AQUATIC HABITAT REPRESENTATION FOR ROBUST WATER RESOURCES MANAGEMENT AND FISH CONSERVATION DECISION-MAKING

by

Gregory C. Goodrum

A dissertation submitted in partial fulfillment
of the requirements of the degree

of

DOCTOR OF PHILOSOPHY

in

Watershed Science

Approved:

Sarah E. Null, Ph.D. Major Professor	Joanna Endter-Wada, Ph.D. Committee Member
Charles Hawkins, Ph.D. Committee Member	David Rosenberg, Ph.D. Committee Member
Timothy Walsworth, Ph.D. Committee Member	David F. Feldon, Ph.D. Vice Provost of Graduate Studies

UTAH STATE UNIVERSITY
Logan, Utah

2025

ABSTRACT

Aquatic Habitat Representation for Robust Water Resources Management

and Fish Conservation Decision-Making

by

Gregory C. Goodrum, Doctor of Philosophy

Utah State University, 2025

Major Professor: Dr. Sarah E. Null
Department: Watershed Sciences

We rely on rivers to provide economic benefits for people and to sustain aquatic ecosystems. The development of water infrastructure to provide benefits for people did not consider environmental impacts to rivers, leading to widespread and persistent declines in freshwater biodiversity, populations, and habitat. Improving environmental outcomes of water management is needed to protect aquatic ecosystems. However, rivers are highly complex and variable, making them difficult to represent alongside hydro-economic objectives for water management. This dissertation uses multi-objective and uncertainty analysis frameworks to improve aquatic habitat representation for water resources management and river conservation and restoration.

Chapter 2 uses water resources systems modeling to evaluate tradeoffs in Utah's Bear River Basin between water supply for people, impacts to stream habitat for fish, and changes to Great Salt Lake with proposed water diversions and reservoirs. New diversions and reservoirs reduced summer stream habitat for threatened Bonneville Cutthroat Trout, and water diversions to the metropolitan areas decreased Great Salt Lake level by over 4 m (11 ft) between 2000 and 2020. I demonstrate that conflicting hydro-economic and environmental objectives for the Bear River exacerbate current threats to Bonneville Cutthroat Trout and pose significant economic, environmental, and human health risks from a declining Great Salt Lake.

Chapter 3 uses Monte-Carlo random sampling to evaluate the robustness of barrier removals for river connectivity restoration to uncertain habitat conditions and species-habitat relationships in Utah's Weber River Basin. Barrier removals were sensitive to environmental data uncertainty for reconnecting summer thermal refugia, and few barrier removals were also robust for decisions about reconnecting growth habitats. I demonstrate that environmental data and suitability function uncertainty influence barrier removal optimization models and should be considered for river connectivity restoration.

Chapter 4 uses an uncertainty analysis approach to systematically evaluate methods for predicting road-crossing barrier passability for river connectivity analysis. Passability prediction methods produced similar river connectivity estimates but were uncertain predicting fish passage for individual barriers. I demonstrate that simple passability prediction methods are sufficient to characterize river connectivity at the watershed scale and highlight limitations for predicting barrier status to support barrier removal optimization for restoring river connectivity.

(185 Pages)

PUBLIC ABSTRACT

Aquatic Habitat Representation for Robust Water Resources Management
and Fish Conservation Decision-Making

Gregory C. Goodrum

We rely on rivers to provide water supply, flood control, and hydroelectricity for people and to sustain aquatic ecosystems. The development of dams and reservoirs to provide water for people did not consider environmental impacts to rivers, leading to widespread decline of freshwater species and habitat. Improving environmental outcomes of water management is needed to protect and restore aquatic ecosystems. However, rivers are complex and variable, making them difficult to represent as objectives for water management. This dissertation explores approaches to improve aquatic habitat representation and environmental objectives for water resources management and river conservation and restoration.

Chapter 2 uses economic and environmental modeling to evaluate tradeoffs in Utah's Bear River Basin between water supply for people, impacts to stream habitat for fish, and changes to Great Salt Lake with proposed water diversions and reservoirs. New diversions and reservoirs reduced summer stream habitat for threatened Bonneville Cutthroat Trout, and water diversions to the metropolitan Wasatch Front decreased Great Salt Lake level by over 4 m (11 ft) between 2000 and 2020. I demonstrate that conflicting economic and environmental objectives for the Bear River exacerbate current threats to Bonneville Cutthroat Trout and pose significant economic, environmental, and human health risks from a declining Great Salt Lake.

Chapter 3 evaluates how barrier removals reconnecting stream reaches for Bonneville Cutthroat Trout perform under uncertain stream temperature conditions in Utah's Weber River Basin. Barrier removals were sensitive to stream temperature data uncertainty for reconnecting summer coldwater stream habitats, and few barrier removals were also selected for reconnecting streams with suitable temperatures for fish growth. I demonstrate that uncertainty stream temperature conditions influence barrier removal selection and should be considered for restoring river connectivity.

Chapter 4 compares methods to predict fish passage at road-stream crossings for measuring connectivity in river systems. My methods for predicting road-crossing passability produced similar river connectivity estimates but vary considerably predicting fish passage for individual barriers. I demonstrate that simple methods for predicting fish passage at road crossings are sufficient to characterize river connectivity and highlight limitations for predicting fish passage to support barrier removal and river restoration.

ACKNOWLEDGMENTS

This dissertation was funded by the Agriculture and Food Research Initiative, project award number 2021-69012-35916, from the US Department of Agriculture National Institute of Food and Agriculture. It was also supported by the National Sciences Foundation Grant #1653452. Any opinions, findings, and conclusions or recommendations expressed are those of the authors and do not necessarily reflect the views of the National Science Foundation.

Science does not happen in a vacuum, and I have been fortunate to be guided by an outstanding group of people in my graduate career. First and foremost, I thank my advisor, Dr. Sarah Null. Sarah, thank you for agreeing to take me on as both a masters and doctoral student, and for sharing a love of rivers, science, and adventure that extends far beyond our work together at USU. Your steadfast support for my work and confidence in my abilities has helped me grow as a scientist and writer and was instrumental for me completing this dissertation. Thank you for embracing my pursuit of extracurricular opportunities like travelling to Colombia with the National Science Foundation and rafting the Salt River and Grand Canyon in the final year of my program; not all of our growth comes from writing and analysis. Your ability to distill science for its relevance in the real world is inspiring, and I am grateful to have worked with you for the past seven years.

To my committee, thank you for your guidance and support throughout this program. My goal was to assemble a committee that would be both rigorous and constructive, and you have not disappointed. Dr. Joanna Endter-Wada, thank you expanding how I think about rivers in the context of policy and management, and for sharing an interest in the fate of the Bear River. Dr. David Rosenberg, thank you for your extensive help coding in GAMS and for shaping the way I design my science to be both reproducible and repeatable. Dr. Charles Hawkins, Chuck, thank you for your steadfast help finding the ways and words to bring my connectivity analysis to fruition, and for always pushing me to be a better scientist and writer. Dr. Tim Walsworth, thank you for your extensive contributions to my work, your willingness to help me work through roadblocks in my research, and your bottomless enthusiasm for science and the natural world. I could not have asked for a better committee.

One of Sarah’s many skills is recruiting excellent collaborators, and I have been fortunate to work with an outstanding group in the ACWA lab. Thanks to J. Neenan, Ali Farshid, Saddy Pineda, Dr. Liana Prudencio, Dr. Sapana Lohani, Dr. Ratha Sor, and Dr. Curtis “Don Cortez” Gray for sharing a broad and abiding love of fish, rivers, and the people who rely on and enjoy them. In particular, I would like to thank Eryn Turney, Gabi Sancho Juarez, and Dr. Christina Morrisett for their endless encouragement, friendship, and willingness to give feedback on figures. You have made BNR 208 a great place to work and been an incredible source of support. Thank you.

Graduate school can be an emotionally draining endeavor, and I offer heartfelt thanks to the numerous friends and colleagues who have shared this experience with me. Thanks to Zach Ahrens and Dr. Kristina Young for sharing their love of deserts, rivers, and adventure, and for always refreshing my love for science and nature. Thank you to Laura and John Tennant for providing much needed respite from the stress of school and research, and for always finding ways to laugh when things go sideways. Thanks to Dr. J. Marshall Wolf and Caitlin Keller for sharing bike rides, ski days, morning soccer coffee, and the ups and downs of living in Logan. Thanks to Julia Aaronson, Dr. Cole Bleke, Dr. Jeff Perala-Dewey, Austin Bartos, Dr. Niall Clancy, Karen Bartelt, Keghan Connor, Jake Van Deursen, Dr. Noah Creany, Dr. Iree Wheeler, Dr. John McLaren, Dominique McLaren, and Dr. Cat McClure for making USU and Logan a great place to live. More adventures to come!

Finally, deepest thanks to my family, Rebecca, Kimberly, and the late Charles Goodrum. No one has given more for this program. Your love and support have been my rock and my greatest motivation to complete this dissertation. Thank you.

Gregory C. Goodrum

CONTENTS

LIST OF TABLES

Page

LIST OF FIGURES

Page

CHAPTER 1

INTRODUCTION

We rely on rivers to provide water supply, flood control, hydropower, and recreational benefits for people and to sustain aquatic species and ecosystems. In the United States, more than 85,000 dams and countless smaller diversion and road crossing structures were built between the 1940s and 1970s to reduce flood risks, generate hydropower, facilitate road construction, and provide water for agriculture, industry, and household use (Graf, 1999). Dams, reservoirs, and other instream infrastructure fundamentally alter freshwater systems by fragmenting river networks (Spinti et al., 2023), modifying natural flow and temperature regimes (Zaidel et al., 2021; Peñas & Barquín, 2019), disrupting sediment transport (Wohl, 2019), and degrading water quality (Ahearn et al., 2005; Maavara et al., 2020), with consequences for aquatic ecosystems that extend far downstream (Graf, 2006). Most infrastructure projects did not consider the environmental consequences of development, leading to widespread and persistent environmental impacts including biodiversity loss (Poff et al., 2007), fish population collapse (Waldman & Quinn, 2022), and the decline of inland lakes and wetlands (Fluet-Chouinard et al., 2023; Wurtsbaugh et al., 2017). In response, minimizing environmental losses and restoring aquatic ecosystems have emerged as a focus for water resources management (Cosgrove & Loucks, 2015).

Environmental objectives for river conservation often reflect ecological systems that are challenging to represent for water resources management. Rivers are complex landscape features with physical, chemical, and ecological characteristics that vary considerably across space and time and exhibit strong longitudinal differentiation between their headwaters and terminus (Biggs et al., 2005; Thoms, 2006). Fish and other aquatic organisms exploit this variability by making large seasonal migrations that allow them to utilize habitats suitable for different life stages, exploit seasonally available resources, and facilitate genetic exchanges necessary for long-term population survival (Moore et al., 2014, Soukup et al., 2022). Rivers also are interconnected dendritic systems, meaning that alterations caused by infrastructure often propagate up- and downstream, causing changes to instream conditions and biological communities (Dević, 2015; Ligon et al., 1995). Environmental data and ecological relationships used to quantify river characteristics are themselves uncertain (Hamilton & Moore, 2012; Luce et al., 2014), and their uncertainty influences ecological models used to represent environmental water management goals (Roloff & Kernohan, 1999; Van Der Lee et al., 2006).

To adapt water management for improving environmental conditions, we must identify decisions that are robust to ecological uncertainty and conflicting water management objectives. Water resources systems modeling can be used to support multi-objective decision-making and evaluate tradeoffs between many potentially competing objectives (Loucks & Van Beek, 2017). Uncertainty analysis frameworks can identify robust decisions that perform well even when data and conditions used to inform decision-making are uncertain (Schindler and Hilborn, 2015). For water resources management, robust and multi-objective decision-making techniques have been used to evaluate infrastructure development and operations with economic and climatic uncertainty (Herman et al., 2014; Kasprzyk et al., 2013; Matrosov et al., 2013). However, little research has focused on quantifying uncertainty and identifying decisions that are robust to change for river restoration and ecosystem management (Null et al., 2021). Here, I incorporate multi-objective and uncertainty analysis frameworks to evaluate water management strategies in northern Utah for robustness to ecological uncertainty and under alternative proposals for future river development and restoration.

In Chapter 2, I use water resources systems modeling to evaluate tradeoffs in Utah's Bear River Basin between water supply for people, impacts to stream habitat for fish, and changing conditions at Great Salt Lake with proposed water diversions and new reservoirs. I developed a hydro-economic optimization model to represent water management under proposed river development alternatives, then coupled model outputs with hydroclimatic data to estimate stream temperature, habitat suitability, and lake elevation at Great Salt Lake. Proposed development increases water storage and supply for agricultural, municipal, and industrial water users, but reduces summer stream habitat for Bonneville Cutthroat Trout and decreases Great Salt Lake elevation by over 3.5 m between 2000 and 2020. This work highlights conflicts between hydro-economic and environmental water management objectives for Utah's portion of the Bear River that exacerbate current threats to Bonneville Cutthroat Trout and pose significant economic, ecosystem, and human health risks from a declining Great Salt Lake.

In Chapter 3, I use a Monte-Carlo random sampling framework to evaluate the robustness of instream barrier removal for river connectivity restoration to uncertain habitat conditions and species-habitat relationships. I estimated thermal habitat suitability for conservation objectives restoring either growth habitat or summer thermal refugia in Utah's Weber River Basin by randomly sampling across a range of uncertain stream temperature data and suitability function parameters. I applied habitat suitability estimates from my Monte-Carlo simulations in a barrier removal optimization model to quantify how habitat uncertainty affects barrier removal robustness. Habitat uncertainty had little influence on barrier removal robustness for either conservation objective, but few barrier removals were robust for restoring both growth and thermal refugia habitats. This study demonstrates that input data and suitability function uncertainty influence barrier removal optimization models and identifies pathways for addressing aquatic habitat uncertainty in river restoration and management.

In Chapter 4, I use an uncertainty analysis approach to systematically evaluate how different predictive methods for estimating instream barrier passability for fish affect river connectivity estimates. I used uniform, random sampling, and presence/absence and passability rating prediction methods to predict Bonneville Cutthroat Trout passage for 2,144 potential road-crossing barriers in the Bear River Basin in Wyoming, Idaho, and Utah. My passability prediction methods produce similar connectivity estimates but vary considerably predicting fish passage for individual barriers. My findings suggest that simple passability prediction methods are sufficient to characterize stream network connectivity and highlight limitations to predicting individual barrier status for river connectivity analysis.

The research presented here evaluates the robustness of aquatic habitat representations needed to improve environmental objectives in water management modeling and environmental decision-making. Populations of freshwater species have declined by 85% since 1970 (World Wildlife Fund, 2024), and river alteration threatens a quarter of all freshwater fauna with extinction (Sayer et al., 2025). As global climate change leads to longer dry periods (Williams et al., 2022), declining surface water availability is likely to exacerbate current conflicts between human and environmental water demands (Dettinger et al., 2015). Moreover, increasingly extreme periodic wet periods and storm events threaten much of our existing river infrastructure (Hansen et al., 2020; Stevenson et al., 2022), which presents an opportunity to re-evaluate current water management and planned development of water resources. To protect rivers and aquatic ecosystems, robust decision-making is needed to identify water management and river restoration strategies that perform well across variable and shifting environmental conditions. If we are to avoid adding to the environmental losses of the 20th century, water resources management must holistically consider the environmental consequences of river infrastructure operation and development decisions to evaluate the tradeoffs and costs of further river alteration. This dissertation presents pathways for improving aquatic habitat representations and incorporating environmental uncertainty for water resources systems modeling, barrier removal optimization, and river connectivity restoration needed to sustain aquatic ecosystems and manage rivers for people and the environment.

