cover crops or riparian buffers are frequently cited as either key motivators or barriers, depending on financial incentives. Similarly, Enloe et al. (2017) identified mistrust in government conservation agencies can be overcome by a trusted relationship with an individual person working at the agency providing technical assistance. Instead of modeling motivations directly, we use the model activation probability (or threshold) as a proxy for an actor's receptivity to practice adoption. One can imagine high probabilities (low thresholds) to simulate circumstances where conservation practice adoption has low social or economic barriers, and low probabilities (high thresholds) simulate conditions where actors are resistant to practice adoption (e.g., costly practice implementation or social constraint). Using this approach we explored the range of activation probability/thresholds and evaluated how patterns of communication and the choice of initial seed actors can support or hinder conservation outcomes across various adoption contexts without specifying individual motives.

Identifying communication patterns

With our second and third research questions, we sought to understand how differences in the effectiveness of top-down vs. bottom-up communication might be driven by differences in the number of edges and edge weights among local, state, federal and NGO actors. For example, some types of organizations may be particularly effective at spreading conservation initiatives because they have on average, a greater number of social connections (i.e., higher degree). Or it may be the case that some types of organizations are effective at spreading conservation initiatives because they communicate more frequently (i.e., have higher edge weights) with other actors.

Our second research question was: how does the number of social connections (i.e., edges) differ among local, state, federal and NGO actors? We used a Chi-square test to evaluate whether the observed number of connections (edges) between organization types differed significantly from what would be expected under a null model of proportional organization connection. The Chi-square test is a non-parametric statistical method to determine whether two categorical variables are independent of one another. In our analysis, the two variables are the organization type nodes connected by each edge. The null hypothesis for the test was that edge connections in the RRB Network are proportionally distributed based on the number of organizations in each category (i.e., any organization is equally likely to connect with any other, regardless of type). The alternative hypothesis is that connections are not independent of organization type, implying that certain types of organizations (nodes) are more or less likely to communicate with one another than expected by chance. A significant chi-square result would indicate non-random connections among organization types, suggesting that communication in the network is structured by governance level or organization type.

Our third research question was: how does communication frequency (i.e., edge weight) differ among local, state, federal and NGO actors? We conducted a one-way analysis of variance (ANOVA) to test whether mean communication frequency differs across organization types. The purpose of ANOVA in this analysis is to determine whether the average level of communication, measured as the mean edge weight, for each organization type (federal, state, local, NGO) is statistically different from the others. The null hypothesis for ANOVA is that all organization types have the same mean communication frequency, while the alternative hypothesis is that at least one group differs significantly. By comparing the variance between groups to the variance within groups, ANOVA allows us to test whether observed differences in communication levels could have occurred by chance or are indicative of meaningful variation based on organizational type.

Because ANOVA only indicates whether a significant difference exists somewhere among the groups, we followed it with a Tukey's Honest Significant Difference (HSD) test to perform pairwise comparisons between organization types. The Tukey HSD procedure controls for Type I error across multiple comparisons and identifies which specific pairs of organization types (e.g., federal vs. NGO, state vs. local) exhibit statistically significant differences in their communication frequencies. This analysis helps clarify whether particular types of organization actors, such as federal agencies or NGOs, tend to communicate more or less frequently within the network. All statistical analysis were executed using base functions in R version 4.2.2.

Results

Research Question 1: Which actors are most effective at initiating the spread of conservation practices?

We found that bottom-up communication consistently outperformed top-down communication. The independent cascade model simulations revealed a consistent node adoption order among seed selection strategies; the bottom-up strategy activated the most nodes (Fig. 3). The maximum influence strategy, which was designed to optimize activation, substantially outperformed all other approaches, achieving an average of 10–22 activated nodes compared to 2.5–15 for other strategies. The bottom-up selection consistently returned the greatest number of activated nodes among the non-optimized approaches, generally activating 5–15 nodes across seed set sizes and normalization functions, while the top-down selection method performed similar to, or only slightly better than, random selection. The performance advantage of bottom-up selection over top-down and random was most pronounced under percentile normalization and sigmoidal functions, with reduced differentiation under linear and inverted growth curve normalizations. Despite these differences in magnitude, the relative order of favorable seed selection strategies remained consistent across all normalization functions.

In the linear threshold (LT) model simulations, activation thresholds strongly influenced how well different seed selection strategies spread adoption across the network (Fig. 4). At low activation thresholds (0.01–0.1), all seed selection strategies performed similarly, and the maximum influence strategy showed only a modest advantage, even at larger seed set sizes where all approaches achieved 10–15 activated nodes. At intermediate activation thresholds (0.2–0.5), differences in seed selection strategy emerged; top-down selection outperformed bottom-up, random, and even occasionally approached maximum influence performance for seed set sizes of three or more. Notably, bottom-up selection continued to have an advantage at the smallest seed set size (n = 1). At high thresholds (0.6–0.9), bottom-up, top-down, and random seed selection strategies had similar low node activation levels (about 2–8 nodes), while maximum influence seeds maintained higher node activation (~15 nodes).

Across both IC and LT models, varying the normalization function for empirical edge weights had little influence on the relative performance of seed selection strategies or overall node activation. Regardless of whether communication frequency was transformed using percentile, linear, half-linear, sigmoidal, or inverted growth curve functions, the relative ordering of favorable seed selection strategies was maintained (Fig. 3, Fig. 4). In the IC model, bottom-up generally exceeded top-down and random selection, while in the LT model, the three non-optimized strategies often had similar performance except at intermediate activation thresholds where top-down held a slight edge. The magnitude of differences between strategies also remained consistent across normalization functions. These results suggest that uncertainty in how communication frequency translates to influence does not disrupt core diffusion dynamics; advantages associated with empirical communication patterns and seed selection methods remain intact across various normalization approaches.

Research Question 2: How does the number of social connections (i.e., edges) differ among local, state, federal and NGO actors?

Connections in the Red River Basin network were unevenly distributed, with some organization types far more connected than others. A chi-square test revealed strong statistical evidence that connections in the Red River Basin network are not distributed proportionally to the number of organizations in each category (X2 = 17.94, degree freedom = 3, $p < 0.001$, Table 2). NGO organizations were the most over-connected group, having 52% more connections than expected, while local organizations were under-connected with 24% fewer connections than expected. This robust presence of NGO connections and, to a lesser extent, local organizations align with the benefits of bottom-up seed selection strategies observed in IC simulation models, where greater node activation was observed from these governance levels. State organizations, which dominate the network numerically, were slightly under-connected (8% fewer connections than expected); the only federal organization was moderately over-connected, maintaining 57% more connections than predicted by proportional distribution. These deviations from proportionality suggest that certain organizational types occupy disproportionately influential positions in the network.

Research Question 3: How does communication frequency (i.e., edge weight) differ between local, state, federal and NGO actors?

Communication frequency varied across the network, with local organizations consistently ranking among the most frequent communicators. The ANOVA and Tukey HSD results indicate that mean communication frequency differs significantly among two organization types ($p < 0.001$, $F = 7.04$; Table 3). The only statistically significant pairwise difference was between local and state organizations, with local organizations communicating more frequently on average (mean normalized edge weight = 0.619) than state organizations (0.414, $p < 0.001$). While no other pairwise differences were statistically significant, local organizations consistently had higher mean communication frequencies than any other group in the network, followed by NGOs (0.501), which also ranked high in the Chi-square analysis for over-connectedness. This combination of frequent communication and a substantial share of network connections for both local and NGO organization nodes mirrors the performance advantage of bottom-up seed selection strategies in the IC model simulations. In contrast, state organizations, despite their numerical dominance, exhibited the lowest mean communication frequencies, matching federal organizations at 0.414. The federal organization in the network was moderately over connected and yet had relatively low communication frequency.

State organizations served as the main communication hubs, while NGOs and local organizations provide valuable cross-network connections. The chord diagram presents the empirical communication flows among organization types in the Red River Basin network (Fig. 5). State organizations dominate communication across the network, with substantial exchanges both among various state organizations and externally with NGOs and local organizations. Local organizations maintain frequent communication and their interactions are distributed across several organization types, which aligns with the higher mean communication frequency observed in the ANOVA results. NGOs communicate most robustly with state organizations, which is consistent with their over-connected status in the chi-square analysis. The single federal organization maintains relatively slim communication links with all other organization types, suggesting limited integration in the network despite being moderately over-connected and hierarchal advantage. These patterns highlight the central role of state organizations as primary communication hubs, while underscoring the active cross network linkages fostered by NGOs and local organization actors.

Discussion

Our findings highlight three key insights for advancing conservation practice adoption in complex social networks. First, bottom-up actors consistently drove the most effective spread of conservation practices across a range of modeling conditions, underscoring the value of engaging local and NGO organizations in programs. Second, the structure and intensity of communication within the network was uneven. NGOs and local organizations combined broad connections and frequent communication interactions, while state agencies were widely present in the network but less connected, and federal actors held dominate structural positions without strong communication ties. Finally, our results point to the potential of aligning top-down policy frameworks with bottom-up engagement to create shared objectives and communication pathways, offering a practical strategy for scaling conservation programs under real-world constraints.

Our results emphasize the central role of bottom-up actors in driving adoption of conservation practices. In the IC model, bottom-up initiation consistently produced the highest activation among practical seed selection strategies, reflecting the structural connections and communication behaviors of different organization types in the RRB network. NGOs were notably over-connected, linking across governance levels, while local organizations, though less connected overall, maintained frequent communication. This combination of network reach and sustained engagement likely underpins the effectiveness of bottom-up initiation, enabling information flow across the network. Similar patterns have been reported in other conservation contexts, where community-led organizations were central to increased communication and engagement, participatory governance, and enhanced management outcomes by strengthening relationships with formal institutions (Enqvist et al., 2020; Farwig et al., 2024; Mc Culloch-Jones et al., 2021). These results reinforce longstanding arguments that conservation interventions benefit when locally embedded organizations lead adoption efforts, especially when programs require legitimacy, trust, and local knowledge to achieve long-term success (N. J. Bennett & Dearden, 2014; Geekiyanage et al., 2020; Mc Culloch-Jones et al., 2021; Ranjan et al., 2019; Toderi et al., 2017).

In contrast, the LT model revealed contexts where top-down initiation provided adoption benefits, particularly under intermediate levels of resistance. This finding aligns with empirical studies showing that top-down programs can be effective when policy direction and resources align with local priorities (Eicken et al., 2021; Mc Culloch-Jones et al., 2021). However, such benefits can be contingent on stakeholder agreement; when shared objectives are absent, participation can stall, and adoption levels plateau as stakeholders selectively engage in actions serving their immediate interests (Fraser et al., 2006; Mc Culloch-Jones et al., 2021). Under the most challenging conditions, represented by the highest activation thresholds, where practice adoption faces complex institutional, social, or economic barriers, all practical seed strategies converged at low activation levels, with only the maximum-influence seed set sustaining substantial adoption. This pattern suggests that in highly resistant circumstances, such as undergoing large-scale ecological or governance transitions, identifying transformational change leaders may be essential to mobilize networks and launch widespread conservation adoption (Iyengar et al., 2011; Valente & Pumpuang, 2007; Westley et al., 2011).

Statistical analyses revealed uneven patterns of connectivity and communication across organization types in the RRB network, with important implications for developing conservation programs. NGOs were highly connected across governance levels and maintained frequent communication interactions, enabling them to link disparate parts of the network (Bodin & Crona, 2009; Mbaru & Barnes, 2017). Local organizations, while less connected overall, demonstrated similarly high levels of communication, positioning them to engage effectively with multiple organization types. In contrast, state organizations occupied central structural positions yet exhibited lower average communication frequency, suggesting that while they may serve as hubs for information flow, they are less likely to promote diffusion compared to NGOs and local actors. The single federal organization was structurally over-connected but maintained only minimal communication ties, indicating limited functional integration despite hierarchical authority and network reach. These patterns suggest that actors combining cross-network connections with frequent interactions, in this case, particularly NGOs and local organizations, hold strategic value for initiating conservation programs and accelerating the spread of new practices.

Taken together, these findings underscore the potential of integrating bottom-up engagement with top-down policy support to accelerate conservation adoption. Engaging well-connected NGOs and highly communicative local organizations can promote information diffusion efficiently without requiring centralized coordination across all actors, while top-down institutions provide enabling policies, regulatory frameworks, and resources that can sustain adoption as programs scale. This aligns with calls for integrated governance approaches that bridge local initiatives with formal institutional directives to create shared objectives and robust communication pathways (Alexander et al., 2018; Conti et al., 2025; Ding et al., 2023; Eicken et al., 2021; Fraser et al., 2006; Toderi et al., 2017). Yet, lessons from decentralized governance approaches should inform future efforts, findings have also demonstrated that that decentralized governance structures can be incumbered by disconnection among actors and governance levels (Borgström, 2019). Likewise, bottom-up collaborations may benefit from some degree of top-down assistance to align social and ecological actions (Guerrero et al., 2015). Recognizing limitations, the structural advantages of network connectivity and communication frequency offer a practical substitute for computationally intensive optimization tools when identifying influential starting points. For conservation practitioners with limited time and resources, strategically engaging actors based on these network attributes provides an evidence-based approach to prioritize outreach efforts and attempts to improve adoption outcomes under real-world constraints.

Although, this study applies two of the most common information diffusion models both the models and their application have limitations. One limitation lies in the Boolean treatment of nodes as either active or inactive, whereas human behavior is more nuanced; for example, individuals may participate partially or for a limited time before engagement declines. Similarly, these models simplify complex human decision-making; edge weights and model activation can only approximate the strength and variability of real-world relationships. While our parameter estimates were reasonable, the models remain simplified representations of social interaction. A further limitation is that activation probabilities and thresholds are not empirically calibrated to observed conservation practice adoption; instead, they represent a range of possibilities that allow comparative insights but not predictive information. Another limitation is the lack of temporal dynamics, as networks and human interactions evolve over time tracking these changes could provide important insights.

It would be useful for additional research to explore the underlying motivations and attributes that shape tie strength within conservation networks, including factors such as trust, reciprocity, and shared objectives (K. Church et al., 2023; Loch & Kleinschmit, 2025; Teixidor-Toneu et al., 2025). While our findings emphasize the importance of communication frequency and structural connectivity for information diffusion, understanding why some actors form stronger or weaker ties could reveal additional leverage points for accelerating conservation practice adoption. Longitudinal studies would also provide critical insight into how network structures and interactions evolve as conservation programs mature (Ingold & Fischer, 2014). For example, does early momentum foster enduring collaboration, and how do connectivity and interaction patterns shift as programs transition from launch to long-term implementation? Conversely, when initiatives lose funding, capacity, or stakeholder engagement, how are these declines reflected in network structure or the nature of actor interactions? Such research could illuminate how governance arrangements, social dynamics, and conservation outcomes co-evolve over time, offering guidance for designing programs that remain effective and resilient under changing ecological and social conditions.

Scaling conservation to address global challenges such as climate change and biodiversity loss requires strategies that balance local initiatives with regional and national program requirements. Bottom-up diffusion processes, as revealed in our findings, align closely with co-management frameworks that emphasize local autonomy, iterative learning, and flexible governance responses (Olsson et al., 2008). Strong roles for local and NGO actors mirror results from community-based conservation studies where trust, frequent communication, and cross-network engagement drive collective action and implementation success (Alix-Garcia et al., 2018; Barnes et al., 2016). Although, top-down agencies remain essential for providing enabling conditions through funding, policy, and technical support, our results suggest they can lack the communication reach necessary to match the diffusion efficiency of local actors. Conservation planning may therefore benefit from hybrid governance strategies where centralized institutions establish regulatory and resource frameworks, while local and NGO organizations spearhead adoption, ensuring programs are both scalable and locally legitimate; such integrated approaches have been widely called for in environmental governance literature (Armitage et al., 2012; J. R. Bennett et al., 2018; Folke et al., 2005; Partelow et al., 2020; Wyborn & Bixler, 2013). Bridging top-down environmental program frameworks with local actor knowledge, motivation, and communication capacity offers a critical pathway toward conservation practices that are both scalable and resilient in the face of dramatic ecological and social change.

References

Agha Mohammad Ali Kermani, M., Ghesmati, R., & Pishvaee, M. S. (2021). A robust optimization model for influence maximization in social networks with heterogeneous nodes. Comput Soc Netw, 8(1), 17. https://doi.org/10.1186/s40649-021-00096-x

Alexander, S. M., Epstein, G., Bodin, Ö., Armitage, D., & Campbell, D. (2018). Participation in planning and social networks increase social monitoring in community-based conservation. CONSERVATION LETTERS, 11(5). https://doi.org/10.1111/conl.12562

Alix-Garcia, J. M., Sims, K. R. E., Orozco-Olvera, V. H., Costica, L. E., Fernández Medina, J. D., & Romo Monroy, S. (2018). Payments for environmental services supported social capital while increasing land management. Proceedings of the National Academy of Sciences, 115(27), 7016–7021. https://doi.org/10.1073/pnas.1720873115

Armitage, D., de Loë, R., & Plummer, R. (2012). Environmental governance and its implications for conservation practice: Environmental governance. Conservation Letters, 5(4), 245–255. https://doi.org/10.1111/j.1755-263X.2012.00238.x

Azaouzi, M., Mnasri, W., & Ben Romdhane, L. (2021). New trends in influence maximization models. Computer Science Review, 40, 100393. https://doi.org/10.1016/j.cosrev.2021.100393

Ballarini, E., D'Adamo, R., Pazienza, G., Zaggia, L., & Vafeidis, A. (2021). Assessing the applicability of a bottom-up or top-down approach for effective management of a coastal lagoon area. Ocean & Coastal Management, 200, 105417. https://doi.org/10.1016/j.ocecoaman.2020.105417

Ban, N. C., Mills, M., Tam, J., Hicks, C. C., Klain, S., Stoeckl, N., Bottrill, M. C., Levine, J., Pressey, R. L., Satterfield, T., & Chan, K. M. (2013). A social–ecological approach to conservation planning: Embedding social considerations. Frontiers in Ecology and the Environment, 11(4), 194–202. https://doi.org/10.1890/110205

Barnes, M. L., Lynham, J., Kalberg, K., & Leung, P. (2016). Social networks and environmental outcomes. Proceedings of the National Academy of Sciences, 113(23), 6466–6471. https://doi.org/10.1073/pnas.1523245113

Bennett, J. R., Maxwell, S. L., Martin, A. E., Chadès, I., Fahrig, L., & Gilbert, B. (2018). When to monitor and when to act: Value of information theory for multiple management units and limited budgets. Journal of Applied Ecology, 55(5), 2102–2113. https://doi.org/10.1111/1365-2664.13132

Bennett, N. J., & Dearden, P. (2014). Why local people do not support conservation: Community perceptions of marine protected area livelihood impacts, governance and management in Thailand. Marine Policy, 44, 107–116. https://doi.org/10.1016/j.marpol.2013.08.017

Bennett, N. J., Roth, R., Klain, S. C., Chan, K., Christie, P., Clark, D. A., Cullman, G., Curran, D., Durbin, T. J., Epstein, G., Greenberg, A., Nelson, M. P., Sandlos, J., Stedman, R., Teel, T. L., Thomas, R., Veríssimo, D., & Wyborn, C. (2017). Conservation social science: Understanding and integrating human dimensions to improve conservation. Biological Conservation, 205, 93–108. https://doi.org/10.1016/j.biocon.2016.10.006

Bodin, Ö., & Crona, B. I. (2009). The role of social networks in natural resource governance: What relational patterns make a difference? Global Environmental Change, 19(3), 366–374. https://doi.org/10.1016/j.gloenvcha.2009.05.002