References

Ahearn, D. S., Sheibley, R. W., & Dahlgren, R. A. (2005). Effects of river regulation on water quality in the lower Mokelumne River, California. *River Research and Applications*, *21*(6), 651–670. https://doi.org/10.1002/rra.853

Biggs, B. J. F., Nikora, V. I., & Snelder, T. H. (2005). Linking scales of flow variability to lotic ecosystem structure and function. *River Research and Applications*, *21*(2–3), 283–298. https://doi.org/10.1002/rra.847

Cosgrove, W. J., & Loucks, D. P. (2015). Water management: Current and future challenges and research directions. *Water Resources Research*, *51*(6), 4823–4839. https://doi.org/10.1002/2014WR016869

Dettinger, M., Udall, B., & Georgakakos, A. (2015). Western water and climate change. *Ecological Applications*, *25*(8), 2069–2093. https://doi.org/10.1890/15-0938.1

Dević, G. (2015). Environmental Impacts of Reservoirs. In R. H. Armon & O. Hänninen (Eds.), *Environmental Indicators* (pp. 561–575). Springer Netherlands. https://doi.org/10.1007/978-94-017-9499-2_33

Fluet-Chouinard, E., Stocker, B. D., Zhang, Z., Malhotra, A., Melton, J. R., Poulter, B., Kaplan, J. O., Goldewijk, K. K., Siebert, S., Minayeva, T., Hugelius, G., Joosten, H., Barthelmes, A., Prigent, C., Aires, F., Hoyt, A. M., Davidson, N., Finlayson, C. M., Lehner, B., … McIntyre, P. B. (2023). Extensive global wetland loss over the past three centuries. *Nature*, *614*(7947), 281–286. https://doi.org/10.1038/s41586-022-05572-6

Graf, W. L. (1999). Dam nation: A geographic census of American dams and their large-scale hydrologic impacts. *Water Resources Research*, *35*(4), 1305–1311. https://doi.org/10.1029/1999WR900016

Graf, W. L. (2006). Downstream hydrologic and geomorphic effects of large dams on American rivers. *Geomorphology*, *79*(3–4), 336–360. https://doi.org/10.1016/j.geomorph.2006.06.022

Hamilton, A. S., & Moore, R. D. (2012). Quantifying Uncertainty in Streamflow Records. *Canadian Water Resources Journal / Revue Canadienne Des Ressources Hydriques*, *37*(1), 3–21. https://doi.org/10.4296/cwrj3701865

Hansen, H. H., Forzono, E., Grams, A., Ohlman, L., Ruskamp, C., Pegg, M. A., & Pope, K. L. (2020). Exit here: Strategies for dealing with aging dams and reservoirs. *Aquatic Sciences*, *82*(1), 2. https://doi.org/10.1007/s00027-019-0679-3

Herman, J. D., Zeff, H. B., Reed, P. M., & Characklis, G. W. (2014). Beyond optimality: Multistakeholder robustness tradeoffs for regional water portfolio planning under deep uncertainty. *Water Resources Research*, *50*(10), 7692–7713. https://doi.org/10.1002/2014WR015338

Kasprzyk, J. R., Nataraj, S., Reed, P. M., & Lempert, R. J. (2013). Many objective robust decision making for complex environmental systems undergoing change. *Environmental Modelling & Software*, *42*, 55–71. https://doi.org/10.1016/j.envsoft.2012.12.007

Ligon, F. K., Dietrich, W. E., & Trush, W. J. (1995). Downstream Ecological Effects of Dams. *BioScience*, *45*(3), 183–192. https://doi.org/10.2307/1312557

Loucks, D. P., & Van Beek, E. (2017). *Water Resource Systems Planning and Management*. Springer International Publishing. https://doi.org/10.1007/978-3-319-44234-1

Luce, C., Staab, B., Kramer, M., Wenger, S., Isaak, D., & McConnell, C. (2014). Sensitivity of summer stream temperatures to climate variability in the Pacific Northwest. *Water Resources Research*, *50*(4), 3428–3443. https://doi.org/10.1002/2013WR014329

Maavara, T., Chen, Q., Van Meter, K., Brown, L. E., Zhang, J., Ni, J., & Zarfl, C. (2020). River dam impacts on biogeochemical cycling. *Nature Reviews Earth & Environment*, *1*(2), 103–116. https://doi.org/10.1038/s43017-019-0019-0

Matrosov, E. S., Padula, S., & Harou, J. J. (2013). Selecting Portfolios of Water Supply and Demand Management Strategies Under Uncertainty—Contrasting Economic Optimisation and 'Robust Decision Making' Approaches. *Water Resources Management*, *27*(4), 1123–1148. https://doi.org/10.1007/s11269-012-0118-x

Moore, J. W., Yeakel, J. D., Peard, D., Lough, J., & Beere, M. (2014). Life-history diversity and its importance to population stability and persistence of a migratory fish: Steelhead in two large North American watersheds. *Journal of Animal Ecology*, *83*(5), 1035–1046. https://doi.org/10.1111/1365-2656.12212

Null, S. E., Olivares, M. A., Cordera, F., & Lund, J. R. (2021). Pareto Optimality and Compromise for Environmental Water Management. *Water Resources Research*, *57*(10), e2020WR028296. https://doi.org/10.1029/2020WR028296

Peñas, F. J., & Barquín, J. (2019). Assessment of large-scale patterns of hydrological alteration caused by dams. *Journal of Hydrology*, *572*, 706–718. https://doi.org/10.1016/j.jhydrol.2019.03.056

Poff, N. L., Olden, J. D., Merritt, D. M., & Pepin, D. M. (2007). Homogenization of regional river dynamics by dams and global biodiversity implications. *Proceedings of the National Academy of Sciences*, *104*(14), 5732–5737. https://doi.org/10.1073/pnas.0609812104

Roloff, G. J., & Kernohan, B. J. (1999). Evaluating reliability of habitat suitability index models. *Wildlife Society Bulletin*, *27*(4), 973–985.

Sayer, C. A., Fernando, E., Jimenez, R. R., Macfarlane, N. B. W., Rapacciuolo, G., Böhm, M., Brooks, T. M., Contreras-MacBeath, T., Cox, N. A., Harrison, I., Hoffmann, M., Jenkins, R., Smith, K. G., Vié, J.-C., Abbott, J. C., Allen, D. J., Allen, G. R., Barrios, V., Boudot, J.-P., … Darwall, W. R. T. (2025). One-quarter of freshwater fauna threatened with extinction. *Nature*, *638*(8049), 138–145. https://doi.org/10.1038/s41586-024-08375-z

Schindler, D. E., & Hilborn, R., 2015. Prediction, precaution, and policy under global climate change. Science. 347, 953-954. https://doi.org/ https://doi.org/10.1126/science.1261824

Soukup, P. R., Näslund, J., Höjesjö, J., & Boukal, D. S. (2022). From individuals to communities: Habitat complexity affects all levels of organization in aquatic environments. *WIREs Water*, *9*(1), e1575. https://doi.org/10.1002/wat2.1575

Spinti, R. A., Condon, L. E., & Zhang, J. (2023). The evolution of dam induced river fragmentation in the United States. *Nature Communications*, *14*(1), 3820. https://doi.org/10.1038/s41467-023-39194-x

Stevenson, S., Coats, S., Touma, D., Cole, J., Lehner, F., Fasullo, J., & Otto-Bliesner, B. (2022). Twenty-first century hydroclimate: A continually changing baseline, with more frequent extremes. *Proceedings of the National Academy of Sciences*, *119*(12), e2108124119. https://doi.org/10.1073/pnas.2108124119

Thoms, M. C. (2006). Variability in riverine ecosystems. *River Research and Applications*, *22*(2), 115–121. https://doi.org/10.1002/rra.900

Van Der Lee, G. E. M., Van Der Molen, D. T., Van Den Boogaard, H. F. P., & Van Der Klis, H. (2006). Uncertainty analysis of a spatial habitat suitability model and implications for ecological management of water bodies. *Landscape Ecology*, *21*(7), 1019–1032. https://doi.org/10.1007/s10980-006-6587-7

Waldman, J. R., & Quinn, T. P. (2022). North American diadromous fishes: Drivers of decline and potential for recovery in the Anthropocene. *Science Advances*, *8*(4), eabl5486. https://doi.org/10.1126/sciadv.abl5486

Williams, A. P., Cook, B. I., & Smerdon, J. E. (2022). Rapid intensification of the emerging southwestern North American megadrought in 2020–2021. *Nature Climate Change*, *12*(3), 232–234. https://doi.org/10.1038/s41558-022-01290-z

Wohl, E. (2019). Forgotten Legacies: Understanding and Mitigating Historical Human Alterations of River Corridors. *Water Resources Research*, *55*(7), 5181–5201. https://doi.org/10.1029/2018WR024433

World Wildlife Fund. (2024). Living Planet Report 2024. Gland, Switzerland: World Wildlife Fund. Retrieved from https://livingplanet.panda.org/en-GB/

Wurtsbaugh, W. A., Miller, C., Null, S. E., DeRose, R. J., Wilcock, P., Hahnenberger, M., Howe, F., & Moore, J. (2017). Decline of the world’s saline lakes. *Nature Geoscience*, *10*(11), 816–821. https://doi.org/10.1038/ngeo3052

Zaidel, P. A., Roy, A. H., Houle, K. M., Lambert, B., Letcher, B. H., Nislow, K. H., & Smith, C. (2021). Impacts of small dams on stream temperature. *Ecological Indicators*, *120*, 106878. https://doi.org/10.1016/j.ecolind.2020.106878

CHAPTER 2

DAMNING THE LAKE: TRADEOFFS BETWEEN WATER SUPPLY, FISH HABITAT, AND GREAT SALT LAKE FROM PROPOSED DAMS IN UTAH'S LOWER BEAR RIVER

Abstract

Dams and reservoirs provide water supply, flood control, and hydropower benefits for people but also harm native fish species and reduce water available to sustain aquatic ecosystems. New reservoirs proposed for Utah's Bear River Basin are designed to supply water for the growing Wasatch Front metropolitan area, but how their development could affect riverine habitat for threatened Bonneville Cutthroat Trout (*Oncorhynchus clarkii utah*) and Utah's iconic Great Salt Lake remains unclear. In this study, I use water resources systems modeling to evaluate tradeoffs between water supply for people, changes to fish habitat, and Great Salt Lake elevation with proposed water diversions and new reservoirs. I developed a hydro-economic optimization model to simulate water management under four development alternatives representing new water diversions, new reservoirs, and new reservoir operations with environmental flows. I coupled model outputs with hydroclimatic data to estimate stream temperature, fish habitat suitability, and Great Salt Lake elevation for the 2000-2020 period. Optimization models showed that proposed dams could deliver an annual average of 497 Mm^3 of water to meet new human demands, but reduced summer stream habitat for Bonneville Cutthroat Trout by over 50 km (9% of total stream length) and decreased lake elevation at Great Salt Lake by over 1 m compared to observed conditions. My findings demonstrate that conflicting water management objectives for the Bear River exacerbate current threats to native

Bonneville Cutthroat Trout and pose significant economic, ecosystem, and human health risks from a declining Great Salt Lake.

1. Introduction

Dams and reservoirs continue to be proposed worldwide to provide water supply, flood control, and hydropower benefits for people (Zarfl et al., 2015). However, hydro-economic benefits and environmental impacts from dams are often studied separately, making comprehensive evaluation of the consequences of dam construction difficult (Di Baldassarre et al., 2021). Dams and reservoirs fundamentally alter freshwater systems by fragmenting river networks (Spinti et al., 2023), shifting natural flow and temperature regimes (Peñas & Barquín, 2019; Zaidel et al., 2021), disrupting sediment transport (Wohl, 2019), and degrading water quality (Ahearn et al., 2005; Maavara et al., 2020), with consequences for aquatic ecosystems that extend far downstream (Graf, 2006). In the United States, dam building peaked with the construction of over 85,000 dams and reservoirs between 1940 and 1970 (Graf, 1999). Most dam construction projects in the United States did not consider environmental impacts, leading to widespread and persistent environmental losses including the collapse of fish populations and decline of inland saline lakes (Waldman & Quinn, 2022). New dam proposals in the United States are rare but are being considered in western US states including Arizona, California, and Utah.

In Utah, new reservoirs have been proposed in Utah's portion of the Bear River Basin (UDWRe, 2019a). The Bear River drains parts of Wyoming, Idaho, and Utah and is managed by the Bear River Compact and other multi-state agreements (Endter-Wada et al., 2009). In 1991, Utah passed the Bear River Development Act, which directs the Utah

Division of Water Resources to plan the construction of reservoirs intended to allocate Utah's remaining 271 Mm^3 (220,000 acre-feet) of Bear River water rights for agricultural, industrial, and household water uses (Utah Code § 73-26, 1991). In addition to human water uses, the Bear River and its tributaries also provide important environmental benefits, including stream habitat for imperiled Bonneville Cutthroat Trout (*Oncorhynchus clarkii utah*) and inflow to Great Salt Lake, the largest lake by area in the western U.S. and the eighth largest saline lake in the world (Null & Wurtsbaugh, 2020). Proposed diversions from new reservoirs and new human consumptive water use present risks for native fish species and the downstream Great Salt Lake ecosystem, both of which rely on flows in the Lower Bear River to maintain aquatic habitats (UDWR, 2019; Wurtsbaugh et al., 2016).

Great Salt Lake currently receives excess water that is not used upstream in the Bear River Basin. The Bear River is Great Salt Lake's largest tributary and largest remaining source of streamflow. However, Great Salt Lake's elevation is decreasing due to consumptive water use throughout its watershed (Wurtsbaugh et al., 2017), threatening the lake's lacustrine and wetland ecosystems, brine shrimp and mineral extraction industries, and human health from toxic airborne dust (Brahney et al., 2024; Wurtsbaugh & Sima, 2022). The state's evaluation suggests that Great Salt Lake would only decline by 0.2-0.4 m (8.5-14 in) under any of the proposed dam scenarios but lacks detail on initial lake elevation and overestimates return flow from applied water use (UDWRe, 2019a), leaving the effect of new water development on Great Salt Lake unknown.

Water resources systems modeling can be used to evaluate tradeoffs between multiple competing objectives for water management decisions. Water resources systems models use mathematical representations and optimization techniques to reflect the hydrologic, economic, infrastructure, and environmental processes that influence rivers and water management (Brown et al., 2015). Often, competing objectives are measured in different units and with different analytical approaches, which make comparison between objectives challenging (Kuby et al., 2005). Water resources systems modeling addresses this challenge by representing how changes in management decisions influence each objective and supports multi-objective decision-making by enabling the direct comparison of tradeoffs between objectives (Hipel, 1992; Yan et al., 2017). Water resources systems modeling has long been used to evaluate infrastructure siting and operations, particularly for maintaining or improving hydro-economic water benefits across different groups of water users (Harou et al., 2009; Yeh, 1985). However, representation of environmental objectives in water resources systems models are often restricted to simple constraints with limited ecological relevance.

When environmental objectives for river management are included in water resources systems models for multi-objective decision-making, they are often represented as environmental flows (Escriva-Bou et al., 2017; Expósito et al., 2020; Herman et al., 2018; Kahil et al., 2016). Environmental flows establish the amount of water required to sustain environmental benefits such as habitat for fish and water for lakes and wetlands (Jowett, 1997). While environmental flows are associated with hydrological and ecological conditions required to sustain aquatic organisms (Rosenfeld, 2017), they are criticized for ignoring the varied life history needs of aquatic organisms and not representing critical instream conditions such as stream temperature (Arthington et al., 2006; Tickner et al., 2020). Despite their limitations, environmental flows are easy to implement and are widely used to guide water management for environmental protection (Olden & Naiman, 2010; Palmer & Ruhi, 2019). Alternatively, some approaches directly represent the environmental objectives of water management, such as streamflow and stream temperature conditions for fish (Null & Lund, 2012) or lake level change under water management (Han et al., 2025) but restrict analyses to singular environmental objectives such as maintaining fish habitat or lake conditions. To my knowledge, no studies have evaluated systematic tradeoffs between water supply for people, changes to fish habitat, and Great Salt Lake level change to assess impacts from the state's proposed water diversions, dams, and reservoirs.