Bodin, Ö., Robins, G., McAllister, R. R. J., Guerrero, A. M., Crona, B., Tengö, M., & Lubell, M. (2016). Theorizing benefits and constraints in collaborative environmental governance: A transdisciplinary social-ecological network approach for empirical investigations. Ecology and Society, 21(1), art40. https://doi.org/10.5751/ES-08368-210140

Borgström, S. (2019). Balancing diversity and connectivity in multi-level governance settings for urban transformative capacity. Ambio, 48(5), 463–477. https://doi.org/10.1007/s13280-018-01142-1

Conti, C., Hall, A., Moallemi, E. A., Laila, A., Bene, C., Fanzo, J., Gibson, M. F., Gordon, L., Hicks, C., Kok, K., Rao, N., Laxminarayan, R., & Mason-D'Croz, D. (2025). Top-down vs bottom-up processes: A systematic review clarifying roles and patterns of interactions in food system transformation. Global Food Security, 44, 100833. https://doi.org/10.1016/j.gfs.2025.100833

Ding, Z., Zheng, H., Wang, J., O'Connor, P., Li, C., Chen, X., Li, R., & Ouyang, Z. (2023). Integrating Top-Down and Bottom-Up Approaches Improves Practicality and Efficiency of Large-Scale Ecological Restoration Planning: Insights from a Social–Ecological System. Engineering, 31, 50–58. https://doi.org/10.1016/j.eng.2022.08.008

Dowd, A.-M., Marshall, N., Fleming, A., Jakku, E., Gaillard, E., & Howden, M. (2014). The role of networks in transforming Australian agriculture. Nature Climate Change, 4(7), 558–563. https://doi.org/10.1038/nclimate2275

Eicken, H., Danielsen, F., Sam, J.-M., Fidel, M., Johnson, N., Poulsen, M. K., Lee, O. A., Spellman, K. V., Iversen, L., Pulsifer, P., & Enghoff, M. (2021). Connecting Top-Down and Bottom-Up Approaches in Environmental Observing. BioScience, 71(5), 467–483. https://doi.org/10.1093/biosci/biab018

Enloe, S. K., Schulte, L. A., & Tyndall, J. C. (2017). Public–Private Partnerships Working Beyond Scale Challenges toward Water Quality Improvements from Private Lands. Environmental Management, 60(4), 574–587. https://doi.org/10.1007/s00267-017-0905-5

Enqvist, J. P., Tengö, M., & Bodin, Ö. (2020). Are bottom-up approaches good for promoting social–ecological fit in urban landscapes? Ambio, 49(1), 49–61. https://doi.org/10.1007/s13280-019-01163-4

Farwig, N., Sprenger, P. P., Baur, B., Böhning-Gaese, K., Brandt, A., Eisenhauer, N., Ellwanger, G., Hochkirch, A., Karamanlidis, A. A., Mehring, M., Pusch, M., Rehling, F., Sommerwerk, N., Spatz, T., Svenning, J.-C., Tischew, S., Tockner, K., Tscharntke, T., Vadrot, A. B. M., … Mosbrugger, V. (2024). Identifying Major Factors for Success and Failure of Conservation Programs in Europe. Environmental Management. https://doi.org/10.1007/s00267-024-02086-x

Folke, C., Hahn, T., Olsson, P., & Norberg, J. (2005). ADAPTIVE GOVERNANCE OF SOCIAL-ECOLOGICAL SYSTEMS. Annu. Rev. Environ. Resour., 30(1), 441–473. https://doi.org/10.1146/annurev.energy.30.050504.144511

Fraser, E. D. G., Dougill, A. J., Mabee, W. E., Reed, M., & McAlpine, P. (2006). Bottom up and top down: Analysis of participatory processes for sustainability indicator identification as a pathway to community empowerment and sustainable environmental management. Journal of Environmental Management, 78(2), 114–127. https://doi.org/10.1016/j.jenvman.2005.04.009

Geekiyanage, D., Fernando, T., & Keraminiyage, K. (2020). Assessing the state of the art in community engagement for participatory decision-making in disaster risk-sensitive urban development. International Journal of Disaster Risk Reduction, 51, 101847. https://doi.org/10.1016/j.ijdrr.2020.101847

Guerrero, A. M., Bodin, Ö., McAllister, R. R. J., & Wilson, K. A. (2015). Achieving social-ecological fit through bottom-up collaborative governance: An empirical investigation. Ecology and Society, 20(4), art41. https://doi.org/10.5751/ES-08035-200441

Gulati, R., Sytch, M., & Tatarynowicz, A. (2012). The Rise and Fall of Small Worlds: Exploring the Dynamics of Social Structure. Organization Science, 23(2), 449–471. https://doi.org/10.1287/orsc.1100.0592

Hunter, R. F., De La Haye, K., Murray, J. M., Badham, J., Valente, T. W., Clarke, M., & Kee, F. (2019). Social network interventions for health behaviours and outcomes: A systematic review and meta-analysis. PLOS Medicine, 16(9), e1002890. https://doi.org/10.1371/journal.pmed.1002890

Hussain, O. (2021). Influence.mining (Version 0.2.4) [Computer software]. https://github.com/seekme94/influence.mining

Ingold, K., & Fischer, M. (2014). Drivers of collaboration to mitigate climate change: An illustration of Swiss climate policy over 15 years. Global Environmental Change, 24, 88–98. https://doi.org/10.1016/j.gloenvcha.2013.11.021

Iyengar, R., Van Den Bulte, C., & Valente, T. W. (2011). Opinion Leadership and Social Contagion in New Product Diffusion. Marketing Science, 30(2), 195–212. https://doi.org/10.1287/mksc.1100.0566

K. Church, E., A. Wilson, K., & J. Dean, A. (2023). Broadening our understanding of what drives stewardship engagement: Relationships between social capital and willingness to engage in nature stewardship. Journal of Environmental Management, 342, 118128. https://doi.org/10.1016/j.jenvman.2023.118128

Kaweesa, S., Mkomwa, S., & Loiskandl, W. (2018). Adoption of Conservation Agriculture in Uganda: A Case Study of the Lango Subregion. Sustainability, 10(10), 3375. https://doi.org/10.3390/su10103375

Koontz, T. M., & Newig, J. (2014). From Planning to Implementation: Top-Down and Bottom-Up Approaches for Collaborative Watershed Management: Implementing Collaborative Watershed Plans. Policy Studies Journal, 42(3), 416–442. https://doi.org/10.1111/psj.12067

Leclère, D., Obersteiner, M., Barrett, M., Butchart, S. H. M., Chaudhary, A., De Palma, A., DeClerck, F. A. J., Di Marco, M., Doelman, J. C., Dürauer, M., Freeman, R., Harfoot, M., Hasegawa, T., Hellweg, S., Hilbers, J. P., Hill, S. L. L., Humpenöder, F., Jennings, N., Krisztin, T., … Young, L. (2020). Bending the curve of terrestrial biodiversity needs an integrated strategy. Nature, 585(7826), 551–556. https://doi.org/10.1038/s41586-020-2705-y

Levin, D. Z., & Cross, R. (2004). The Strength of Weak Ties You Can Trust: The Mediating Role of Trust in Effective Knowledge Transfer. Management Science, 50(11), 1477–1490. https://doi.org/10.1287/mnsc.1030.0136

Lin, Y., & Lui, J. C. S. (2014). Algorithmic Design for Competitive Influence Maximization Problems (No. arXiv:1410.8664). arXiv. http://arxiv.org/abs/1410.8664

Loch, T. K., & Kleinschmit, D. (2025). Building connections: Exploring social network research in forest sciences. Forest Policy and Economics, 170, 103382. https://doi.org/10.1016/j.forpol.2024.103382

Mbaru, E. K., & Barnes, M. L. (2017). Key players in conservation diffusion: Using social network analysis to identify critical injection points. Biological Conservation, 210, 222–232. https://doi.org/10.1016/j.biocon.2017.03.031
Mc Culloch-Jones, S., Novellie, P., Roux, D. J., & Currie, B. (2021). Exploring the alignment between the bottom-up and top-down objectives of a landscape-scale conservation initiative. Environmental Conservation, 48(4), 255–263. https://doi.org/10.1017/S0376892921000321

Montgomery, S. C., Donnelly, M., Bhatnagar, P., Carlin, A., Kee, F., & Hunter, R. F. (2020). Peer social network processes and adolescent health behaviors: A systematic review. Preventive Medicine, 130, 105900. https://doi.org/10.1016/j.ypmed.2019.105900

Nesbitt, H. K., Metcalf, A. L., Floyd, T. M., Uden, D. R., Chaffin, B. C., Gulab, S., Banerjee, S., Vallury, S., Hamlin, S. L., Metcalf, E. C., Fogarty, D. T., Twidwell, D., & Allen, C. R. (2024). Social networks and transformative behaviours in a grassland social-ecological system. People and Nature, 6(5), 1877–1892. https://doi.org/10.1002/pan3.10695

Niemiec, R. M., Gruby, R., Quartuch, M., Cavaliere, C. T., Teel, T. L., Crooks, K., Salerno, J., Solomon, J. N., Jones, K. W., Gavin, M., Lavoie, A., Stronza, A., Meth, L., Enrici, A., Lanter, K., Browne, C., Proctor, J., & Manfredo, M. (2021). Integrating social science into conservation planning. Biological Conservation, 262, 109298. https://doi.org/10.1016/j.biocon.2021.109298

Olsson, P., Folke, C., & Hughes, T. P. (2008). Navigating the transition to ecosystem-based management of the Great Barrier Reef, Australia. Proceedings of the National Academy of Sciences, 105(28), 9489–9494. https://doi.org/10.1073/pnas.0706905105

Partelow, S., Schlüter, A., Armitage, D., Bavinck, M., Carlisle, K., Gruby, R. L., Hornidge, A.-K., Le Tissier, M., Pittman, J. B., Song, A. M., Sousa, L. P., Văidianu, N., & Van Assche, K. (2020). Environmental governance theories: A review and application to coastal systems. E&S, 25(4), art19. https://doi.org/10.5751/ES-12067-250419

Ranjan, P., Church, S. P., Floress, K., & Prokopy, L. S. (2019). Synthesizing Conservation Motivations and Barriers: What Have We Learned from Qualitative Studies of Farmers' Behaviors in the United States? Society & Natural Resources, 32(11), 1171–1199. https://doi.org/10.1080/08941920.2019.1648710

Rathwell, K. J., & Peterson, G. D. (2012). Connecting Social Networks with Ecosystem Services for Watershed Governance: A Social-Ecological Network Perspective Highlights the Critical Role of Bridging Organizations. Ecology and Society, 17(2), art24. https://doi.org/10.5751/ES-04810-170224

Rilov, G., Fraschetti, S., Gissi, E., Pipitone, C., Badalamenti, F., Tamburello, L., Menini, E., Goriup, P., Mazaris, A. D., Garrabou, J., Benedetti-Cecchi, L., Danovaro, R., Loiseau, C., Claudet, J., & Katsanevakis, S. (2020). A fast-moving target: Achieving marine conservation goals under shifting climate and policies. Ecological Applications, 30(1), e02009. https://doi.org/10.1002/eap.2009
Saito, K., Kimura, M., Ohara, K., & Motoda, H. (2016). Super mediator – A new centrality measure of node importance for information diffusion over social network. Information Sciences, 329, 985–1000. https://doi.org/10.1016/j.ins.2015.03.034

Shakarian, P., Bhatnagar, A., Aleali, A., Shaabani, E., & Guo, R. (2015). Diffusion in social networks. Springer.

Singh, S. S., Kumar, A., Singh, K., & Biswas, B. (2019). LAPSO-IM: A learning-based influence maximization approach for social networks. Applied Soft Computing, 82, 105554. https://doi.org/10.1016/j.asoc.2019.105554

Szilágyi, G. A. (2017). Exploration Knowledge Sharing Networks Using Social Network Analysis Methods. Economics & Sociology, 10(3), 179–191. https://doi.org/10.14254/2071-789X.2017/10-3/13

Teixidor-Toneu, I., Fernández-Llamazares, Á., Alvarez Abel, R., Batdelger, G., Bell, E., Caillon, S., Cantor, M., Correia, J. E., Díaz, S., Fisk, J., Greene, A., Greening, S., Hoyte, S., Kalle, R., Loayza, G., Mattalia, G., Montúfar, R., Ojeda, J., Phatthanaphraiwan, S., … Ban, N. C. (2025).

Human–nature relationships through the lens of reciprocity: Insights from Indigenous and local knowledge systems. People and Nature, 7(5), 922–933. https://doi.org/10.1002/pan3.70036

Tickner, D., Opperman, J. J., Abell, R., Acreman, M., Arthington, A. H., Bunn, S. E., Cooke, S. J., Dalton, J., Darwall, W., Edwards, G., Harrison, I., Hughes, K., Jones, T., Leclère, D., Lynch, A. J., Leonard, P., McClain, M. E., Muruven, D., Olden, J. D., … Young, L. (2020). Bending the Curve of Global Freshwater Biodiversity Loss: An Emergency Recovery Plan. BioScience, 70(4), 330–342. https://doi.org/10.1093/biosci/biaa002

Toderi, M., Francioni, M., Seddaiu, G., Roggero, P. P., Trozzo, L., & D'Ottavio, P. (2017). Bottom-up design process of agri-environmental measures at a landscape scale: Evidence from case studies on biodiversity conservation and water protection. Land Use Policy, 68, 295–305. https://doi.org/10.1016/j.landusepol.2017.08.002

Uzzi, B., & Spiro, J. (2005). Collaboration and Creativity: The Small World Problem. American Journal of Sociology, 111(2), 447–504. https://doi.org/10.1086/432782

Valente, T. W., & Pumpuang, P. (2007). Identifying Opinion Leaders to Promote Behavior Change. Health Educ Behav, 34(6), 881–896. https://doi.org/10.1177/1090198106297855

Westley, F., Olsson, P., Folke, C., Homer-Dixon, T., Vredenburg, H., Loorbach, D., Thompson, J., Nilsson, M., Lambin, E., Sendzimir, J., Banerjee, B., Galaz, V., & van der Leeuw, S. (2011). Tipping Toward Sustainability: Emerging Pathways of Transformation. AMBIO, 40(7), 762–780. https://doi.org/10.1007/s13280-011-0186-9

Wineland, S. M., Fovargue, R., York, B., Lynch, A. J., Paukert, C. P., & Neeson, T. M. (2021). Is there enough water? How bearish and bullish outlooks are linked to decision maker perspectives on environmental flows. Journal of Environmental Management, 280, 111694. https://doi.org/10.1016/j.jenvman.2020.111694

Wineland, S. M., & Neeson, T. M. (2022). Maximizing the spread of conservation initiatives in social networks. Conservation Science and Practice. https://doi.org/10.1111/csp2.12740

Wyborn, C., & Bixler, R. P. (2013). Collaboration and nested environmental governance: Scale dependency, scale framing, and cross-scale interactions in collaborative conservation. Journal of Environmental Management, 123, 58–67. https://doi.org/10.1016/j.jenvman.2013.03.014

Tables

Table 3-1 Summary of experiments and simulation parameters used to evaluate information diffusion in the Red River Basin Network. Edge weights, seed set size, activation probability/threshold, seed selection strategy, and communication normalization functions were varied across both the IC and LT models to evaluate information diffusion.

Simulation parameter values	
Parameter	
Model	Independent Cascade (IC) & Linear Threshold (LT)
Edge weights	Empirical communication frequency (survey data)
Seed set size	1,2,3,4,5
Activation probability (IC model)	Edge weights
Activation threshold (LT model)	0.01, 0.05, 0.1-0.9 at interval of 0.1
Seed selection strategy	• Top-down • Bottom-up • Random • Maximum
Communication normalization functions	• Percentile normalization • Linear, zero to 1 • Linear, zero to 0.5 • Sigmoidal • Inverted growth curve

Table 3-2 Chi-square test of proportional connections by organization type in the Red River Basin network. NGOs were significantly over connected organization type ($p < 0.001$).

Chi Square Test						
Org. Type	**Count of Org.**	**Observed Conn.**	**Expected Conn.**	**Proportion of Conn.**	**Residual**	**Conn. Status**
Federal	1	14	9	0.065	+1.70	Moderate over connected
State	12	98	107	0.46	-0.87	Slightly under connected
Local	7	47	62	0.22	-1.95	Considerabl e under connected
NGO	4	55	36	0.26	+3.24	Extremely over connected

Table 3-3 Results of ANOVA and Tukey HSD comparison of mean normalized communication frequency between organize types. The only statistically significant difference was between local and state organizations, with local organizations communicating more frequently on average.

ANOVA Summary				
Comparison	**Org 1 Mean (SD)**	**Org 2 Mean (SD)**	**Adjusted P-val**	**Significant**
Local-Fed	0.619 (0.307)	0.414 (0.306)	0.0766	No
NGO-Fed	0.501 (0.300)	0.414 (0.306)	0.7319	No
State-Fed	0.414 (0.267)	0.414 (0.306)	1.0000	No
NGO-Local	0.501 (0.300)	0.619 (0.307)	0.1232	No
State-Local	0.414 (0.267)	0.619 (0.307)	6.9e-05	Yes
State-NGO	0.414 (0.267)	0.501 (0.300)	0.2148	No
Normalized edge weights were used for this analysis				

Figures

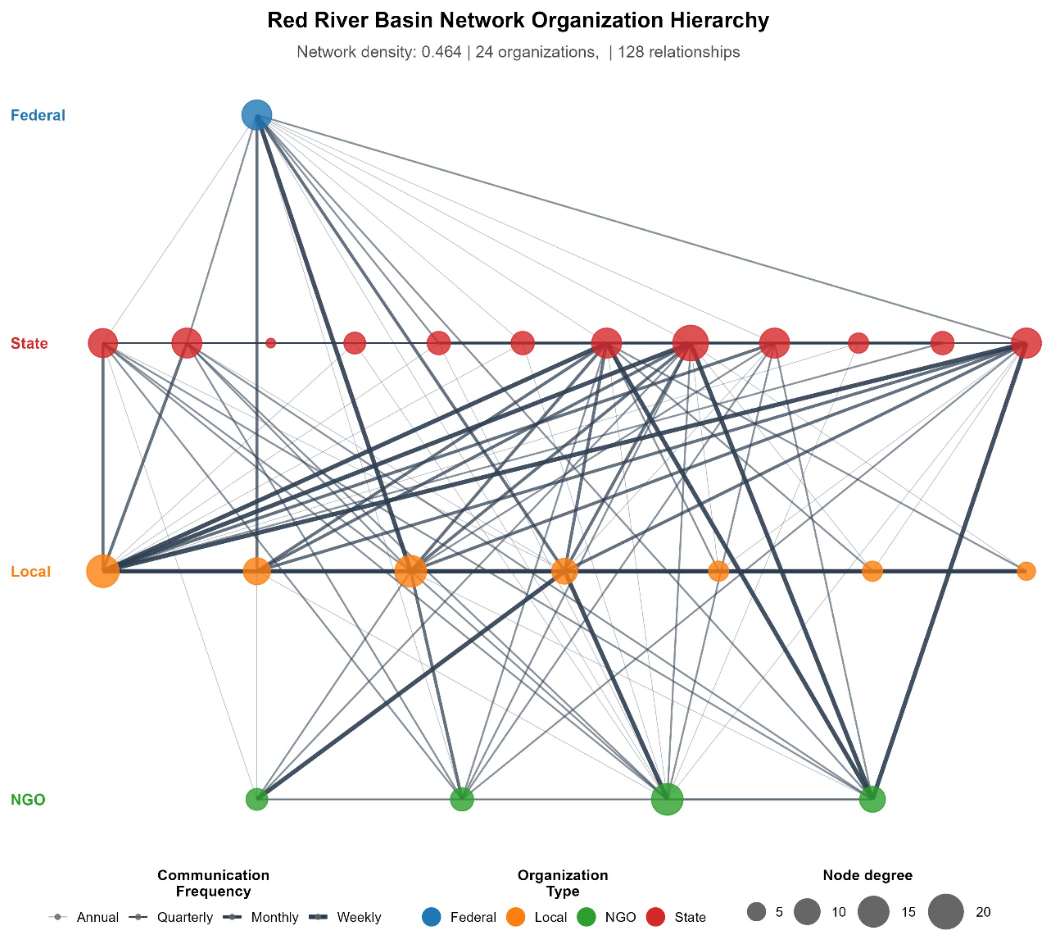

Figure 3-1 Network diagram of the Red River Basin (RRB) communication network illustrating the relationships among 24 organizations (nodes) and 128 reported communication links (edges). Nodes are color-coded by organization type (Federal = blue, State = red, Local = orange, NGO = green) and sized by node degree (number of connections). Edges are weighted and vary in thickness and darkness to represent communication frequency (annual, quarterly, monthly, or weekly). Thicker and darker lines indicate more frequent communication. Node positions are arranged hierarchically by organizational level to highlight directional patterns in cross-level communication. Network density is 0.464, indicating a relatively high level of connectivity among actors in the RRB conservation network.