The goal of this study is to evaluate hydro-economic and environmental tradeoffs of proposed new dams in the Lower Bear River Basin in Utah, USA. I developed a water management optimization model that maximizes water supply for agricultural and municipal and industrial (M&I) uses within physical and operational constraints. I use monthly hydrological data for 2000-2020 to optimize hydro-economic water management under historical conditions and proposed combinations of new dams. I coupled modeled streamflow and reservoir releases with hydroclimatic data from the same period to estimate stream temperature and habitat conditions for Bonneville Cutthroat Trout in the Bear River and water level in Great Salt Lake. My approach considers four development alternatives that represent new water demands on Utah's Wasatch Front, five proposed reservoirs in the Lower Bear River Watershed, and two environmental flows for aquatic ecosystem protection. I evaluate trade-offs between water supply from new dams, changes to stream habitat for fish, and Great Salt Lake level. This study provides a detailed analysis of Utah's proposed dams and their anticipated effects on riverine species and Great Salt Lake.

2. Methods

2.1. Study area and system

The Bear River Basin drains 35,156 km^2 in Wyoming, Idaho, and Utah before ultimately terminating as the largest inflow to Utah's Great Salt Lake (Figure 2.1). Basin hydrology is snowpack-driven, and approximately 60% of annual streamflow occurs between April and June (DeRose et al., 2015; UDWRe, 2004). This study focuses on the Lower Bear River, the downstream half of the Bear River Basin in Idaho and Utah (Figure 2.1). The Lower Bear River begins in eastern Idaho where the Bear River is diverted from its natural channel into Bear Lake. Bear Lake is a natural lake that has been plumbed to provide water storage and acts as the largest reservoir in the Bear River Basin with an active storage capacity of 1.75 Bm^3 (Welsh et al., 2013). Water released from Bear Lake provides irrigation for over 3,000 km^2 of agricultural land from May through November and diverts, on average, 2,267 Mm^3 of surface water per year (Baldwin et al., 2020; Hjerpe et al., 2023). Additional water is used to supply M&I demands that divert, on average, 112 Mm^3 of surface water per year. Hydropower generation is also a primary objective for the Lower Bear River, where three hydropower dams at Alexander, Oneida Narrows, and Cutler Reservoirs maintain full reservoirs for power generation (FERC, 2003; Pacificorp, 2019).

The Bear River Development Act directs the Utah Division of Water Resources to develop reservoir storage in the Lower Bear River to increase water supply for growing metropolitan communities in northern Utah. The state of Utah is currently considering the construction of up to five new reservoirs in the Lower Bear River Basin that would increase total water storage by as much as 767 Mm^3 (622 taf) and enable trans-basin diversion from the Lower Bear River to supply additional water to Wasatch Front communities in the Weber and Jordan River Basins (UDWRe, 2019a) (Figure 2.1). Two proposed reservoirs, Above Cutler and Fielding, are sited along the mainstem Lower Bear River, while the proposed Cub River and Temple Fork (Logan River) proposed reservoirs are located on tributaries. A fifth proposed reservoir is located off-channel in Whites Valley and would require pumping and pipeline facilities from the Fielding site. Proposed reservoirs and dams are intended to increase water storage and not significantly alter hydropower generation within the system (UDWRe, 2019a).

The Lower Bear River's Cub and Logan River tributaries support the largest remaining metapopulations of Bonneville Cutthroat Trout *Oncorhynchus clarkii utah* (Budy et al., 2012; Teuscher & Capurso, 2007). Bonneville Cutthroat Trout are a salmonid species native to the rivers and lakes of the Bear River Basin (Behnke, 1992). Once prevalent throughout the Bear River Basin, Bonneville Cutthroat Trout are now limited to as little as 35%-40% of their historic range and are managed for conservation in Utah and Idaho (Budy et al., 2020). Bonneville Cutthroat Trout that exhibit fluvial life histories migrate between mainstem rivers or freshwater lakes in the winter and headwater tributaries in the summer (Colyer et al., 2005; Schrank & Rahel, 2004). These migrations allow Bonneville Cutthroat Trout to access stream reaches with seasonally beneficial streamflow and water temperature conditions that provide thermal refuge and spawning and rearing habitats (Budy et al., 2012; Carlson & Rahel, 2010). Dams and reservoirs negatively impact Cutthroat Trout and other migratory fish by blocking access to critical habitat and altering streamflow and stream temperature conditions (Ardren & Bernall, 2017; Muhlfeld et al., 2012) and are a leading cause for population declines among migratory fish species worldwide (Huang & Li, 2024).

The Bear River delivers over 1,480 Mm^3 of water on average to Great Salt Lake annually. Great Salt Lake and its surrounding wetlands provide habitat for millions of migratory birds that are federally protected by the North American Migratory Bird Treaty Act of 1918 (Downard et al., 2014) and support mineral extraction, brine shrimp harvesting operations, and recreation that were valued over US $1.85 billion in 2023 (Great Salt Lake Strike Team, 2025). Consumptive water uses have reduced inflow to Great Salt Lake and caused the lake level to drop 5.5 m (18 ft) from its high in the 1980s, a decline of 66% in total water volume under natural conditions (USGS, 2024). As lake level drops, mineral companies lose access to brines for processing, brine shrimp that form the base of Great Salt Lake's food web are exposed to stressful conditions from increasing salinity, and exposed lake bed sediments contribute to dust storms that impair air quality for over two and a half million people in northern Utah (Munroe et al., 2025). The State of Utah's feasibility study of proposed Lower Bear River reservoirs estimates lake level will drop by 0.2-0.4 m (8.5-14 in) (UDWRe, 2019a). However, return flows to the lake from indoor and outdoor uses were calculated incorrectly in the State's assessment and were nearly doubled because of a simple math error (reported as 62 – 80% instead of 32 – 44 %) (UDWRe, 2019a; S. Null, personal communication, 2025). Also, the initial lake level used in their analysis was not provided, leaving the effects of proposed Bear River development on Great Salt Lake largely unknown (UDWRe, 2019a).

2.2. Conceptual overview

I developed coupled models to evaluate tradeoffs among (1) water supply for agricultural and M&I demands, (2) suitable stream habitat for fish, and (3) streamflow contributions to Great Salt Lake (Figure 2.2). I used a monthly timestep for a 20-year period from January 2000 to January 2020. To represent the water supply objective, I developed a hydro-economic optimization model for agricultural and M&I water deliveries, streamflow, and reservoir storage. Hydropower generation is ignored in this model, although I maintain full storage at hydropower reservoirs to mimic hydropower operations. For the fish habitat objective, I passed modeled streamflow from optimization model outputs to an equilibrium stream temperature model, which assumes stream temperatures are driven by atmospheric heating and cooling. I classified stream temperatures and streamflows using Bonneville Cutthroat Trout habitat suitability criteria to estimate quality-weighted habitat. For the lake level objective, I passed modeled streamflows from optimization model outputs to a water mass balance model to predict changes to lake volume and the corresponding level of the wetted portion of Great Salt Lake. Model alternatives include new human water demands, proposed dam scenarios, and environmental flow constraints. I describe each objective and model component in detail in the following sub-sections.

2.3. Water supply objective using hydro-economic optimization modeling

I developed a generalized network flow hydro-economic optimization model of the Lower Bear River to minimize total economic cost, represented as water scarcity, to agricultural and M&I demand areas.

The objective function is expressed mathematically as

$$Minimize\ Z = \sum_j \sum_k \sum_t X_{j,k,t} * c_{k,t} \tag{1}$$

where Z is the total cost (US dollars) of water scarcity to agricultural and M&I demand areas throughout the system, $X_{j,k,t}$ is the flow from node j to node k in month t (Mm^3 per month), and $c_{k,t}$ is the cost per unit of water at node k in month t (US dollars per Mm^3). Target human demands are the volume of water demanded for agricultural and M&I uses. Water scarcity is the difference between target human demands and water deliveries and occurs when target demands are unmet.

The objective function is bound by physical and environmental constraints. Water mass is conserved within the system (Equation 2), and upper and lower bounds limit channel flows and reservoir capacity while maintaining environmental flows (Equation 3).

$$\sum_k X_{j,k,t} = \sum_k X_{k,j,t} * a_{k,j,t} + b_{k,t}, \forall j, t \tag{2}$$

$$minX_{j,k} \leq X_{j,k,t} \leq maxX_{j,k}, \forall j, t \tag{3}$$

In these equations, $X_{j,k,t}$ is the flow from node j to node k in month t (Mm^3 month^{-1}), $a_{k,j,t}$ is reach gains or losses on link jk in month t, $b_{k,t}$ is external inflows to node k in month t, and $minX_{j,k}$ and $maxX_{j,k}$ are the lower and upper bound at node j or on link jk, respectively. Proposed reservoirs are modeled by adjusting the maximum capacity in Equation 3.

I coded the model in the General Algebraic Modeling System software (GAMS Development Corporation, 2023) and solved the model with the non-linear global solver Linear, Interactive, and Discrete Optimizer (LINDO; Lin & Schrage, 2009). Model outputs include time series of monthly optimized water deliveries to agricultural and M&I demand areas, storage at reservoirs and proposed reservoirs, and streamflow through river reaches.

2.3.1. Optimization model data and implementation

The Lower Bear River model includes four existing reservoirs, five proposed reservoirs, seven agricultural and M&I demand areas, and 16 stream reaches that provide potential habitat for Bonneville Cutthroat Trout in the Lower Bear Watershed (Figure 2.3). This model represents approximately 82% of populated and irrigable land in the Bear River Basin.

Agricultural water demands were represented with monthly diversions into large irrigation canals during the 2000-2020 time period at a standard cost of \$0.42 per m^3 (\$521 per acre-foot), the rate for agricultural water compensation in the adjacent Colorado River Basin (Zulauf, 2023) (Table 2.1). M&I water demands were represented with 2010 population-weighted per capita applied water use data collected by the Utah Division of Water Rights and compiled by Jackson-Smith (2017). Monthly M&I water costs were represented by linear approximations of seasonal M&I economic loss functions for northern Utah metropolitan areas based on 2010 population, water prices, applied water, and M&I sector water use fractions (Null, 2018). Water scarcity costs for

M&I demand areas are more than double those for agricultural areas, with costs varying seasonally between \$0.98-1.26 per m^3 (\$1,210-1,550 per acre-foot) for Lower Bear River M&I demand areas and between \$1.44-1.77 per m^3 (\$1,780-2,290 per acre-foot) for Wasatch Front M&I demand. Hydropower is represented as a constraint that requires storage at Alexander, Oneida Narrows, and Cutler Reservoirs in any timestep to equal or exceed 75% of capacity.

Mean monthly inflows and system gains and losses for January 2000 to January 2020 were compiled from daily streamflow time series data provided by PacifiCorp and US Geological Survey (USGS) stream gage data (USGS, 2024) (Table 2.1). Streamflow data for the Cub River were available from October 2005 to September 2010. I estimated missing Cub River streamflow data with a linear regression to Logan River streamflow observations ($R^2 = 0.93$). I gathered initial reservoir storage from reservoir storage time series data provided by PacifiCorp. I did not explicitly represent reservoir evaporation but estimated evaporative losses by closing a water balance at each existing reservoir expressed as gains or losses. For reaches connecting demand areas, I represented unconsumed portions of agricultural and M&I diversions with consumptive use fractions for Lower Bear River and Wasatch Front communities from Utah's state water budget model (UDWRe, 2024). These consumptive use fractions are estimates in the absence of more certain data.

I evaluated model performance by comparing modeled monthly streamflow to mean monthly observed streamflow at seven gaging stations in the Lower Bear River. At each gaging station, I used 240 monthly observations for each site collected from January 2000 to January 2020. Streamflow values were $\log_{10}$-transformed to normalize differences between seasonally large spring runoff flows and low fall baseflows (Goodrum & Null, 2023; Wenger et al., 2010; Young et al., 2009). I selected performance evaluation criteria recommended for hydrological and water quality models that provide clear and quantitative performance measures at the watershed scale (Krause et al., 2005; Moriasi et al., 2015). I assessed differences between modeled and observed streamflow with the coefficient of determination (R^2), Nash-Sutcliffe efficiency (NSE) index, percent bias (PBIAS), mean absolute error (MAE), and root mean square error (RMSE). R^2 and NSE describe goodness-of-fit between observed and simulated data, PBIAS describes over- and underestimation, MAE and RMSE describe the size of errors (Moriasi et al., 2015; Wenger et al., 2010). For $\log_{10}$-transformed streamflow, I normalized MAE and RMSE as a percentage difference from the $\log_{10}$-transformed mean of observed values (Young et al., 2009).

2.4. Fish habitat objective using habitat suitability

I used streamflow and stream temperature to estimate suitable stream habitat for Bonneville Cutthroat Trout (Buisson et al., 2008; Dunham et al., 2003; Li et al., 2022). I input modeled streamflows from the optimization model discussed above into an equilibrium temperature model to predict longitudinal changes to stream temperature from meteorological conditions for each month and stream reach. I then used streamflow and stream temperature to classify habitat suitability criteria for Bonneville Cutthroat Trout as suitable, stressful, or unsuitable for each stream reach and month.

2.4.1. Equilibrium temperature model

I modeled monthly stream temperature using a one-dimensional equilibrium temperature model. Equilibrium temperature models assume rivers are advection dominated and that longitudinal changes to stream temperature are driven by exposure to meteorological conditions (Bogan et al., 2003). I calculated stream temperature using a simplified form of the advection-dispersion equation described in Null et al., (2013a) where net heat exchange is calculated as heat mass balance (Equation 4).

$$\frac{\partial T_w}{\partial t} = \frac{H_{net}}{C_p \rho d} \tag{4}$$

In this equation, T_w is stream temperature (°C), t is the model timestep, H_{net} is net heat exchange at the water's surface (Wm^{-2}), C_p is the specific heat of water (4,185 J kg^{-1} °C^{-1}), ρ is water density (1,000 kg), and d is water depth (m).

Equilibrium temperature models are governed by travel time, river geometry, and boundary stream temperature conditions (Null et al., 2013b). I assumed uniform conditions within stream reaches. Stream reaches ranged in length from 4-66 km, with an average reach length of 23 km. Travel time is controlled by stream length and velocity, which I estimated for modeled streamflows in each reach and month using generalized hydraulic geometry power functions and coefficients for rivers in the western United States (Leopold et al., 1995; Null et al., 2013a). Coefficients for depth and velocity had values of 0.43 and 0.45, respectively. I assumed channel geometry is rectangular where the water surface is the same width as the stream bed. I estimated stream temperature separately for rivers and tributaries and used a heat mass balance to account for thermal mixing at confluences. I represented boundary stream temperature conditions using stream temperature measurements collected at inflows and below existing reservoirs in the Lower Bear River watershed (LRO, 2025b; Turney et al., 2025). Reservoirs affect water temperatures from thermal stratification and from the design of outlet infrastructure (Null et al., 2024). For boundary conditions below proposed reservoirs, I used stream temperature measured below nearby reservoirs with similar storage capacity, surface area, and depth as the proposed reservoir.