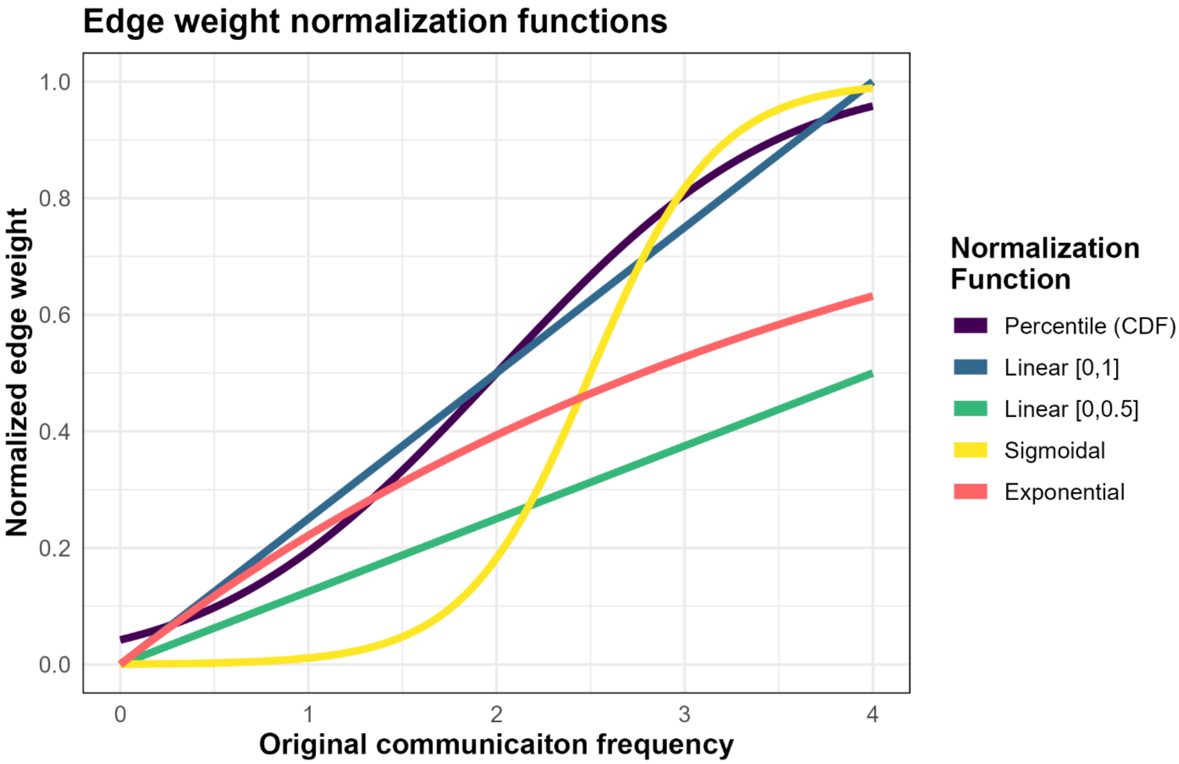

Figure 3-2 Comparison of five normalization functions used to transform original communication frequencies (0 never, 1 annually, 2 quarterly, 3 monthly, 4 weekly) into normalized edge weights for simulation experiments. Functions include percentile (CDF), linear (0-1), linear (0-0.5), sigmoidal, and exponential (inverted growth curve).

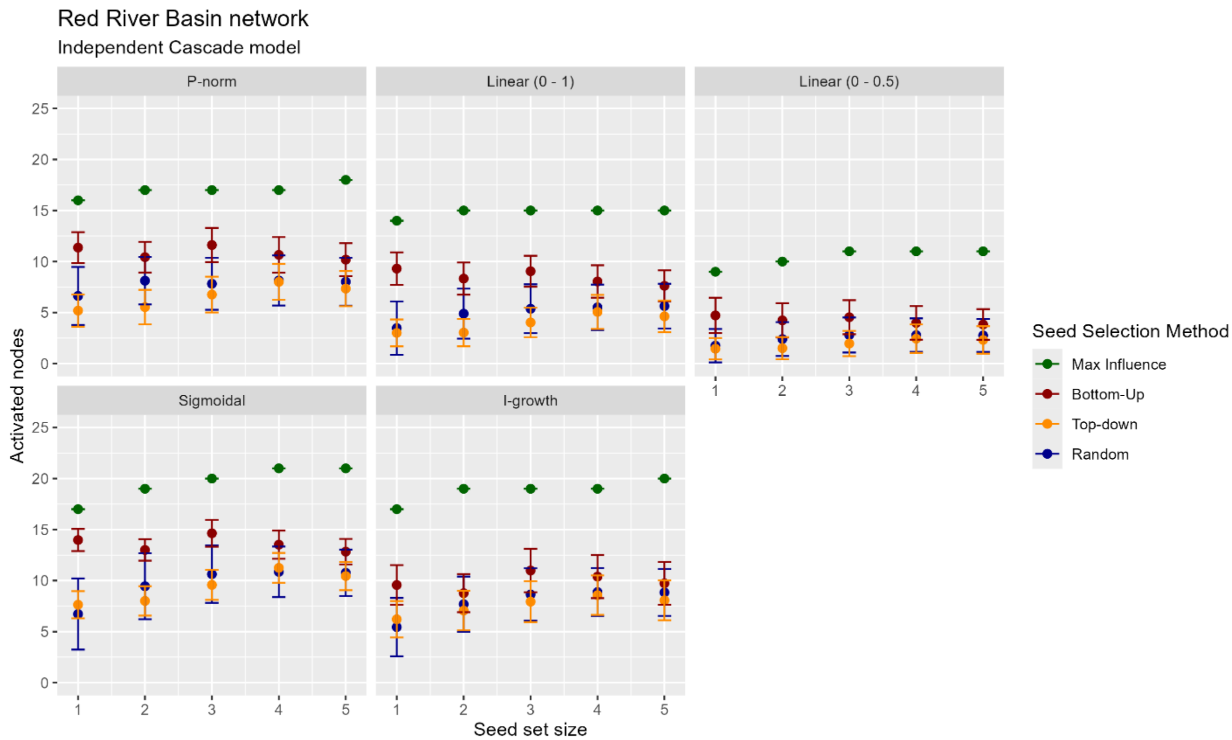

Figure 3-3 Independent Cascade simulations for the Red River Basin network with empirical edge weights across five communication normalization functions. Points show mean number of activated nodes for each combination of seed set size and selection strategy.

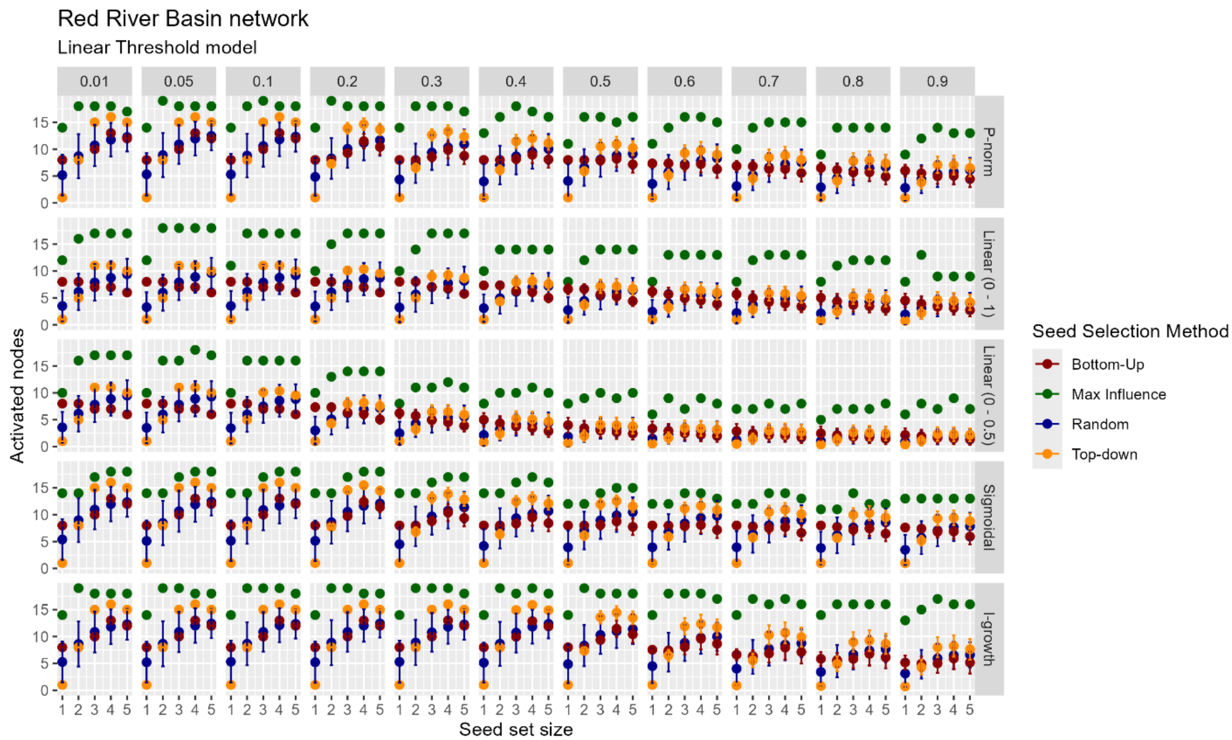

Figure 3-4 Linear Threshold simulations for the Red River Basin network with empirical edge weights across five communication normalization functions. Points show mean number of activated nodes for each combination of seed set size and selection strategy.

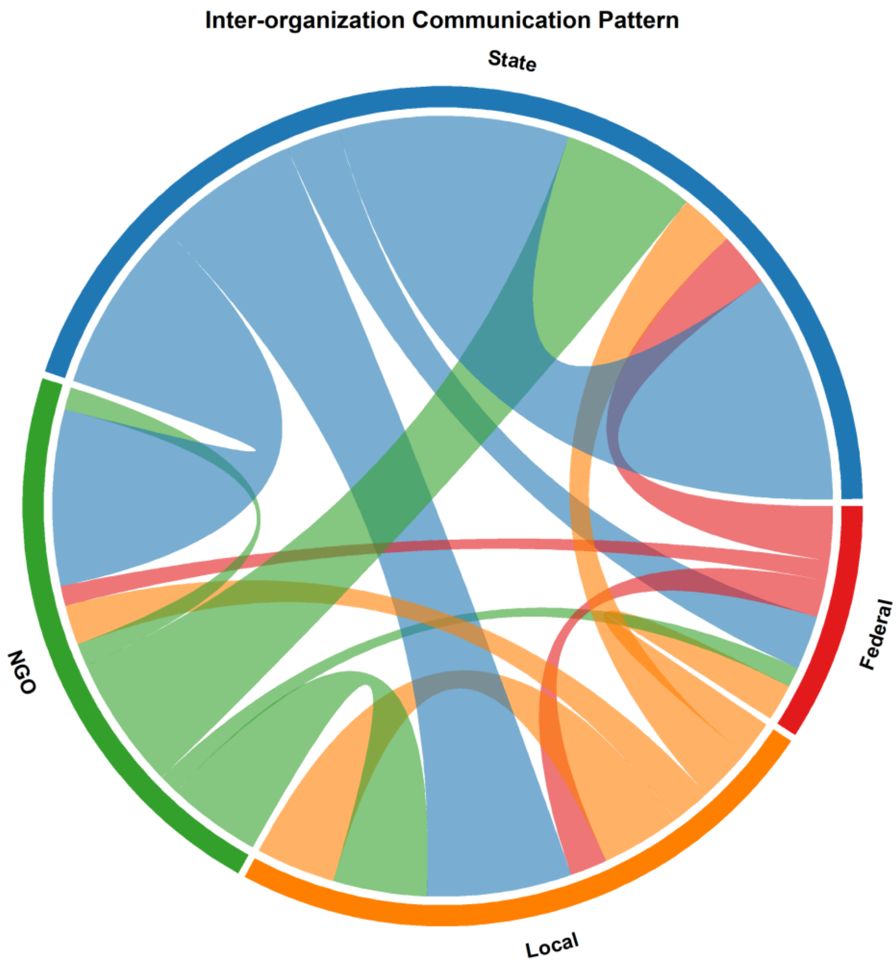

Figure 3-5 Chord diagram of empirical communication flows among the organization types in the Red River Basin network. Ribbon thickness indicates the relative frequency of communication between organizations based on network edge weights.

Conclusion

Conservation outcomes depend not only on ecological conditions but also on the social systems of conservation actors that guide decisions, shape collaboration, and determine whether practices are adopted (Farwig et al., 2024; K. Maxwell et al., 2019; Neeson et al., 2022; Nesbitt et al., 2024). Findings from these studies highlight that conservation is both a social and ecological process, formed by the interaction of data, relationships, and institutional structures that can both promote or constrain how decisions are made and practices implemented

The first chapter demonstrates that despite the widespread use of spatial data, critical information desired by water resource managers was missing. Managers routinely identified a need for economic and socio-political information such as project costs, incentives, and organizational responsibilities, which were rarely included in biophysical datasets. The most significant barriers to watershed improvement were not technical, but organizational and financial, with limited coordination and funding identified as stronger barriers than data availability. These findings show that the most pressing needs for watershed management go beyond mapping physical conditions and highlight that conservation planning cannot be disentangled from the social and political structures in which it occurs.

The second chapter shows that interventions in the structure of conservation networks were influential in shaping practice adoption outcomes. By using information diffusion models to simulate how new relationships might influence adoption, I found that relationship-building can both help and hinder the spread of conservation initiatives. Under the independent cascade model, the addition of ties generally enhanced diffusion, especially when actors were already predisposed to practice adoption. In contrast, under the linear threshold model, additional ties sometimes diluted influence and reduced adoption. These results highlight that not all new relationships are equally beneficial and that new network connections should be pursued strategically rather than indiscriminately. The implications also offer practical advice for conservation programs; those seeking to accelerate adoption benefit from carefully considering how to target new connections and under what social conditions new connections are likely to have the greatest effect.

The third chapter emphasizes the role of governance and organizational type in driving conservation practice adoption. Using the Red River Basin network, I showed that bottom-up communication initiated by NGOs and local organizations consistently outperformed top-down initiation by federal and state agencies. This pattern reflects both the structural advantages of NGOs, which had greater connections across governance levels, and the communication frequency of local governments. State and federal actors maintained formal authority and resources but were less effective initiators of diffusion. These findings suggest that conservation programs benefit from hybrid governance strategies, where top-down actors provide institutional frameworks and resources while bottom-up actors supply network reach and sustained engagement.

Several cross-cutting themes emerge from these chapters. First, conservation effectiveness is closely tied to the social systems in which it occurs. Whether through the data available to resource managers, the network ties that connect practitioners, or the governance structures that frame collaboration, socio-political systems play a defining role in determining conservation outcomes. Second, local actors play a critical role; across both network and governance analyses, NGOs and local governments were central to adoption, due both to their communication patterns and their ability to bridge across groups. Third, these results show the importance of linking technical and social dimensions. Biophysical data and ecological knowledge remain essential but alone are insufficient. Conservation also requires information about costs and institutions, receptive conditions for practice adoption, network wide communication, and governance arrangements that balance authority with local legitimacy.

Future research could explore how to integrate economic and socio-political data into existing biophysical spatial tools and evaluate whether such interdisciplinary products measurably improve conservation decision making and project implementation. Research could also evaluate how real-world network interventions, for example at workshops or technical assistance partnerships, alter network structures over time and whether these changes align with diffusion model predictions. Moreover, further work could examine how hybrid governance strategies can be implemented in practice and explore how motivations (e.g., monetary incentives, trust, shared purpose) influence communication patterns between groups and if this impacts resource management. Collectively, these directions would advance understanding of how data integration, social network interventions, and governance alignment can strengthen conservation outcomes across scales.

This dissertation contributes to the growing recognition that conservation science must explicitly account for the interaction of ecological, social, and institutional systems (Bennett, et al., 2017; Bennett, et al., 2017; Niemiec et al., 2021). By showing how data gaps constrain decisions, how network structure can amplify or dampen adoption, and how governance hierarchy mediates diffusion dynamics, this research offers insights that are both theoretically useful and practically actionable. As conservation challenges intensify under the experience of global climate change, these insights point toward a future where conservation success depends not only on ecological knowledge but also on our collective ability to navigate and leverage the social systems in which that knowledge is put into practice.

References

Alix-Garcia, J. M., Sims, K. R. E., Orozco-Olvera, V. H., Costica, L. E., Fernández Medina, J. D., & Romo Monroy, S. (2018). Payments for environmental services supported social capital while increasing land management. Proceedings of the National Academy of Sciences, 115(27), 7016–7021. https://doi.org/10.1073/pnas.1720873115

Allan, J. D. (2004). Landscapes and Riverscapes: The Influence of Land Use on Stream Ecosystems. Annual Review of Ecology, Evolution, and Systematics, 35(1), 257–284. https://doi.org/10.1146/annurev.ecolsys.35.120202.110122

Allan, J. D., McIntyre, P. B., Smith, S. D. P., Halpern, B. S., Boyer, G. L., Buchsbaum, A., Burton, G. A., Campbell, L. M., Chadderton, W. L., Ciborowski, J. J. H., Doran, P. J., Eder, T., Infante, D. M., Johnson, L. B., Joseph, C. A., Marino, A. L., Prusevich, A., Read, J. G., Rose, J. B., … Steinman, A. D. (2013). Joint analysis of stressors and ecosystem services to enhance restoration effectiveness. Proceedings of the National Academy of Sciences, 110(1), 372–377. https://doi.org/10.1073/pnas.1213841110

Arai, Y., Maswadi, M., Oktoriana, S., Suharyani, A., Didik, D., & Inoue, M. (2021). How Can We Mitigate Power Imbalances in Collaborative Environmental Governance? Examining the Role of the Village Facilitation Team Approach Observed in West Kalimantan, Indonesia. Sustainability, 13(7), 3972. https://doi.org/10.3390/su13073972

Azaouzi, M., Mnasri, W., & Ben Romdhane, L. (2021). New trends in influence maximization models. Computer Science Review, 40, 100393. https://doi.org/10.1016/j.cosrev.2021.100393

Baird, J., Jollineau, M., Plummer, R., & Valenti, J. (2016). Exploring agricultural advice networks, beneficial management practices and water quality on the landscape: A geospatial social-ecological systems analysis. Land Use Policy, 51, 236–243. https://doi.org/10.1016/j.landusepol.2015.11.017