2.4.2. Fish habitat suitability

For each reach and month, I intersected streamflow and stream temperature suitability criteria to estimate habitat suitability and calculate monthly quality-weighted fish habitat for each stream reach (Table 2.2). A reach was categorized as suitable if streamflow exceeded 25% of the mean annual flow (MAF) and stream temperature was below 20°C, stressful if either streamflow was between 10% and 25% of MAF or stream temperature was between 20-24°C, and unsuitable if either streamflow was less than 10% of MAF or stream temperature exceeded 24°C (Caissie et al., 2015; Johnstone & Rahel, 2003; Schrank et al., 2003). I assessed streamflow suitability as a percentage of a reach's MAF because it indicates physical habitat availability and is strongly associated with observed species presence and habitat use (Goodrum & Null, 2023; Hatfield & Bruce, 2000; Rosenfeld et al., 2007). Better estimates of streamflow suitability are unavailable, although functional flow targets are currently being developed for the Bear River (Nusrat et al., 2024). I intersected streamflow and temperature suitability estimates, rather than use mean suitability, to reflect the assumption that suitable conditions for one habitat variable do not mitigate unsuitable conditions for another variable (Morrisett et al., 2023). Finally, I multiplied reach length by habitat suitability to estimate the quality-weighted habitat available to fish in each reach and month.

2.4.3. Fish habitat modeling data and implementation

Stream temperature data were unavailable for the 2000-2020 modeling period, so I represented boundary conditions with mean monthly stream temperatures calculated from daily average temperatures collected between July 2022 and June 2023 on the Bear and Logan Rivers (LRO, 2025b; Turney et al., 2025) (Table 2.3). Stream temperature data for the Cub River were unavailable and were represented by Logan River stream temperatures. I represented monthly atmospheric conditions by averaging daily meteorological data collected between July 2014 and June 2020 at the Logan River Observatory's climate monitoring station in Cache Valley (LRO, 2025a). Meteorological data includes shortwave solar radiation, air temperature, relative humidity, windspeed, barometric pressure, and cloud cover. Unregulated mean annual flow for river reaches were extracted from the National Hydrography Dataset Plus Version 2 (USGS, 2023b). NHD estimates streamflow with a geospatial flow balance model with precipitation data collected between 1971 and 2000 (McKay et al., 2012). Stream lengths for river reaches were calculated from the National Stream Internet geospatial stream network (Nagel et al., 2017). Stream temperature and habitat suitability modeling was conducted in R version 4.3.1 (R Core Team, 2023). Outputs include a monthly timeseries of stream temperature for all river reaches, habitat suitability classifications, and quality-weighted habitat fish habitat for river reaches.

2.5. Great Salt Lake elevation objective and water balance

I used a monthly water balance model from Mohammed & Tarboton (2012) to estimate Great Salt Lake volume, surface area, and elevation. Estimates of Bear River streamflow are from the water optimization model. The water balance uses the following equation:

$$V_t = V_{t-1} + (P_t * A_t) + Q_t + (SGainLoss_t * A_t)$$

where V_t is lake volume in month t (Mm^3), V_{t-1} is lake volume in the preceding month (Mm^3), P_t is the precipitation over the lake surface in month t (m), A_t is the lake surface in month t (m^2), Q_t is inflow to the lake in month t (Mm^3), and $SGainLoss_t$ is observed lake elevation change in month t (m). Inflows to the lake are modeled Bear River streamflow, return flow from optimized water deliveries to the Wasatch Front M&I demand area, and observed surface and groundwater inflows, including from the Weber and Jordan Rivers. Streamflow in the terminal reach was increased by 8% to account for reach gains that occur downstream of Corinne (UDWRe, 2024). Lake surface gain and loss is a water balance closure term to approximate lake evaporation and mineral extraction water depletions.

2.5.1. Mass balance model data and implementation

My water balance model requires hydrological, precipitation, and bathymetric input data that I retrieved from a previous time series analysis of Great Salt Lake (Tarboton, 2024). Monthly precipitation time series data for the 2000-2020 period were from PRISM climate datasets for Great Salt Lake surface area (Tarboton, 2023). I used known relationships between lake volume and bathymetry to estimate surface area and level in each month (Tarboton, 2017). I evaluated the performance of the water balance model by comparing modeled lake elevation from a model run constrained for historical conditions to the monthly average observed elevation at Great Salt Lake (USGS, 2024). As with streamflow, I assessed differences between modeled to observed lake elevation with the coefficient of determination (R^2), Nash-Sutcliffe efficiency (NSE) index, percent bias (PBIAS), mean absolute error (MAE), and root mean square error (RMSE).

In this study, I represented Great Salt Lake as a single waterbody for simplicity. Great Salt Lake is divided into two arms by a solid-fill railroad causeway bisecting the lake, and flow between the arms is regulated by openings in the causeway (Mohammed & Tarboton, 2012). I assume that Lower Bear River water reaches the wetted portion of Great Salt Lake so that Lower Bear River streamflow directly influences GSL level. Wetlands surround the lake, using an unmeasured portion of water, with playas separating the wetlands from the wetted lake. At its confluence with Great Salt Lake, the Bear River is managed by the US Fish and Wildlife Service to maintain a large complex of emergent and open water wetlands that provide habitat for waterfowl and colonial nesting birds (Downard et al., 2014; Alminagorta et al., 2016). In other parts of the Great Salt Lake watershed, wetlands and undocumented diversions reduce streamflow from the downstream-most gaging stations on the Weber and Jordan Rivers (Lukens et al., 2024). Evaluating how to distribute water to Great Salt Lake is an active area of research.

I assessed Great Salt Lake conditions using an elevation matrix that relates lake elevation to salt concentration thresholds affecting more than 90 ecological, economic, recreation, and human health interests at Great Salt Lake (FFSL, 2013). Great Salt Lake mass balance modeling was conducted in R version 4.3.1 (R Core Team, 2023). Model output includes monthly timeseries of Great Salt Lake elevation, volume, and surface area.

2.6. Model runs for development alternatives

I ran 5 models representing development alternatives for the Lower Bear River (Table 2.4). I compared a *historical* model run with observed water management for the 2000-2020 period and used it to evaluate model performance. In the historical run, streamflow between Alexander and Oneida Narrows Reservoirs was constrained so that it was less than or equal to 42.5 $m^3 s^{-1}$ (1,500 $ft^3 s^{-1}$) to prevent flooding in Gentile Valley, and reservoir storage at Bear Lake was constrained to be less than or equal to 1.436 Bm^3 (1,165 taf) to reflect PacifiCorp's high-runoff management operations (Baldwin et al., 2020). These constraints were relaxed for all other model runs.

A *Wasatch demands* model run represented the Lower Bear River without new reservoirs and with Wasatch Front M&I water demands, and a *proposed reservoirs* model run included both Wasatch Front M&I water demands and all proposed reservoirs. All future alternatives assumed water conveyance infrastructure linking the Lower Bear River to Wasatch Front demands (Figure 2.3). Thirteen combinations of the five proposed reservoirs were considered in the Bear River development report, but some combinations had similar water storage capacity, with a mean, min, and max of 560 Mm^3 (560 taf), 300 Mm^3 (244 taf), and 767 Mm^3 (622 taf), respectively (UDWRe, 2019a). I included all five proposed reservoirs simultaneously to evaluate how dams influence stream habitat for fish. The model run with proposed reservoirs also included pumping and pipeline infrastructure to off-channel Whites Valley Reservoir (UDWRe, 2019a).

Two additional model runs, *10% MAF e-flows* and *25% MAF e-flows*, were identical to the proposed reservoirs model run, but included environmental flow constraints of 10% and 25% of unregulated mean annual flow on all river reaches. I included these runs to evaluate the potential to mitigate impacts to river habitat and Great Salt Lake elevation while maintaining water deliveries for human use. Environmental flows with 10% of mean annual flow represent the threshold below which streams no longer provide suitable physical habitat for aquatic species, while environmental flows exceeding 25% of mean annual flow generally provide suitable physical habitat (Annear & Conder, 1984; Jowett, 1997; Rosenfeld et al., 2007). Environmental flow criteria are ecologically based, simple to implement, and widely applied to mitigate environmental impacts of flow regulation (Caissie et al., 2015; Gopal, 2013).

3. Results

3.1. Optimization model evaluation

Modeled historical streamflow matched observed streamflow well for the 2000-2020 period (Table 2.5). R^2 and NSE exceeded 0.8 at all gaging stations and exceeded 0.9 at most sites, suggesting strong agreement between modeled and observed streamflow. RMSE was within 15% of log-transformed mean observed streamflow and MAE was within 8% of mean observed streamflow for all seven sites throughout the study area. PBIAS ranged from -1.4% to -4.8%, indicating that the model slightly underestimated observed streamflow. Underestimation bias is expected in hydro-economic water management optimization models because models have perfect knowledge of water demands and system operations, meaning that water deliveries never exceed demands downstream (Null et al., 2014). Modeled Great Salt Lake elevation showed strong agreement with observed lake elevation for the 2000-2020 period, with R^2 and NSE both equal to 0.94, and small estimation errors, where RMSE and MAE were both less than 0.2 m.

3.2. Water supply for agricultural and M&I demand areas

M&I water demands in Lower Bear River and Wasatch Front demand areas were met under all alternatives except for the 25% MAF e-flow alternative, where average annual M&I water scarcity was 44.6 Mm^3 (36.2 taf) representing 8% of annual M&I demand. When it occurred, water scarcity was born by agricultural water users (Figure 2.4). M&I demand areas have a higher willingness to pay for water, and when scarcity exists, agricultural users would transfer water to M&I areas through temporary leases (Null et al., 2014). The transfer of agricultural water to M&I demand areas is common in hydro-economic optimization models where water markets, rather than water right priorities, are used to determine water deliveries (Harou et al., 2010; Medellín-Azuara et al., 2008; Tanaka et al., 2006).

Agricultural water demands are represented by diversions into irrigation canals that are completely satisfied under historical conditions. Annual agricultural water scarcity was 152 Mm^3 (124 taf) for the Wasatch demands alternative, which represents approximately 30% of annual agricultural water demands, and scarcity occurred in all years from 2000-2020 (Figure 2.4). The proposed reservoirs and 10% MAF e-flow alternatives limited average annual agricultural water scarcity to 36 Mm^3 (29 taf) and 92 Mm^3 (75 taf), respectively, which occurred during the first four to five years and coincided with drought conditions in the Great Salt Lake Basin. Annual agricultural water scarcity was 276 Mm^3 (402 taf) under the 25% MAF e-flow alternative, which represented over 50% of average annual agricultural demand, suggesting that maintaining 25% MAF streamflows would require substantial water transfers from agricultural or M&I users or restricting interbasin water transfers to the Wasatch Front.

Observed average annual total water storage was 910 Mm^3 (737 taf) from 2000-2020 (Figure 2.5). Average annual total water storage decreased to 764 Mm^3 (619 taf) under the Wasatch demands alternative, a 16% decrease from observed storage, despite ending the period with more water stored than under observed conditions. This suggests that meeting new water demands on the Wasatch Front required some reservoir depletion, but that existing reservoirs were able to compensate for short-term storage losses by the end of the period. Average annual total water storage increased by 34% to 1,221 Mm^3 (990 taf) in the proposed reservoirs alternative. Under 10% MAF and 25% MAF e-flow alternatives, total water storage was similar to observed conditions, with average annual total water storage of 980 Mm^3 (795 taf) and 939 Mm^3 (761 taf), respectively.

Proposed reservoirs rarely filled in any scenario and often operated at less than 50% of total capacity. Proposed reservoirs only reached full capacity in two months in the proposed reservoir alternative, three months in the 10% MAF e-flows alternative, and eight months in the 25% MAF e-flows alternative. Proposed reservoir storage was less than half of capacity for over 90% of the modeled time period under the proposed reservoir and 10% MAF e-flow alternatives, and proposed reservoir storage was less than half of capacity for over 80% of months in the 25% MAF e-flow alternative.

3.3. Stream habitat for Bonneville Cutthroat Trout

Water diversions to Wasatch demands and the addition of proposed reservoirs reduced stream habitat for Bonneville Cutthroat Trout (Figure 2.6). Average monthly stream habitat declined by 31 km from historical conditions in the Wasatch demands alternative, and total stream habitat declined by 8% from 2000-2020. Stream habitat loss was the most severe in the proposed reservoirs alternative, where average monthly stream habitat decreased by over 50 km from historical conditions, representing a 13% loss in total habitat for the modeling period. Environmental flows mitigated some habitat loss from increasing diversions to M&I demands and proposed reservoirs. Monthly stream habitat declined by 11 km on average from historical conditions in the 10% MAF e-flow alternative but only reduced overall habitat availability by 2% between 2000-2020. Monthly stream habitat increased by over 32 km on average for the 25% MAF e-flow alternative, representing an overall increase of 9% in stream habitat from historical conditions.

Under historical conditions, stream habitat for Bonneville Cutthroat Trout was most limited during the summer months of July and August (Figure 2.6). Adding diversions to supply the Wasatch Front M&I demand area did not significantly alter summer habitat availability. However, adding proposed reservoirs reduced summer stream habitat, on average, by between 40 and 70 km, and e-flows did not improve summer stream habitat losses from proposed reservoir construction.. Summer stream habitats are important for Bonneville Cutthroat Trout, which migrate during summer months to escape warm stream temperatures, and summer coldwater habitats are a focus for salmonid conservation (Isaak & Young, 2023). In modeled alternatives including proposed dams, summer stream habitat declined even when suitable streamflow was maintained, suggesting summer habitat loss is driven by stream temperatures.

In the historical scenario, the Logan and Cub Rivers were the only reaches that provide year-round suitable Cutthroat Trout habitat, while all mainstem Bear River reaches had stressful or critical habitat conditions (Figure 2.7). Proposed dams did not change habitat conditions along the mainstem Bear River, but Temple Fork Dam created critical habitat conditions in the Logan River (Figure 2.7b). The 10% and 25% MAF E-Flow alternatives improved fish habitat in the Logan River and Bear River downstream of Bear Lake (Figure 2.7b,c). However, with Temple Fork Dam, the Logan River had stressful habitat conditions, even with 25% MAF minimum flows, suggesting that minimum flow requirements cannot compensate for adverse stream temperature changes downstream of the proposed dam. In all modeled scenarios that include proposed dams, the Cub River was the only tributary that retains suitable habitat for Bonneville Cutthroat Trout year-round.

3.4. Great Salt Lake elevation and condition

Increasing water demands—and consumptive water use—by Wasatch Front M&I demands reduced Great Salt Lake elevation compared to observed levels in all modeled alternatives (Figure 2.8). Between January 2000 and January 2020, observed Great Salt Lake elevation decreased from 1280.8 m to 1278.1 m, a net decrease of 2.7 m. Adding Wasatch demands exacerbated lake level decline, and reduced Great Salt Lake's elevation to 1277 m by the end of the model period. Under the proposed reservoirs alternative, Great Salt Lake elevation declined over 4 m to 1276.8 m by January 2020. The 10% MAF e-flow alternative resulted in a similar overall elevation decrease to the proposed reservoirs alternative of 4 m, suggesting that these flows were insufficient to offset consumptive water losses caused by Wasatch Front M&I demands. The 25% MAF e-flows alternative limited lake level decline to 3.7 m over the study period. These findings indicate that diverting the Lower Bear River to supply Wasatch Front M&I water demands will lead to further lake level decline.

While observed lake levels fell into critical condition for limited periods in 2015 and 2016, lake level for all modeled alternatives fell into critical condition by 2014 and largely remained there from 2015 to 2020 (Figure 2.8). These findings suggest that new M&I demands and proposed reservoirs will lead to further lake elevation decline at Great Salt Lake, and that declines will increase salinity. Together these changes threaten brine shrimp viability, mineral production activities, and human health from airborne playa dust in surrounding Wasatch Front communities (Grineski et al., 2024).

4. Discussion

4.1. Impacts of new water demands and proposed dams

Constructing new reservoirs could deliver an annual average of 497 Mm^3 of water to new demands but would reduce annual average stream habitat for Bonneville Cutthroat Trout by 50 km and lower Great Salt Lake elevation by over 4 m from 2000 to 2020. While building new dams and reservoirs magnified habitat loss for Bonneville Cutthroat Trout, dams only slightly decreased Great Salt Lake elevation relative to the scenario including just new Wasatch Front M&I demands. My findings support previous studies that identify both consumptive water use (Damiani et al., 2019, 2021) and dams and reservoirs (Liermann et al., 2012; Reid et al., 2019) as contributing to fish habitat loss, but that consumptive water use, rather than reservoir operation, drives lake level decline at Great Salt Lake and other terminal lakes (Wurtsbaugh et al., 2016, 2017). Arresting lake level decline at Great Salt Lake requires reconciling human water demands in the

Great Salt Lake Basin with finite water supplies from the Bear River and other rivers feeding Great Salt Lake.

Modeled environmental flow scenarios had limited capacity to meet ecological objectives in the Lower Bear River with the construction of new reservoirs and water delivery to the Wasatch Front. The 10% MAF e-flow alternative supported approximately 10% less Bonneville Cutthroat Trout habitat compared to historical conditions, and Great Salt Lake elevation was over one meter lower than the observed end-of-period level. While Bonneville Cutthroat Trout stream habitat increased overall with 25% MAF e-flow alterative, stream habitat decreased during the warmest period of the summer when habitat is most limited. My results suggest that habitat bottlenecks could be exacerbated by proposed reservoirs that cause stream temperature warming and not rectified with environmental flows. My findings are consistent with previous criticism of static environmental flow rules that ignore natural hydrological and ecological complexity necessary for aquatic species to complete varied life history requirements (Arthington et al., 2006; Tickner et al., 2020). Alternatively, environmental flows that maintain or restore ecologically important attributes of hydrological regimes and instream conditions such as wet season peak flows and cold stream temperatures have been shown to promote native fish recovery (Baruch et al., 2024) and are currently being developed for the Great Salt Lake Basin (Nusrat et al., 2024). However, Utah has largely opposed regulating instream flows for environmental purposes (Womble et al., 2022). Environmental flows simulated herein rely on a level of regulation that the state has been reluctant to implement.

4.2. Limitations

My hydro-economic model was limited by data availability and the simplification of real-world conditions. My approach ignored legal, political, and institutional practices to emphasize water supply system capabilities rather than how people choose to operate the system. My hydro-economic optimization model operated with perfect foresight and without flood control or reservoir operation rules, meaning that the model can optimize for flood and drought periods and represents a best-case scenario for water management. My optimization model also did not represent hydropower or recreational benefits of reservoirs, although these are important uses in the Lower Bear River (Hjerpe et al., 2023). I represented M&I water scarcity costs with linear economic demand functions that do not completely represent nonlinear willingness-to-pay among M&I water users (Coleman, 2009). My approach underestimates water prices when water demands go unmet and overestimates prices when water demands are mostly satisfied.

I optimized water management to minimize economic scarcity for agricultural and M&I water demands but did not optimize stream habitat or Great Salt Lake elevation objectives. While my modeling approach allowed me to assess environmental impacts from optimized water management decisions, my environmental representations were not dynamic and did not allow us to evaluate optimal solutions for achieving specific environmental objectives such as maximizing thermal habitat for fish or lake elevations for Great Salt Lake. Nonetheless, my work expands water resources systems modeling by including ecologically-based habitat representations for multi-objective decision-making needed to inform river management decisions with competing hydro-economic and environmental objectives.

Additional limitations of this study included data and methods used to represent stream habitat and Great Salt Lake objectives of water management. Stream temperature data were unavailable for the 2000-2020 modeling period, which I approximated with single-year measurements from July 2022 to June 2023 that underrepresent interannual variability in stream temperature, and thus stream habitat suitability (Luce et al., 2014). I estimated stream habitat suitability from streamflow and stream temperature, which are linked to fish population dynamics (Van Vliet et al., 2013) but do not represent spawning habitat availability and non-native species presence that also influence Bonneville Cutthroat Trout survival and population persistence (Budy et al., 2007; McHugh & Budy, 2006). My study also ignores habitat loss caused by inundation beneath reservoirs, which often favor non-native species that displace native species but also provide economic benefits through recreational fisheries (Murphy et al., 2021; Pennock et al., 2021). For Great Salt Lake, I did not explicitly represent evaporation or water extraction but estimated these losses and measurement error by closing a water balance. In reality, evaporation decreases as surface area shrinks and salinity increases (Mohammed & Tarboton, 2012).

4.3. Implications for Lower Bear River and Great Salt Lake water management

My analysis focused on new consumptive water use and proposed reservoir impacts for the 2000-2020 period, although future climatic conditions when dams would be built are likely to be warmer, drier, and more variable than historical conditions (Allan & Douville, 2024). Prolonged drying results in less surface water for water supply and storage (Dettinger et al., 2015), which could mean that reservoirs will operate with less water than my models show. In California's Sacramento-San Joaquin River Basin, reservoir storage expansion rarely improved water supply when modeled for an 82-year period with warmer and drier climatic conditions (Nover et al., 2019). Warmer atmospheric conditions also reduce snowpack and increase stream temperatures, necessitating thermal refuges like the Logan and Cub Rivers for cold water species (Isaak & Young, 2023). Similarly, warming climatic conditions are likely to increase evaporation and reduce surface water in rivers supplying Great Salt Lake, which could exacerbate Great Salt Lake decline by as much as a meter (Hassan et al., 2023). Climatic change is also expected to intensify wet periods separated by extended dry periods, which threaten reservoirs and other water infrastructure that were not designed for extreme weather events (Kreibich et al., 2022). The effects of these proposed reservoirs with hydroclimate alteration and intensification have not been studied and remain unknown in the Lower Bear River and Great Salt Lake Basin.

In addition to new reservoirs, Utah is considering changes to water management policy and operations in the Lower Bear River and Great Salt Lake Basin (Great Salt Lake Strike Team, 2025). Water banking, which allows for temporary water transfers through voluntary leasing agreements, can reallocate water to economically and environmentally beneficial uses, while maintaining legal protections for water right holders (Null, 2022). Water banking and similar types of transactions are currently being evaluated and implemented in the Lower Bear River and Great Salt Lake Basin (Carney et al., 2021; Edwards & Null, 2019). Managed aquifer recharge diverts excess streamflow, such as flood flows and snowmelt, for artificial recharge to offset negative impacts of groundwater withdrawal (Levintal et al., 2023). Managed aquifer recharge has been shown to improve baseflow conditions for fish without jeopardizing existing water uses (Morrisett et al., 2023). Recharge could be used to mitigate groundwater overdraft that has contributed to Great Salt Lake decline (Zamora & Inkenbrandt, 2024). I found that modeled existing Lower Bear River reservoirs rarely filled during the 2000-2020 period. Previous studies have similarly found that re-operating Bear Lake, the system's largest reservoir, could increase water storage for downstream agriculture (Baldwin et al., 2020) and that reservoirs could be re-operated to benefit native fish and ecosystems (Null et al., 2024). Moreover, dam and reservoir construction typically have extended time horizons and costs overruns (Petheram & McMahon, 2019), suggesting that new reservoirs should be evaluated alongside complementary supply- and demand-side water management strategies that could offset or negate the need for costly new infrastructure.

5. Conclusion

The American West is experiencing a decades-long megadrought that threatens water supplies for people and the environment (Williams et al., 2022). Great Salt Lake decline presents an economic, environmental, and human health crisis for surrounding communities. Previous studies have shown that water depletion for human uses drives the decline of terminal lakes (Schulz et al., 2020; Wurtsbaugh et al., 2017) and that their collapse leads to toxic airborne pollution, ecosystem collapse, and economic losses that are difficult to reverse (Borlina & Rennó, 2017; Micklin, 2010; Wurtsbaugh & Sima, 2022). Utah's Bear River Development Act mandates that state agencies build new reservoirs to expand current water supply for the state's growing population (Utah Code § 73-26, 1991). However, Utah has also created environmental policies and allocated funding to preserve Great Salt Lake (Great Salt Lake Strike Team, 2025). I developed a hydro-economic optimization model to represent water management with proposed reservoirs, then coupled model outputs with hydroclimatic data to estimate stream temperature, habitat suitability for fish, and Great Salt Lake elevation. My study advances environmental water management by demonstrating that expanding water storage in the Lower Bear River and consumptive water use in the Great Salt Lake Basin conflicts with environmental objectives for native fish habitat and Great Salt Lake, and we demonstrate that environmental flows are insufficient to offset the long-term loss of Bear River water to consumptive uses along Utah's Wasatch Front. My findings suggest that, rather than building costly new infrastructure, ensuring water supplies for people, fish, and Great Salt Lake requires coordinated management of water resources and existing infrastructure that balance human water demands with finite water supplies from the Bear River and other rivers that supply Great Salt Lake.

Acknowledgments

Funding for this study was provided by the Agriculture and Food Research Initiative Competitive Grant number 2021-69012-35916 from the USDA National Institute of Food and Agriculture and the National Sciences Foundation Grant #1653452. I thank Connely Baldwin (PacifiCorp) and Ethan Geisler (Idaho Department of Water Resources) for providing streamflow, reservoir level, and diversion data in the Bear River Basin. I thank David Rosenberg (Utah State University) for contributing to GAMS code for my hydro-economic optimization model and Eryn Turney (Utah State University) for collecting and processing Bear River stream temperature data.

References

Ahearn, D. S., Sheibley, R. W., & Dahlgren, R. A. (2005). Effects of river regulation on water quality in the lower Mokelumne River, California. *River Research and Applications*, *21*(6), 651–670. https://doi.org/10.1002/rra.853

Allan, R. P., & Douville, H. (2024). An even drier future for the arid lands. *Proceedings of the National Academy of Sciences*, *121*(2), e2320840121. https://doi.org/10.1073/pnas.2320840121

Alminagorta, O., Rosenberg, D. E., & Kettenring, K. M. (2016). Systems modeling to improve the hydro-ecological performance of diked wetlands. *Water Resources Research*, *52*(9), 7070-7085. https://doi.org/10.1002/2015wr018105

Annear, T. C., & Conder, A. L. (1984). Relative Bias of Several Fisheries Instream Flow Methods. *North American Journal of Fisheries Management*, *4*(4B), 531–539. https://doi.org/10.1577/1548-8659(1984)4<531:RBOSFI>2.0.CO;2

Ardren, W. R., & Bernall, S. R. (2017). Dams impact westslope cutthroat trout metapopulation structure and hybridization dynamics. *Conservation Genetics*, *18*(2), 297–312. https://doi.org/10.1007/s10592-016-0906-6

Arthington, A. H., Bunn, S. E., Poff, N. L., & Naiman, R. J. (2006). The challenge of providing environmental flow rules to sustain river ecosystems. *Ecological Applications*, *16*(4), 1311–1318. https://doi.org/10.1890/1051-0761(2006)016[1311:TCOPEF]2.0.CO;2

Baldwin, C. K., Hoekema, D. J., Geisler, E. T., Burton, C., & Neumann, D. W. (2020). *Impacts on Bear Lake Storage under Alternative High- Runoff Management Operations*. Utah Department of Natural Resources, Division of Water Resources. Retrieved from https://water.utah.gov/wp-content/uploads/2020/12/BearLakeReport.pdf

Baruch, E. M., Yarnell, S. M., Grantham, T. E., Ayers, J. R., Rypel, A. L., & Lusardi, R. A. (2024). Mimicking functional elements of the natural flow regime promotes native fish recovery in a regulated river. *Ecological Applications*, *34*(6), e3013. https://doi.org/10.1002/eap.3013

Behnke, R. J. (1992). *Native trout of western North America*. American Fisheries Society.

Bigalke, S. J. (2023). Hydroclimate Effects on Great Salt Lake Decline Since 1980. *All Graduate Plan B and other Reports*. Utah State University, Logan, Utah, USA. Retrieved from https://digitalcommons.usu.edu/gradreports/1699/

Bogan, T., Mohseni, O., & Stefan, H. G. (2003). Stream temperature-equilibrium temperature relationship. *Water Resources Research*, *39*(9), 2003WR002034. https://doi.org/10.1029/2003WR002034

Borlina, C. S., & Rennó, N. O. (2017). The Impact of a Severe Drought on Dust Lifting in California's Owens Lake Area. *Scientific Reports*, *7*(1), 1784. https://doi.org/10.1038/s41598-017-01829-7

Brahney, J., Heindel, R. C., Gill, T. E., Carling, G., González-Olalla, J. M., Hand, J., et al. (2024). Dust in the Critical Zone: North American case studies. *Earth-Science Reviews*, *258*, 104942. https://doi.org/10.1016/j.earscirev.2024.104942

Brown, C. M., Lund, J. R., Cai, X., Reed, P. M., Zagona, E. A., Ostfeld, A., et al. (2015). The future of water resources systems analysis: Toward a scientific framework for sustainable water management. *Water Resources Research*, *51*(8), 6110–6124. https://doi.org/10.1002/2015WR017114

Budy, P., Thiede, G. P., & McHugh, P. (2007). Quantification of the Vital Rates, Abundance, and Status of a Critical, Endemic Population of Bonneville Cutthroat Trout. *North American Journal of Fisheries Management*, *27*(2), 593–604. https://doi.org/10.1577/M06-085.1

Budy, P., Wood, S., & Roper, B. (2012). A Study of the Spawning Ecology and Early Life History Survival of Bonneville Cutthroat Trout. *North American Journal of Fisheries Management*, *32*(3), 436–449. https://doi.org/10.1080/02755947.2012.675945

Budy, P., Thompson, P. D., McKell, M. D., Thiede, G. P., Walsworth, T. E., & Conner, M. M. (2020). A Multifaceted Reconstruction of the Population Structure and Life History Expressions of a Remnant Metapopulation of Bonneville Cutthroat Trout: Implications for Maintaining Intermittent Connectivity. *Transactions of the American Fisheries Society*, *149*(4), 443–461. https://doi.org/10.1002/tafs.10240

Buisson, L., Blanc, L., & Grenouillet, G. (2008). Modelling stream fish species distribution in a river network: the relative effects of temperature versus physical factors. *Ecology of Freshwater Fish*, *17*(2), 244–257. https://doi.org/10.1111/j.1600-0633.2007.00276.x

Caissie, J., Caissie, D., & El-Jabi, N. (2015). Hydrologically Based Environmental Flow Methods Applied to Rivers in the Maritime Provinces (Canada). *River Research and Applications*, *31*(6), 651–662. https://doi.org/10.1002/rra.2772

Carlson, A. J., & Rahel, F. J. (2010). Annual Intrabasin Movement and Mortality of Adult Bonneville Cutthroat Trout among Complementary Riverine Habitats. *Transactions of the American Fisheries Society*, *139*(5), 1360–1371. https://doi.org/10.1577/T09-010.1

Carney, C. P., Endter-Wada, J., & Welsh, L. W. (2021). The Accumulating Interest in Water Banks: Assessing Their Role in Mitigating Water Insecurities. *JAWRA Journal of the American Water Resources Association*, *57*(4), 552–571. https://doi.org/10.1111/1752-1688.12940

Coleman, E. A. (2009). A Comparison of Demand-Side Water Management Strategies Using Disaggregate Data. *Public Works Management & Policy*, *13*(3), 215–223. https://doi.org/10.1177/1087724X08327648

Colyer, W. T., Kershner, J. L., & Hilderbrand, R. H. (2005). Movements of Fluvial Bonneville Cutthroat Trout in the Thomas Fork of the Bear River, Idaho–Wyoming. *North American Journal of Fisheries Management*, *25*(3), 954–963. https://doi.org/10.1577/M04-078.1

Damiani, M., Lamouroux, N., Pella, H., Roux, P., Loiseau, E., & Rosenbaum, R. K. (2019). Spatialized freshwater ecosystem life cycle impact assessment of water consumption based on instream habitat change modeling. *Water Research*, *163*, 114884. https://doi.org/10.1016/j.watres.2019.114884