Ballarini, E., D'Adamo, R., Pazienza, G., Zaggia, L., & Vafeidis, A. (2021). Assessing the applicability of a bottom-up or top-down approach for effective management of a coastal lagoon area. Ocean & Coastal Management, 200, 105417. https://doi.org/10.1016/j.ocecoaman.2020.105417

Ban, N. C., Mills, M., Tam, J., Hicks, C. C., Klain, S., Stoeckl, N., Bottrill, M. C., Levine, J., Pressey, R. L., Satterfield, T., & Chan, K. M. (2013). A social–ecological approach to conservation planning: Embedding social considerations. Frontiers in Ecology and the Environment, 11(4), 194–202. https://doi.org/10.1890/110205

Bennett, N. J., Roth, R., Klain, S. C., Chan, K., Christie, P., Clark, D. A., Cullman, G., Curran, D., Durbin, T. J., Epstein, G., Greenberg, A., Nelson, M. P., Sandlos, J., Stedman, R., Teel, T. L., Thomas, R., Veríssimo, D., & Wyborn, C. (2017). Conservation social science: Understanding and integrating human dimensions to improve conservation. Biological Conservation, 205, 93–108. https://doi.org/10.1016/j.biocon.2016.10.006

Bennett, N. J., Roth, R., Klain, S. C., Chan, K. M. A., Clark, D. A., Cullman, G., Epstein, G., Nelson, M. P., Stedman, R., Teel, T. L., Thomas, R. E. W., Wyborn, C., Curran, D., Greenberg, A., Sandlos, J., & Veríssimo, D. (2017). Mainstreaming the social sciences in conservation. Conservation Biology, 31(1), 56–66. https://doi.org/10.1111/cobi.12788

Bodin, Ö., & Crona, B. I. (2009). The role of social networks in natural resource governance: What relational patterns make a difference? Global Environmental Change, 19(3), 366–374. https://doi.org/10.1016/j.gloenvcha.2009.05.002

Bodin, Ö., & Prell, C. (Eds.). (2011). Social Networks and Natural Resource Management: Uncovering the Social Fabric of Environmental Governance. Cambridge University Press; Cambridge Core. https://doi.org/10.1017/CBO9780511894985

Botts, E. A., Pence, G., Holness, S., Sink, K., Skowno, A., Driver, A., Harris, L. R., Desmet, P., Escott, B., Lötter, M., Nel, J., Smith, T., Daniels, F., Sinclair, S., Stewart, W., & Manuel, J. (2019). Practical actions for applied systematic conservation planning. Conservation Biology, 33(6), 1235–1246. https://doi.org/10.1111/cobi.13321

Budhathoki, N. R., Bruce, B. (Chip), & Nedovic-Budic, Z. (2008). Reconceptualizing the role of the user of spatial data infrastructure. GeoJournal, 72(3–4), 149–160. https://doi.org/10.1007/s10708-008-9189-x

Christian-Smith, J., & Merenlender, A. M. (2010). The Disconnect Between Restoration Goals and Practices: A Case Study of Watershed Restoration in the Russian River Basin, California. Restoration Ecology, 18(1), 95–102. https://doi.org/10.1111/j.1526-100X.2008.00428.x

Cunningham, R., Cvitanovic, C., Measham, T., Jacobs, B., Dowd, A.-M., & Harman, B. (2016). Engaging communities in climate adaptation: The potential of social networks. Climate Policy, 16(7), 894–908. https://doi.org/10.1080/14693062.2015.1052955

Curtis, A., Byron, I., & MacKay, J. (2005). Integrating Socio-Economic And Biophysical Data To Underpin Collaborative Watershed Management. Journal of the American Water Resources Association, 41(3), 549–563. https://doi.org/10.1111/j.1752-1688.2005.tb03754.x

Daily, G. C., Polasky, S., Goldstein, J., Kareiva, P. M., Mooney, H. A., Pejchar, L., Ricketts, T. H., Salzman, J., & Shallenberger, R. (2009). Ecosystem services in decision making: Time to deliver. Frontiers in Ecology and the Environment, 7(1), 21–28. https://doi.org/10.1890/080025

de Lange, E., Dobson, A. D. M., Milner-Gulland, E. J., & Keane, A. (2021). Combining simulation and empirical data to explore the scope for social network interventions in conservation. Biological Conservation, 261, 109292. https://doi.org/10.1016/j.biocon.2021.109292 de Lange, E., Milner-Gulland, E. J., & Keane, A. (2019). Improving Environmental Interventions by Understanding Information Flows. Trends in Ecology & Evolution, 34(11), 1034–1047. https://doi.org/10.1016/j.tree.2019.06.007

Ding, L., Chen, L., Ding, C., & Tao, J. (2019). Global Trends in Dam Removal and Related Research: A Systematic Review Based on Associated Datasets and Bibliometric Analysis. Chinese Geographical Science, 29(1), 1–12. https://doi.org/10.1007/s11769-018-1009-8

Eicken, H., Danielsen, F., Sam, J.-M., Fidel, M., Johnson, N., Poulsen, M. K., Lee, O. A., Spellman, K. V., Iversen, L., Pulsifer, P., & Enghoff, M. (2021). Connecting Top-Down and Bottom-Up Approaches in Environmental Observing. BioScience, 71(5), 467–483. https://doi.org/10.1093/biosci/biab018

Enqvist, J. P., Tengö, M., & Bodin, Ö. (2020). Are bottom-up approaches good for promoting social–ecological fit in urban landscapes? Ambio, 49(1), 49–61. https://doi.org/10.1007/s13280-019-01163-4

Farwig, N., Sprenger, P. P., Baur, B., Böhning-Gaese, K., Brandt, A., Eisenhauer, N., Ellwanger, G., Hochkirch, A., Karamanlidis, A. A., Mehring, M., Pusch, M., Rehling, F., Sommerwerk, N., Spatz, T., Svenning, J.-C., Tischew, S., Tockner, K., Tscharntke, T., Vadrot, A. B. M., … Mosbrugger, V. (2024). Identifying Major Factors for Success and Failure of Conservation Programs in Europe. Environmental Management. https://doi.org/10.1007/s00267-024-02086-x

Floress, K., Connolly, S., Halvorsen, K. E., Egan, A., Schuler, T., Hill, A., DeSenze, P., Fenimore, S., & Karriker, K. (2018). Implementing Landscape Scale Conservation across Organizational Boundaries: Lessons from the Central Appalachian Region, United States. Environmental Management, 62(5), 845–857. https://doi.org/10.1007/s00267-018-1081-y

Floress, K., Mangun, J. C., Davenport, M. A., & Williard, K. W. J. (2009). Constraints to Watershed Planning: Group Structure and Process 1: Constraints To Watershed Planning : Group Structure and Process. JAWRA Journal of the American Water Resources Association, 45(6), 1352–1360. https://doi.org/10.1111/j.1752-1688.2009.00368.x

Flotemersch, J. E., Leibowitz, S. G., Hill, R. A., Stoddard, J. L., Thoms, M. C., & Tharme, R. E. (2016). A Watershed Integrity Definition and Assessment Approach to Support Strategic Management of Watersheds. River Research and Applications, 32(7), 1654–1671. https://doi.org/10.1002/rra.2978

Frame, T. M., Gunton, T., & Day, J. C. (2004). The role of collaboration in environmental management: An evaluation of land and resource planning in British Columbia. Journal of Environmental Planning and Management, 47(1), 59–82. https://doi.org/10.1080/0964056042000189808

Fraser, E. D. G., Dougill, A. J., Mabee, W. E., Reed, M., & McAlpine, P. (2006). Bottom up and top down: Analysis of participatory processes for sustainability indicator identification as a pathway to community empowerment and sustainable environmental management. Journal of Environmental Management, 78(2), 114–127. https://doi.org/10.1016/j.jenvman.2005.04.009

Grimm, N. B., Groffman, P., Staudinger, M., & Tallis, H. (2016). Climate change impacts on ecosystems and ecosystem services in the United States: Process and prospects for sustained assessment. Climatic Change, 135(1), 97–109. https://doi.org/10.1007/s10584-015-1547-3

Isaak, D. J., Young, M. K., Nagel, D. E., Horan, D. L., & Groce, M. C. (2015). The cold-water climate shield: Delineating refugia for preserving salmonid fishes through the 21st century. Global Change Biology, 21(7), 2540–2553. https://doi.org/10.1111/gcb.12879

Kaushal, S. S., Likens, G. E., Pace, M. L., Utz, R. M., Haq, S., Gorman, J., & Grese, M. (2018). Freshwater salinization syndrome on a continental scale. Proceedings of the National Academy of Sciences, 115(4). https://doi.org/10.1073/pnas.1711234115

Kaweesa, S., Mkomwa, S., & Loiskandl, W. (2018). Adoption of Conservation Agriculture in Uganda: A Case Study of the Lango Subregion. Sustainability, 10(10), 3375. https://doi.org/10.3390/su10103375

Koontz, T. M., & Newig, J. (2014). From Planning to Implementation: Top-Down and Bottom-Up Approaches for Collaborative Watershed Management: Implementing Collaborative Watershed Plans. Policy Studies Journal, 42(3), 416–442. https://doi.org/10.1111/psj.12067

Koundouri, P., Ker Rault, P., Pergamalis, V., Skianis, V., & Souliotis, I. (2016). Development of an integrated methodology for the sustainable environmental and socio-economic management of river ecosystems. Science of The Total Environment, 540, 90–100. https://doi.org/10.1016/j.scitotenv.2015.07.082

Krishnamurthy, R., & Awazu, Y. (2016). Liberating data for public value: The case of Data.gov. International Journal of Information Management, 36(4), 668–672. https://doi.org/10.1016/j.ijinfomgt.2016.03.002

Leclère, D., Obersteiner, M., Barrett, M., Butchart, S. H. M., Chaudhary, A., De Palma, A., DeClerck, F. A. J., Di Marco, M., Doelman, J. C., Dürauer, M., Freeman, R., Harfoot, M., Hasegawa, T., Hellweg, S., Hilbers, J. P., Hill, S. L. L., Humpenöder, F., Jennings, N., Krisztin, T., … Young, L. (2020). Bending the curve of terrestrial biodiversity needs an integrated strategy. Nature, 585(7826), 551–556. https://doi.org/10.1038/s41586-020-2705-y