Damiani, M., Roux, P., Loiseau, E., Lamouroux, N., Pella, H., Morel, M., & Rosenbaum, R. K. (2021). A high-resolution life cycle impact assessment model for continental freshwater habitat change due to water consumption. *Science of The Total Environment*, *782*, 146664. https://doi.org/10.1016/j.scitotenv.2021.146664

DeRose, R. J., Bekker, M. F., Wang, S.-Y., Buckley, B. M., Kjelgren, R. K., Bardsley, T., et al. (2015). A millennium-length reconstruction of Bear River stream flow, Utah. *Journal of Hydrology*, *529*, 524–534. https://doi.org/10.1016/j.jhydrol.2015.01.014

Dettinger, M., Udall, B., & Georgakakos, A. (2015). Western water and climate change. *Ecological Applications*, *25*(8), 2069–2093. https://doi.org/10.1890/15-0938.1

Di Baldassarre, G., Mazzoleni, M., & Rusca, M. (2021). The legacy of large dams in the United States. *Ambio*, *50*(10), 1798–1808. https://doi.org/10.1007/s13280-021-01533-x

Downard, R., Endter-Wada, J., & Kettenring, K. M. (2014). Adaptive wetland management in an uncertain and changing arid environment. *Ecology and Society*, *19*(2). Retrieved from https://www.jstor.org/stable/26269537

Dunham, J., Rieman, B., & Chandler, G. (2003). Influences of Temperature and Environmental Variables on the Distribution of Bull Trout within Streams at the Southern Margin of Its Range. *North American Journal of Fisheries Management*, *23*(3), 894–904. https://doi.org/10.1577/M02-028

Edwards, E. C., & Null, S. E. (2019). The cost of addressing saline lake level decline and the potential for water conservation markets. *Science of The Total Environment*, *651*, 435–442. https://doi.org/10.1016/j.scitotenv.2018.09.006

Endter-Wada, J., Selfa, T., & Welsh, L. (2009). Hydrologic Interdependencies and Human Cooperation: The Process of Adapting to Droughts. *Weather, Climate, and Society*, *1* (1), 55-71. https://doi.org/ 10.1175/2009WCAS1009.1

Escriva-Bou, A., Pulido-Velazquez, M., & Pulido-Velazquez, D. (2017). Economic Value of Climate Change Adaptation Strategies for Water Management in Spain's Jucar Basin. *Journal of Water Resources Planning and Management*, *143*(5), 04017005. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000735

Expósito, A., Beier, F., & Berbel, J. (2020). Hydro-Economic Modelling for Water-Policy Assessment Under Climate Change at a River Basin Scale: A Review. *Water*, *12*(6), 1559. https://doi.org/10.3390/w12061559

FERC. (2003). Order Approving Settlement Agreement and Issuing New License (No. 105). Federal Energy Regulatory Commission. Retrieved from https://lowimpacthydro.org/lihi-certificate-53-bear-river-hydroelectric-project-idaho/

FFSL. (2013). GSL Lake Level Matrix. Utah Division of Forestry, Fire, and State Lands. Retrieved from https://ffsl.utah.gov/wp-content/uploads/Elevation_Matrix_3_1_13Cropped.pdf

GAMS Development Corporation. (2023). General Algebraic Modeling System (GAMS) Release 44.3.0. Fairfax, VA, USA.

Goodrum, G. C., & Null, S. E. (2023). Reduced complexity models for regional aquatic habitat suitability assessment. *JAWRA Journal of the American Water Resources Association*, *59*(1), 107–126. https://doi.org/10.1111/1752-1688.13077

Gopal, B. (2013). Methodologies for the Assessment of Environmental Flows. In *Environmental Flows An Introduction for Water Resources Managers*. National Institute of Ecology Cap-Net New Delhi (India).

Graf, W. L. (1999). Dam nation: A geographic census of American dams and their large-scale hydrologic impacts. *Water Resources Research*, *35*(4), 1305–1311. https://doi.org/10.1029/1999WR900016

Graf, W. L. (2006). Downstream hydrologic and geomorphic effects of large dams on American rivers. *Geomorphology*, *79*(3–4), 336–360. https://doi.org/10.1016/j.geomorph.2006.06.022

Great Salt Lake Strike Team. (2025). Great Salt Lake data and insights summary. Retrieved from https://d36oiwf74r1rap.cloudfront.net/wp-content/uploads/2025/01/GSL-Jan2025.pdf

Grineski, S. E., Mallia, D. V., Collins, T. W., Araos, M., Lin, J. C., Anderegg, W. R. L., & Perry, K. (2024). Harmful dust from drying lakes: Preserving Great Salt Lake (USA) water levels decreases ambient dust and racial disparities in population exposure. *One Earth*, *7*(6), 1056–1067. https://doi.org/10.1016/j.oneear.2024.05.006

Han, Y., Dong, Z., Cui, C., Zhang, T., & Luo, Y. (2025). Multi-objective optimization scheduling for extensive plain lake water resources incorporating flood resource utilization. *Journal of Hydrology*, *651*, 132584. https://doi.org/10.1016/j.jhydrol.2024.132584

Harou, J. J., Pulido-Velazquez, M., Rosenberg, D. E., Medellín-Azuara, J., Lund, J. R., & Howitt, R. E. (2009). Hydro-economic models: Concepts, design, applications, and future prospects. *Journal of Hydrology*, *375*(3–4), 627–643. https://doi.org/10.1016/j.jhydrol.2009.06.037

Harou, J. J., Medellín-Azuara, J., Zhu, T., Tanaka, S. K., Lund, J. R., Stine, S., et al. (2010). Economic consequences of optimized water management for a prolonged, severe drought in California. *Water Resources Research*, *46*(5), 2008WR007681. https://doi.org/10.1029/2008WR007681

Hassan, D., Burian, S. J., Johnson, R. C., Shin, S., & Barber, M. E. (2023). The Great Salt Lake Water Level is Becoming Less Resilient to Climate Change. *Water Resources Management*, *37*(6–7), 2697–2720. https://doi.org/10.1007/s11269-022-03376-x

Hatfield, T., & Bruce, J. (2000). Predicting Salmonid Habitat–Flow Relationships for Streams from Western North America. *North American Journal of Fisheries Management*, *20*(4), 1005–1015. https://doi.org/10.1577/1548-8675(2000)020<1005:PSHFRF>2.0.CO;2

Herman, J., Ferer, M., Dogan, M., Jenkins, M., Medellín-Azuara, J., & Lund, J. (2018). *Advancing Hydro-Economic Optimization to Identify Vulnerabilities and Adaptation Opportunities in California's Water System* (No. CCCA4- CNRA-2018– 016). California Natural Resources Agency. Retrieved from https://cawaterlibrary.net/document/advancing-hydro-economic-optimization-to-identify-vulnerabilities-and-adaptation-opportunities-in-californias-water-system/

Hipel, K. W. (1992). MULTIPLE OBJECTIVE DECISION MAKING IN WATER RESOURCES[1]. *JAWRA Journal of the American Water Resources Association*, *28*(1), 3–12. https://doi.org/10.1111/j.1752-1688.1992.tb03150.x

Hjerpe, E., Aldrich, G., Buckley, M., Wirkkala, T., Jain, S., Taraghi, P., et al. (2023). *Regional Economic Values of the Bear River*. Cache Water District, Bear River Water Conservancy District, Utah Division of Water Resources, Great Salt Lake Advisory Council, Box Elder County, Blacksmith Fork Conservation District, North Cache Conservation District, Northern Utah Conservation District, Bear River Water Users Association, and Cache County.

Huang, Z., & Li, H. (2024). Dams trigger exponential population declines of migratory fish. *Science Advances*, *10*(19), eadi6580. https://doi.org/10.1126/sciadv.adi6580

Isaak, D. J., & Young, M. K. (2023). Cold-water habitats, climate refugia, and their utility for conserving salmonid fishes. *Canadian Journal of Fisheries and Aquatic Sciences*, *80*(7), 1187–1206. https://doi.org/10.1139/cjfas-2022-0302

Jackson-Smith, D. (2017). Water Use Data by Municipality, 2010 [Data set]. HydroShare. Retrieved from https://hydroshare.org/resource/c0174577fae8417c8c4730e8f5fc2cee/

Johnstone, H. C., & Rahel, F. J. (2003). Assessing Temperature Tolerance of Bonneville Cutthroat Trout Based on Constant and Cycling Thermal Regimes. *Transactions of the American Fisheries Society*, *132*(1), 1–175. https://doi.org/10.1577/T05-244.1

Jowett, I. G. (1997). Instream flow methods: a comparison of approaches. *Regulated Rivers: Research & Management*, *13*(2), 115–127. https://doi.org/10.1002/(SICI)1099-1646(199703)13:2<115::AID-RRR440>3.0.CO;2-6

Kahil, M. T., Ward, F. A., Albiac, J., Eggleston, J., & Sanz, D. (2016). Hydro-economic modeling with aquifer–river interactions to guide sustainable basin management. *Journal of Hydrology*, *539*, 510–524. https://doi.org/10.1016/j.jhydrol.2016.05.057

Krause, P., Boyle, D. P., & Bäse, F. (2005). Comparison of different efficiency criteria for hydrological model assessment. *Advances in Geosciences*, *5*, 89–97. https://doi.org/10.5194/adgeo-5-89-2005

Kreibich, H., Van Loon, A. F., Schröter, K., Ward, P. J., Mazzoleni, M., Sairam, N., et al. (2022). The challenge of unprecedented floods and droughts in risk management. *Nature*, *608*(7921), 80–86. https://doi.org/10.1038/s41586-022-04917-5

Kuby, M. J., Fagan, W. F., ReVelle, C. S., & Graf, W. L. (2005). A multiobjective optimization model for dam removal: an example trading off salmon passage with hydropower and water storage in the Willamette basin. *Advances in Water Resources*, *28*(8), 845–855. https://doi.org/10.1016/j.advwatres.2004.12.015

Leopold, L. B., Wolman, M. G., & Miller, J. P. (1995). *Fluvial processes in geomorphology*. New York, USA: Dover Publications.

Levintal, E., Kniffin, M. L., Ganot, Y., Marwaha, N., Murphy, N. P., & Dahlke, H. E. (2023). Agricultural managed aquifer recharge (Ag-MAR)—a method for sustainable groundwater management: A review. *Critical Reviews in Environmental Science and Technology*, *53*(3), 291–314. https://doi.org/10.1080/10643389.2022.2050160

Li, D., Dorber, M., Barbarossa, V., & Verones, F. (2022). Global characterization factors for quantifying the impacts of increasing water temperature on freshwater fish. *Ecological Indicators*, *142*, 109201. https://doi.org/10.1016/j.ecolind.2022.109201

Liermann, C. R., Nilsson, C., Robertson, J., & Ng, R. Y. (2012). Implications of Dam Obstruction for Global Freshwater Fish Diversity. *BioScience*, *62*(6), 539–548. https://doi.org/10.1525/bio.2012.62.6.5

Lin, Y., & Schrage, L. (2009). The global solver in the LINDO API. *Optimization Methods and Software*, *24*(4–5), 657–668. https://doi.org/10.1080/10556780902753221

LRO. (2025a). Logan River Observatory: Logan River Golf Course Climate Site (LR_GC_C) Quality Controlled Data [Data set]. HydroShare. Retrieved from https://www.hydroshare.org/resource/86a27290e1b443a488f0b84cb9e2af91/

LRO. (2025b). Logan River Observatory: Logan River near Tony Grove Aquatic Site (LR_TG_BA) Quality Controlled Data [Data set]. HydroShare. Retrieved from http://www.hydroshare.org/resource/b93121c191a94abbb288acabba07f954

Luce, C., Staab, B., Kramer, M., Wenger, S., Isaak, D., & McConnell, C. (2014). Sensitivity of summer stream temperatures to climate variability in the Pacific Northwest. *Water Resources Research*, *50*(4), 3428–3443. https://doi.org/10.1002/2013WR014329

Lukens, E., Turney, E. K., Null, S., & Neilson, B. (2024). Measurement and Infrastructure Gap Analysis in Utah’s Great Salt Lake Basin [Data set]. HydroShare. https://doi.org/10.4211/hs.8bf055dbe78b46d184cc7a4bb53931c7

Maavara, T., Chen, Q., Van Meter, K., Brown, L. E., Zhang, J., Ni, J., & Zarfl, C. (2020). River dam impacts on biogeochemical cycling. *Nature Reviews Earth & Environment*, *1*(2), 103–116. https://doi.org/10.1038/s43017-019-0019-0

McHugh, P., & Budy, P. (2006). Experimental Effects of Nonnative Brown Trout on the Individual- and Population-Level Performance of Native Bonneville Cutthroat Trout. *Transactions of the American Fisheries Society*, *135*(6), 1441–1455. https://doi.org/10.1577/T05-309.1

McKay, L., Bondelid, T., Dewald, T., Johnston, J., Moore, R., & Rea, A. (2012). NHDPlus Version 2: User Guide [Data set].

Medellín-Azuara, J., Harou, J. J., Olivares, M. A., Madani, K., Lund, J. R., Howitt, R. E., et al. (2008). Adaptability and adaptations of California's water supply system to dry climate warming. *Climatic Change*, *87*(S1), 75–90. https://doi.org/10.1007/s10584-007-9355-z

Micklin, P. (2010). The past, present, and future Aral Sea. *Lakes & Reservoirs: Science, Policy and Management for Sustainable Use*, *15*(3), 193–213. https://doi.org/10.1111/j.1440-1770.2010.00437.x

Mohammed, I. N., & Tarboton, D. G. (2012). An examination of the sensitivity of the Great Salt Lake to changes in inputs. *Water Resources Research*, *48*(11), 2012WR011908. https://doi.org/10.1029/2012WR011908

Moriasi, D. N., Gitau, M. W., Pai, N., & Daggupati, P. (2015). Hydrologic and Water Quality Models: Performance Measures and Evaluation Criteria. *Transactions of the ASABE*, *58*(6), 1763–1785. https://doi.org/10.13031/trans.58.10715

Morrisett, C. N., Van Kirk, R. W., & Null, S. E. (2023). Assessing downstream aquatic habitat availability relative to headwater reservoir management in the Henrys Fork Snake River. *River Research and Applications*, *39*(9), 1749–1762. https://doi.org/10.1002/rra.4175

Muhlfeld, C. C., Jones, L., Kotter, D., Miller, W. J., Geise, D., Tohtz, J., & Marotz, B. (2012). ASSESSING THE IMPACTS OF RIVER REGULATION ON NATIVE BULL TROUT (SALVELINUS CONFLUENTUS) AND WESTSLOPE CUTTHROAT TROUT (ONCORHYNCHUS CLARKII LEWISI) HABITATS IN THE UPPER FLATHEAD RIVER, MONTANA, USA. *River Research and Applications*, *28*(7), 940–959. https://doi.org/10.1002/rra.1494

Munroe, J. S., Carling, G. T., Perry, K. D., Fernandez, D. P., & Mallia, D. V. (2025). Mixing of natural and urban dust along the Wasatch Front of northern Utah, USA. *Scientific Reports*, *15*(1), 3851. https://doi.org/10.1038/s41598-025-88529-9

Murphy, C. A., Romer, J. D., Stertz, K., Arismendi, I., Emig, R., Monzyk, F., & Johnson, S. L. (2021). Damming salmon fry: evidence for predation by non-native warmwater fishes in reservoirs. *Ecosphere*, *12*(9), e03757. https://doi.org/10.1002/ecs2.3757

Nagel, D., Sharon Parkes-Payne, Sherry Wollrab, Peterson, E., Isaak, D., & Hoef, J. V. (2017). National Stream Internet hydrography datasets for spatial-stream-network (SSN) analysis [Data set]. Retrieved from https://www.fs.usda.gov/rm/boise/AWAE/projects/NationalStreamInternet/NSI_network.html

NOAA. (2024). Global Historical Climatology Network daily (GHCNd) [Data set]. National Centers for Environmental Information. Retrieved from https://www.ncei.noaa.gov/products/land-based-station/global-historical-climatology-network-daily

Nover, D. M., Dogan, M. S., Ragatz, R., Booth, L., Medellín-Azuara, J., Lund, J. R., & Viers, J. H. (2019). Does More Storage Give California More Water? *JAWRA Journal of the American Water Resources Association*, *55*(3), 759–771. https://doi.org/10.1111/1752-1688.12745

Null, S. E., & Lund, J. R. (2012). FISH HABITAT OPTIMIZATION TO PRIORITIZE RIVER RESTORATION DECISIONS. *River Research and Applications*, *28*(9), 1378–1393. https://doi.org/10.1002/rra.1521

Null, Sarah E. (2018). Economic Water Demand Functions to Value Urban Water Scarcity along Utah's Wasatch Front [Data set]. HydroShare. https://doi.org/10.4211/hs.a6921eef1cbf4968b271d972bd997ab3

Null, Sarah E. (2022). *Water banking can help Great Salt Lake* (Watershed Sciences Faculty Publications No. Paper 1159). Logan, Utah, USA: Utah State University. Retrieved from https://digitalcommons.usu.edu/wats_facpub/1159

Null, Sarah E., & Wurtsbaugh, W. A. (2020). Water Development, Consumptive Water Uses, and Great Salt Lake. In B. K. Baxter & J. K. Butler (Eds.), *Great Salt Lake Biology* (pp. 1–21). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-40352-2_1

Null, Sarah E., Ligare, S. T., & Viers, J. H. (2013). A Method to Consider Whether Dams Mitigate Climate Change Effects on Stream Temperatures. *JAWRA Journal of the American Water Resources Association*, *49*(6), 1456–1472. https://doi.org/10.1111/jawr.12102

Null, Sarah E., Viers, J. H., Deas, M. L., Tanaka, S. K., & Mount, J. F. (2013a). Stream temperature sensitivity to climate warming in California's Sierra Nevada: impacts to coldwater habitat. *Climatic Change*, *116*(1), 149–170. https://doi.org/10.1007/s10584-012-0459-8

Null, Sarah E., Viers, J. H., Deas, M. L., Tanaka, S. K., & Mount, J. F. (2013b). Stream temperature sensitivity to climate warming in California's Sierra Nevada: impacts to coldwater habitat. *Climatic Change*, *116*(1), 149–170. https://doi.org/10.1007/s10584-012-0459-8

Null, Sarah E., Medellín-Azuara, J., Escriva-Bou, A., Lent, M., & Lund, J. R. (2014). Optimizing the dammed: Water supply losses and fish habitat gains from dam removal in California. *Journal of Environmental Management*, *136*, 121–131. https://doi.org/10.1016/j.jenvman.2014.01.024

Null, Sarah E., Zeff, H., Mount, J., Gray, B., Sturrock, A. M., Sencan, G., et al. (2024). Storing and managing water for the environment is more efficient than mimicking natural flows. *Nature Communications*, *15*(1), 5462. https://doi.org/10.1038/s41467-024-49770-4

Nusrat, F., Lane, B. A. A., Ostermiller, J., Null, S. E., Neilson, B. T., Thompson, P., & Baker, M. A. (2024). *Establishing a Functional Flows Framework for the Great Salt Lake Basin*. Presented at the WaterSciCon24, St. Paul, Minnesota, USA. Retrieved from https://uwrl.usu.edu/files/pdf/research-projects/developing-a-functional-flows-framework.pdf

Olden, J. D., & Naiman, R. J. (2010). Incorporating thermal regimes into environmental flows assessments: modifying dam operations to restore freshwater ecosystem integrity. *Freshwater Biology*, *55*(1), 86–107. https://doi.org/10.1111/j.1365-2427.2009.02179.x

Pacificorp. (2019). Cutler Hydroelectric Project (Pre-Application Document No. 2420). Retrieved from https://lowimpacthydro.org/lihi-certificate-62-cutler-hydroelectric-project-utah/

Palmer, M., & Ruhi, A. (2019). Linkages between flow regime, biota, and ecosystem processes: Implications for river restoration. *Science*, *365*(6459), eaaw2087. https://doi.org/10.1126/science.aaw2087

Peñas, F. J., & Barquín, J. (2019). Assessment of large-scale patterns of hydrological alteration caused by dams. *Journal of Hydrology*, *572*, 706–718. https://doi.org/10.1016/j.jhydrol.2019.03.056

Pennock, C. A., Ahrens, Z. T., McKinstry, M. C., Budy, P., & Gido, K. B. (2021). Trophic niches of native and nonnative fishes along a river-reservoir continuum. *Scientific Reports*, *11*(1), 12140. https://doi.org/10.1038/s41598-021-91730-1

Petheram, C., & McMahon, T. A. (2019). Dams, dam costs and damnable cost overruns. *Journal of Hydrology X*, *3*, 100026. https://doi.org/10.1016/j.hydroa.2019.100026

R Core Team. (2023). R: A language and environment for statistical computing (Version 4.3.1). Vienna, Austria: R Foundation for Statistical Computing. Retrieved from https://www.R-project.org/

Reid, A. J., Carlson, A. K., Creed, I. F., Eliason, E. J., Gell, P. A., Johnson, P. T. J., et al. (2019). Emerging threats and persistent conservation challenges for freshwater biodiversity. *Biological Reviews*, *94*(3), 849–873. https://doi.org/10.1111/brv.12480

Rosenfeld, J. S. (2017). Developing flow–ecology relationships: Implications of nonlinear biological responses for water management. *Freshwater Biology*, *62*(8), 1305–1324. https://doi.org/10.1111/fwb.12948

Rosenfeld, J. S., Post, J., Robins, G., & Hatfield, T. (2007). Hydraulic geometry as a physical template for the River Continuum: application to optimal flows and longitudinal trends in salmonid habitat. *Canadian Journal of Fisheries and Aquatic Sciences*, *64*(5), 755–767. https://doi.org/10.1139/f07-020

Schrank, A. J., & Rahel, F. J. (2004). Movement patterns in inland cutthroat trout (Oncorhynchus clari utah): management and conservation implications. *Canadian Journal of Fisheries and Aquatic Sciences*, *61*(8), 1528–1537. https://doi.org/10.1139/f04-097

Schrank, A. J., Rahel, F. J., & Johnstone, H. C. (2003). Evaluating Laboratory-Derived Thermal Criteria in the Field: An Example Involving Bonneville Cutthroat Trout. *Transactions of the American Fisheries Society*, *132*(1), 100–109. https://doi.org/10.1577/1548-8659(2003)132<0100:ELDTCI>2.0.CO;2

Schulz, S., Darehshouri, S., Hassanzadeh, E., Tajrishy, M., & Schüth, C. (2020). Climate change or irrigated agriculture – what drives the water level decline of Lake Urmia. *Scientific Reports*, *10*(1), 236. https://doi.org/10.1038/s41598-019-57150-y

Spinti, R. A., Condon, L. E., & Zhang, J. (2023). The evolution of dam induced river fragmentation in the United States. *Nature Communications*, *14*(1), 3820. https://doi.org/10.1038/s41467-023-39194-x

Tanaka, S. K., Zhu, T., Lund, J. R., Howitt, R. E., Jenkins, M. W., Pulido, M. A., et al. (2006). Climate Warming and Water Management Adaptation for California. *Climatic Change*, *76*(3–4), 361–387. https://doi.org/10.1007/s10584-006-9079-5

Tarboton, D. (2017). Great Salt Lake Area Volume Data [Data set]. HydroShare. Retrieved from https://www.hydroshare.org/resource/89125e9a3af544eab2479b7a974100ba/

Tarboton, D. (2023). Precipitation and Temperature over the Great Salt Lake and its Basin [Data set]. HydroShare. Retrieved from https://www.hydroshare.org/resource/654daab6d2a04d8f828c075dd5e7dcdb/

Tarboton, D. (2024). Great Salt Lake Level and Volume Time Series [Data set]. HydroShare. Retrieved from https://www.hydroshare.org/resource/45b43d72928048a8bc10a009d932f769/

Teuscher, D., & Capurso, J. (2007). *Management Plan for Conservation of Bonneville Cutthroat Trout in Idaho* (No. IDGF 07-48). USDA Forest. Retrieved from https://www.webpages.uidaho.edu/fish510/PDF/Bonn%20CT%20Final%20Plan.pdf

Tickner, D., Opperman, J. J., Abell, R., Acreman, M., Arthington, A. H., Bunn, S. E., et al. (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

Turney, E. K., Goodrum, G. C., Saunders, W. C., Walsworth, T. E., & Null, S. E. (2025). Comparing commonly used aquatic habitat modeling methods for native fish. *Ecological Modelling*, *499*, 110909. https://doi.org/10.1016/j.ecolmodel.2024.110909

UDWR. (2019). *Bonneville cutthroat trout range-wide conservation agreement and strategy* (No. Publication Number 18-11). Salt Lake City, UT: Utah Division of Wildlife Resources. Retrieved from https://westernnativetrout.org/wp-content/uploads/2020/01/Signed-Version-of-BCT-Plan-December-2019.pdf

UDWRe. (2004). Bear River Basin: Planning for the future. Salt Lake City, UT, USA: Utah Division of Water Resources. Retrieved from https://geodata.geology.utah.gov/pages/view.php?ref=7921&k=&search=&offset=0&order_by=&sort=&archive=#

UDWRe. (2019a). Bear River Development Report: Volume I of III. Utah Division of Water Resources.

UDWRe. (2019b). Bear River Development Report: Volume II of III. Utah Division of Water Resources.

UDWRe. (2024). Utah Water Budget Model. Salt Lake City, UT, USA: Utah Division of Water Resources. Retrieved from https://dwre-utahdnr.opendata.arcgis.com/pages/water-budget

USGS. (2023a). National Hydrography Dataset (NHD) [Data set]. Retrieved from https://www.usgs.gov/national-hydrography/national-hydrography-dataset

USGS. (2023b). NHDPlus (National Hydrograph Dataset Plus) (Version 2) [Data set]. USEPA Water Data and Tools Database. Retrieved from https://www.epa.gov/waterdata/nhdplus-national-hydrography-dataset-plus

USGS. (2024). National Water Information System [Data set]. Retrieved from http://waterdata.usgs.gov/nwis/

Van Vliet, M. T. H., Ludwig, F., & Kabat, P. (2013). Global streamflow and thermal habitats of freshwater fishes under climate change. *Climatic Change*, *121*(4), 739–754. https://doi.org/10.1007/s10584-013-0976-0

Waldman, J. R., & Quinn, T. P. (2022). North American diadromous fishes: Drivers of decline and potential for recovery in the Anthropocene. *Science Advances*, *8*(4), eabl5486. https://doi.org/10.1126/sciadv.abl5486

Welsh, L. W., Endter-Wada, J., Downard, R., & Kettenring, K. M. (2013). Developing Adaptive Capacity to Droughts: the Rationality of Locality. *Ecology and Society*, *18*(2), art7. https://doi.org/10.5751/ES-05484-180207

Wenger, S. J., Luce, C. H., Hamlet, A. F., Isaak, D. J., & Neville, H. M. (2010). Macroscale hydrologic modeling of ecologically relevant flow metrics. *Water Resources Research*, *46*(9), 2009WR008839. https://doi.org/10.1029/2009WR008839

Williams, A. P., Cook, B. I., & Smerdon, J. E. (2022). Rapid intensification of the emerging southwestern North American megadrought in 2020–2021. *Nature Climate Change*, *12*(3), 232–234. https://doi.org/10.1038/s41558-022-01290-z

Wohl, E. (2019). Forgotten Legacies: Understanding and Mitigating Historical Human Alterations of River Corridors. *Water Resources Research*, *55*(7), 5181–5201. https://doi.org/10.1029/2018WR024433

Womble, P., Townsend, A., & Szeptycki, L. F. (2022). Decoupling environmental water markets from water law. *Environmental Research Letters*, *17*(6), 065007. https://doi.org/10.1088/1748-9326/ac6d6d

Wurtsbaugh, W. A., & Sima, S. (2022). Contrasting Management and Fates of Two Sister Lakes: Great Salt Lake (USA) and Lake Urmia (Iran). *Water*, *14*(19), 3005. https://doi.org/10.3390/w14193005

Wurtsbaugh, W. A., Miller, C., Null, S., Wilcock, P., Hahnenberger, M., & Howe, F. (2016). Impacts of water development on Great Salt Lake and the Wasatch Front (White Paper). Logan, Utah, USA: Utah State University.

Wurtsbaugh, W. A., Miller, C., Null, S. E., DeRose, R. J., Wilcock, P., Hahnenberger, M., et al. (2017). Decline of the world's saline lakes. *Nature Geoscience*, *10*(11), 816–821. https://doi.org/10.1038/ngeo3052

Yan, D., Ludwig, F., Huang, H. Q., & Werners, S. E. (2017). Many-objective robust decision making for water allocation under climate change. *Science of The Total Environment*, *607–608*, 294–303. https://doi.org/10.1016/j.scitotenv.2017.06.265

Yeh, W. W. (1985). Reservoir Management and Operations Models: A State-of-the-Art Review. *Water Resources Research*, *21*(12), 1797–1818. https://doi.org/10.1029/WR021i012p01797

Young, C. A., Escobar-Arias, M. I., Fernandes, M., Joyce, B., Kiparsky, M., Mount, J. F., et al. (2009). Modeling the Hydrology of Climate Change in California's Sierra Nevada for Subwatershed Scale Adaptation[1]. *JAWRA Journal of the American Water Resources Association*, *45*(6), 1409–1423. https://doi.org/10.1111/j.1752-1688.2009.00375.x

Zaidel, P. A., Roy, A. H., Houle, K. M., Lambert, B., Letcher, B. H., Nislow, K. H., & Smith, C. (2021). Impacts of small dams on stream temperature. *Ecological Indicators*, *120*, 106878. https://doi.org/10.1016/j.ecolind.2020.106878

Zamora, H., & Inkenbrandt, P. (2024). Estimate of groundwater flow and salinity contribution to the Great Salt Lake using groundwater levels and spatial analysis. *Great Salt Lake and the Bonneville Basin: Geologic History and Anthropocene Issues*, *51*, 1–24. https://doi.org/10.31711/ugap.v51i.141

Zarfl, C., Lumsdon, A. E., Berlekamp, J., Tydecks, L., & Tockner, K. (2015). A global boom in hydropower dam construction. *Aquatic Sciences*, *77*(1), 161–170. https://doi.org/10.1007/s00027-014-0377-0

Zulauf, G. (2023, June 6). Colorado River deal forever changes the price of water in the West. *CalMatters*. Retrieved from https://calmatters.org/commentary/2023/06/colorado-river-deal-west-water/#:~:text=Arizona%2C%20Nevada%20and%20California%20recently,water%20they%20don't%20use.

Tables and Figures

Table 2.1. Input data and sources for the Lower Bear River hydro-economic optimization model.

Model component	Data item	Source
Economic demands	Agricultural demands	PacifiCorp, Idaho Department of Water Resources
	Agricultural water price	Zulauf (2023)
	M&I demand functions	Null (2018)
Physical constraints	Inflows	PacifiCorp, USGS (2024)
	Reach gains and losses	PacifiCorp, USGS (2024)
	Initial reservoir storage	PacifiCorp
	Reservoir gains and losses	PacifiCorp
	Consumptive use fractions	UDWRe (2024)
Infrastructure constraints	Reservoir capacity	PacifiCorp
	Proposed reservoir capacity	UDWRe (2019a, 2019b)
Environmental constraints	Mean annual flow in rivers	(USGS, 2023b)

Table 2.2. Habitat suitability criteria to determine monthly habitat conditions for Bonneville Cutthroat Trout. MAF is the 1971-2000 mean annual flow of a stream reach.