Lubell, M., Jasny, L., & Hastings, A. (2017). Network Governance for Invasive Species Management. Conservation Letters, 10(6), 699–707. https://doi.org/10.1111/conl.12311

Mancilla García, M., Hileman, J., Bodin, Ö., Nilsson, A., & Jacobi, P. R. (2019). The unique role of municipalities in integrated watershed governance arrangements: A new research frontier. Ecology and Society, 24(1), art28. https://doi.org/10.5751/ES-10793-240128

Maxwell, K., Hubbell, B., & Eisenhauer, E. (2019). Institutional insights on integrating social and environmental science for solutions-driven research. Environmental Science & Policy, 101, 97–105. https://doi.org/10.1016/j.envsci.2019.08.003

Maxwell, S. L., Cazalis, V., Dudley, N., Hoffmann, M., Rodrigues, A. S. L., Stolton, S., Visconti, P., Woodley, S., Kingston, N., Lewis, E., Maron, M., Strassburg, B. B. N., Wenger, A., Jonas, H. D., Venter, O., & Watson, J. E. M. (2020). Area-based conservation in the twenty-first century. Nature, 586(7828), 217–227. https://doi.org/10.1038/s41586-020-2773-z

Mazor, R. D., Rehn, A. C., Ode, P. R., Engeln, M., Schiff, K. C., Stein, E. D., Gillett, D. J., Herbst, D. B., & Hawkins, C. P. (2016). Bioassessment in complex environments: Designing an index for consistent meaning in different settings. Freshwater Science, 35(1), 249–271. https://doi.org/10.1086/684130

Mbaru, E. K., & Barnes, M. L. (2017). Key players in conservation diffusion: Using social network analysis to identify critical injection points. Biological Conservation, 210, 222–232. https://doi.org/10.1016/j.biocon.2017.03.031

Mc Culloch-Jones, S., Novellie, P., Roux, D. J., & Currie, B. (2021). Exploring the alignment between the bottom-up and top-down objectives of a landscape-scale conservation initiative. Environmental Conservation, 48(4), 255–263. https://doi.org/10.1017/S0376892921000321

Mills, M., Bode, M., Mascia, M. B., Weeks, R., Gelcich, S., Dudley, N., Govan, H., Archibald, C. L., Romero-de-Diego, C., Holden, M., Biggs, D., Glew, L., Naidoo, R., & Possingham, H. P. (2019). How conservation initiatives go to scale. Nature Sustainability, 2(10), 935–940. https://doi.org/10.1038/s41893-019-0384-1

Mu, M., Gao, L., Zhang, H., Ge, J., Zhang, Z., Qiu, Y., & Zhao, X. (2023). Effects of land use on water quality at different spatial scales in the middle reaches of Huaihe River. Journal of Freshwater Ecology, 38(1), 2176373. https://doi.org/10.1080/02705060.2023.2176373

Neeson, T. M., Wineland, S. M., Phillips, E., & McFadden, J. (2022). The dynamics of mature and emerging freshwater conservation programs. Frontiers in Environmental Science, 10, 888521. https://doi.org/10.3389/fenvs.2022.888521

Nesbitt, H. K., Metcalf, A. L., Floyd, T. M., Uden, D. R., Chaffin, B. C., Gulab, S., Banerjee, S., Vallury, S., Hamlin, S. L., Metcalf, E. C., Fogarty, D. T., Twidwell, D., & Allen, C. R. (2024). Social networks and transformative behaviours in a grassland social-ecological system. People and Nature, 6(5), 1877–1892. https://doi.org/10.1002/pan3.10695

Niemiec, R. M., Gruby, R., Quartuch, M., Cavaliere, C. T., Teel, T. L., Crooks, K., Salerno, J., Solomon, J. N., Jones, K. W., Gavin, M., Lavoie, A., Stronza, A., Meth, L., Enrici, A., Lanter, K., Browne, C., Proctor, J., & Manfredo, M. (2021). Integrating social science into conservation planning. Biological Conservation, 262, 109298. https://doi.org/10.1016/j.biocon.2021.109298

Ode, P. R., Rehn, A. C., & May, J. T. (2005). A Quantitative Tool for Assessing the Integrity of Southern Coastal California Streams. Environmental Management, 35(4), 493–504. https://doi.org/10.1007/s00267-004-0035-8

Olsson, P., Folke, C., & Hughes, T. P. (2008). Navigating the transition to ecosystem-based management of the Great Barrier Reef, Australia. Proceedings of the National Academy of Sciences, 105(28), 9489–9494. https://doi.org/10.1073/pnas.0706905105

Park, S.-R., & Lee, S.-W. (2020). Spatially Varying and Scale-Dependent Relationships of Land Use Types with Stream Water Quality. International Journal of Environmental Research and Public Health, 17(5), 1673. https://doi.org/10.3390/ijerph17051673

Paukert, C. P., Pitts, K. L., Whittier, J. B., & Olden, J. D. (2011). Development and assessment of a landscape-scale ecological threat index for the Lower Colorado River Basin. Ecological Indicators, 11(2), 304–310. https://doi.org/10.1016/j.ecolind.2010.05.008

Pierre, J., Røiseland, A., Peters, B. G., & Gustavsen, A. (2017). Comparing local politicians' and bureaucrats' assessments of democratic participation: The cases of Norway and Sweden. International Review of Administrative Sciences, 83(4), 658–675. https://doi.org/10.1177/0020852315598214

Rilov, G., Fraschetti, S., Gissi, E., Pipitone, C., Badalamenti, F., Tamburello, L., Menini, E., Goriup, P., Mazaris, A. D., Garrabou, J., Benedetti-Cecchi, L., Danovaro, R., Loiseau, C., Claudet, J., & Katsanevakis, S. (2020). A fast-moving target: Achieving marine conservation goals under shifting climate and policies. Ecological Applications, 30(1), e02009. https://doi.org/10.1002/eap.2009

Rothrock, P. E., Simon, T. P., & Stewart, P. M. (2008). Development, calibration, and validation of a littoral zone plant index of biotic integrity (PIBI) for lacustrine wetlands. Ecological Indicators, 8(1), 79–88. https://doi.org/10.1016/j.ecolind.2007.01.002

Scown, M. W., Flotemersch, J. E., Spanbauer, T. L., Eason, T., Garmestani, A., & Chaffin, B. C. (2017). People and water: Exploring the social-ecological condition of watersheds of the United States. Elementa: Science of the Anthropocene, 5, 64. https://doi.org/10.1525/elementa.189

Shakarian, P., Bhatnagar, A., Aleali, A., Shaabani, E., & Guo, R. (2015). Diffusion in social networks. Springer.

Shifflett, Newcomer-Johnson, Yess, & Jacobs. (2019). Interdisciplinary Collaboration on Green Infrastructure for Urban Watershed Management: An Ohio Case Study. Water, 11(4), 738. https://doi.org/10.3390/w11040738

Shunglu, R., Köpke, S., Kanoi, L., Nissanka, T. S., Withanachchi, C. R., Gamage, D. U., Dissanayake, H. R., Kibaroglu, A., Ünver, O., & Withanachchi, S. S. (2022). Barriers in

Participative Water Governance: A Critical Analysis of Community Development Approaches. Water, 14(5), 762. https://doi.org/10.3390/w14050762

Sun, Y., Li, Y., Ma, R., Gao, C., & Wu, Y. (2022). Mapping urban socio-economic vulnerability related to heat risk: A grid-based assessment framework by combing the geospatial big data. Urban Climate, 43, 101169. https://doi.org/10.1016/j.uclim.2022.101169

Tickner, D., Opperman, J. J., Abell, R., Acreman, M., Arthington, A. H., Bunn, S. E., Cooke, S. J., Dalton, J., Darwall, W., Edwards, G., Harrison, I., Hughes, K., Jones, T., Leclère, D., Lynch, A. J., Leonard, P., McClain, M. E., Muruven, D., Olden, J. D., … Young, L. (2020). Bending the Curve of Global Freshwater Biodiversity Loss: An Emergency Recovery Plan. BioScience, 70(4), 330–342. https://doi.org/10.1093/biosci/biaa002

Tsvetkova, O., & Randhir, T. O. (2019). Spatial and temporal uncertainty in climatic impacts on watershed systems. Science of The Total Environment, 687, 618–633. https://doi.org/10.1016/j.scitotenv.2019.06.141

Valente, T. W., & Pumpuang, P. (2007). Identifying Opinion Leaders to Promote Behavior Change. Health Educ Behav, 34(6), 881–896. https://doi.org/10.1177/1090198106297855

Webb, N. P., Stokes, C. J., & Marshall, N. A. (2013). Integrating biophysical and socio-economic evaluations to improve the efficacy of adaptation assessments for agriculture. Global Environmental Change, 23(5), 1164–1177. https://doi.org/10.1016/j.gloenvcha.2013.04.007

Weston, S., & Conrad, C. (2015). Community-Based Water Monitoring in Nova Scotia: Solutions for Sustainable Watershed Management. Environment and Natural Resources Research, 5(2), p1. https://doi.org/10.5539/enrr.v5n2p1

White, T. B., Petrovan, S. O., Booth, H., Correa, R. J., Gatt, Y., Martin, P. A., Newell, H., Worthington, T. A., & Sutherland, W. J. (2022). Determining the economic costs and benefits of conservation actions: A decision support framework. Conservation Science and Practice, 4(12), e12840. https://doi.org/10.1111/csp2.12840

Wulder, M. A., Masek, J. G., Cohen, W. B., Loveland, T. R., & Woodcock, C. E. (2012). Opening the archive: How free data has enabled the science and monitoring promise of Landsat. Remote Sensing of Environment, 122, 2–10. https://doi.org/10.1016/j.rse.2012.01.010