Habitat condition	Suitability weight	Streamflow (% MAF)		Stream temperature (°C)
Suitable	1	> 25	AND	< 20
Stressful	0.5	10-25	OR	20-24
Unsuitable	0	< 10	OR	> 24

Table 2.3. Input data and sources for equilibrium temperature and Bonneville Cutthroat Trout habitat suitability models.

Model component	Data item	Source
Equilibrium temperature	Streamflow	Optimization model output (see Section 2.3.)
	Boundary stream temperature	LRO (2025); Turney et al. (2025)
	Hydraulic geometry functions	Leopold et al. (1995); Null et al. (2013)
	Meteorological conditions	LRO (2025a); NOAA (2024)
	Stream length	Nagel et al. (2017)
Habitat suitability	Mean annual flow	USGS (2023b)
	Streamflow suitability criteria	Caissie et al. (2015)
	Temperature suitability criteria	Johnstone & Rahel (2003); Schrank et al. (2003)

Table 2.4. Model runs and reservoir capacities representing Lower Bear River development alternatives. Environmental flows (e-flows) are expressed as a percentage of the unregulated mean annual flow.

				Proposed reservoir storage capacity (Mm^3)					
Modeled alternative	**Operation constraints**	**Wasatch demands (Mm^3/year)**	**e-flows (% MAF)**	Whites Valley	Fielding	Above Cutler	Cub River	Temple Fork	Total
Historical	X	-	-	-	-	-	-	-	-
Wasatch demands	-	497	-	-	-	-	-	-	-
Proposed reservoirs	-	497	-	209.6	86.3	62.8	33.3	50.6	442.6
10% MAF e-flow	-	497	10%	209.6	86.3	62.8	33.3	50.6	442.6
25% MAF e-flow	-	497	25%	209.6	86.3	62.8	33.3	50.6	442.6

Table 2.5. Performance metrics for predicted versus observed mean monthly streamflow at 7 sites in the Lower Bear River Basin for the 2000-2020 time period. All sites have 240 observations measured in log base 10 m^3s^{-1}.

Site ID	Site Name	R2	NSE	PBIAS	MAE (%)	RMSE (%)
10068500	Bear River at Pescadero, ID	0.91	0.91	-4	7.9	14.6
10075000	Bear River at Soda Springs, ID	0.92	0.92	-2.2	4.8	9.6
10079500	Bear River at Alexander, ID	0.91	0.91	-1.8	4.4	7.9
10086500	Bear River at Oneida, ID	0.86	0.86	-1.4	4	6.4
10092700	Bear River at ID-UT State Line	0.82	0.82	-1.7	4	6.4
10118000	Bear River near Collinston, UT	0.90	0.90	-4.8	6.5	12.9
10126000	Bear River near Corinne, UT	0.95	0.95	-2.4	3.7	7.5

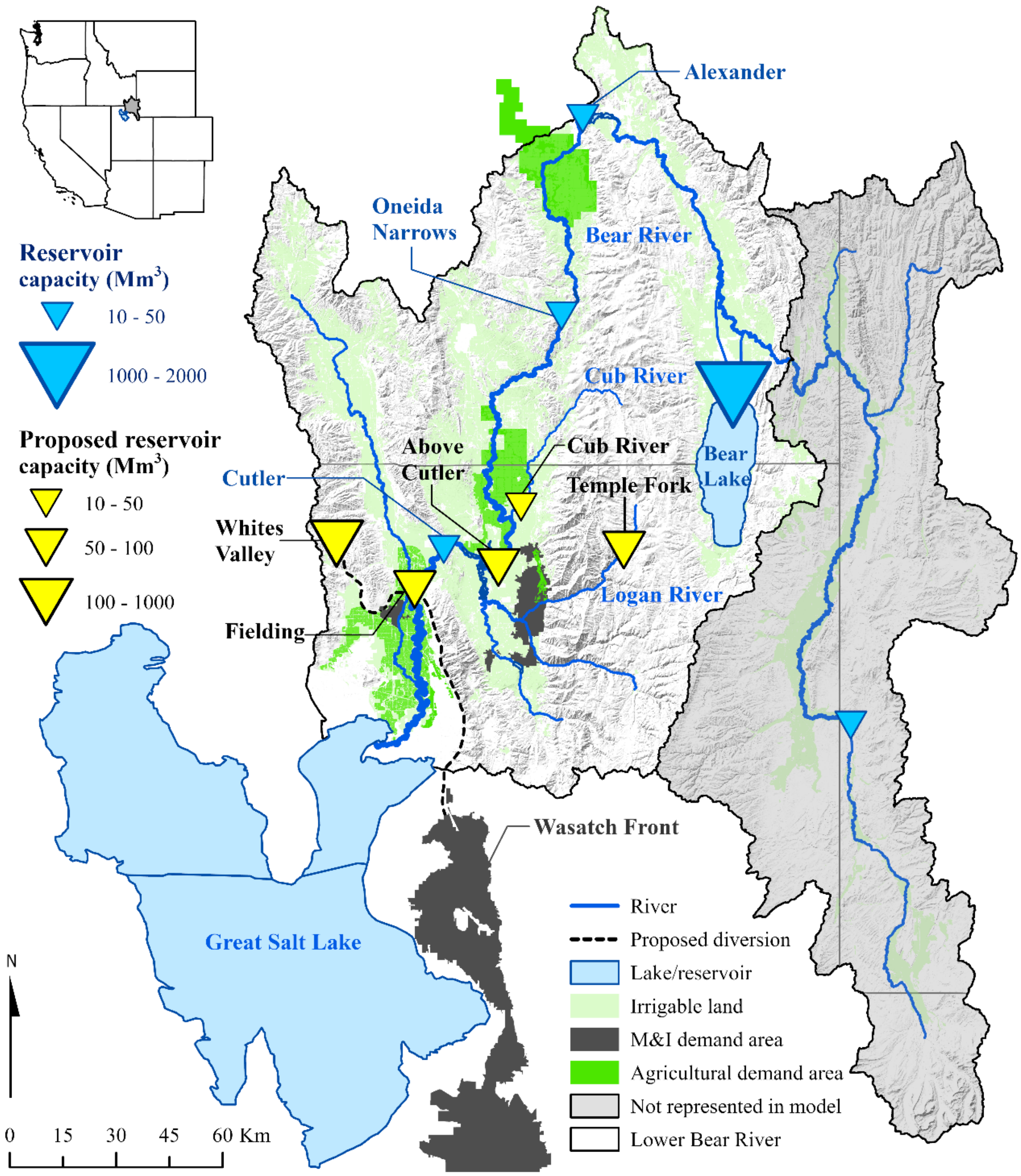

Figure 2.1. The Bear River Basin and Lower Bear River study area showing major rivers, lakes, reservoirs, proposed reservoirs, and agricultural and municipal and industrial (M&I) demand areas.

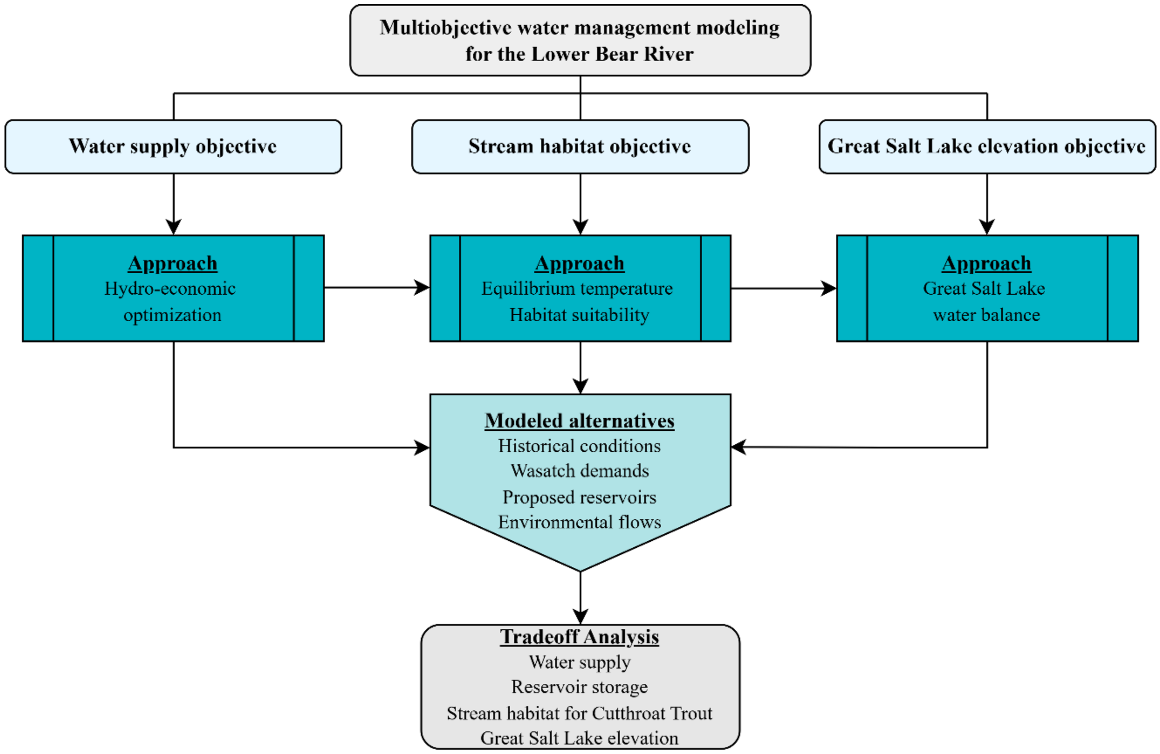

Figure 2.2. Conceptual diagram of study workflow with water management objectives, model coupling, and alternatives used to support tradeoff analysis for multi-objective water management in the Lower Bear River.

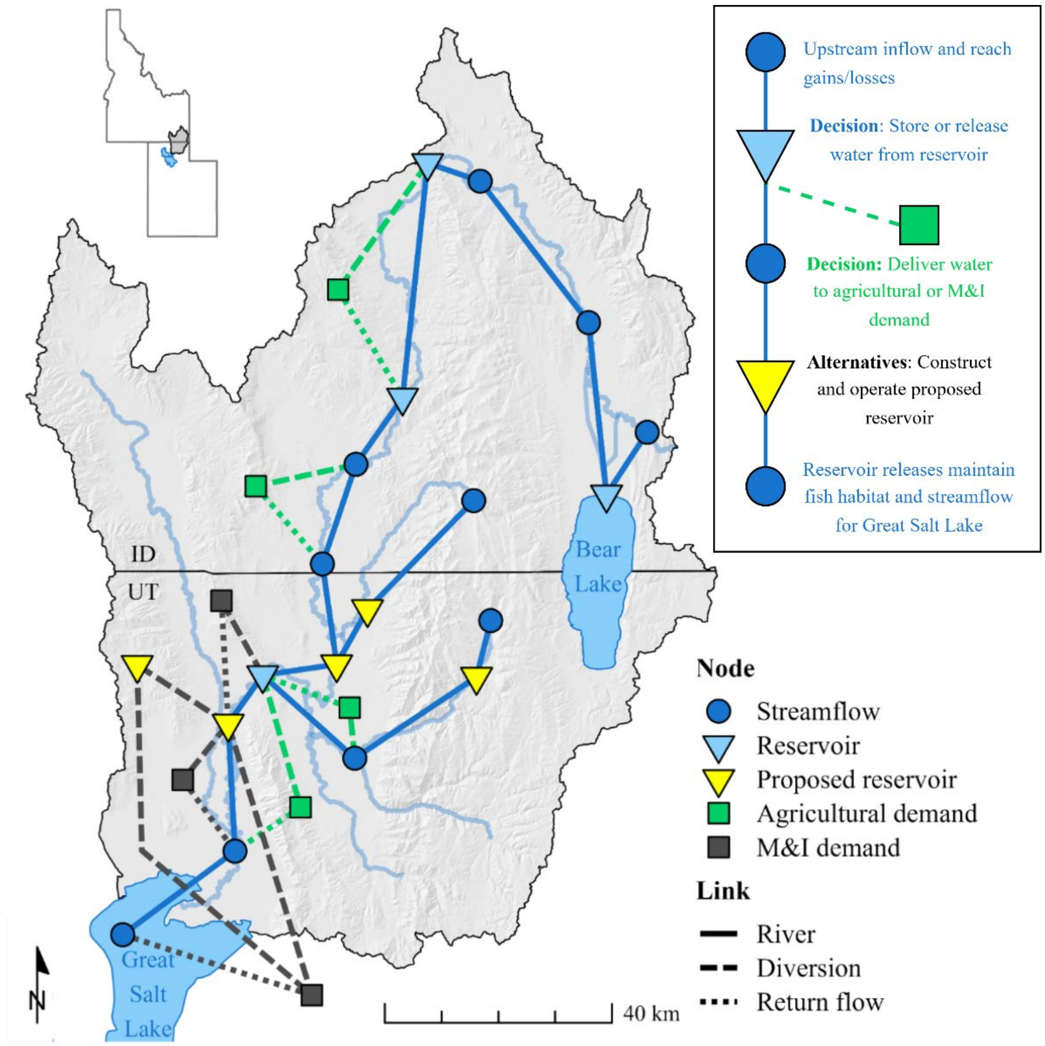

Figure 2.3. Optimization model representation of the Lower Bear River with reservoirs, proposed reservoirs, diversions to agricultural and M&I demand areas, and return flows representing unconsumed portions of diversions. The inset panel summarizes model decisions to minimize water scarcity costs for agricultural and M&I demand areas.

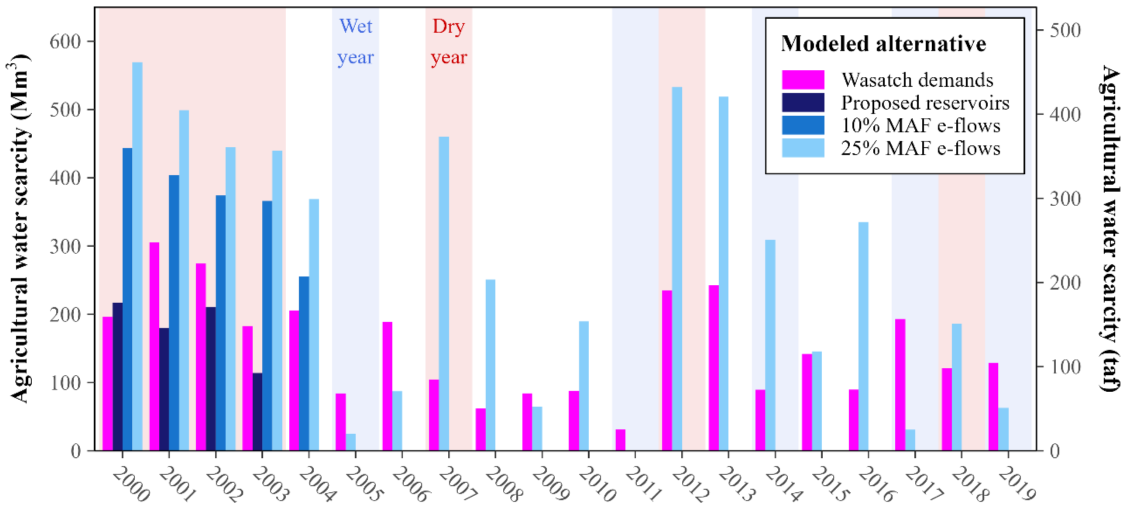

Figure 2.4. Annual agricultural water scarcity in the Lower Bear River with Wasatch demand, proposed reservoir, and e-flow modeled alternatives. Wet and dry years occur when average annual Standardized Precipitation Evaporation Index (SPEI) for the Great Salt Lake Basin is greater or less than one standard deviation for the 1900-2020 period (Bigalke, 2023).

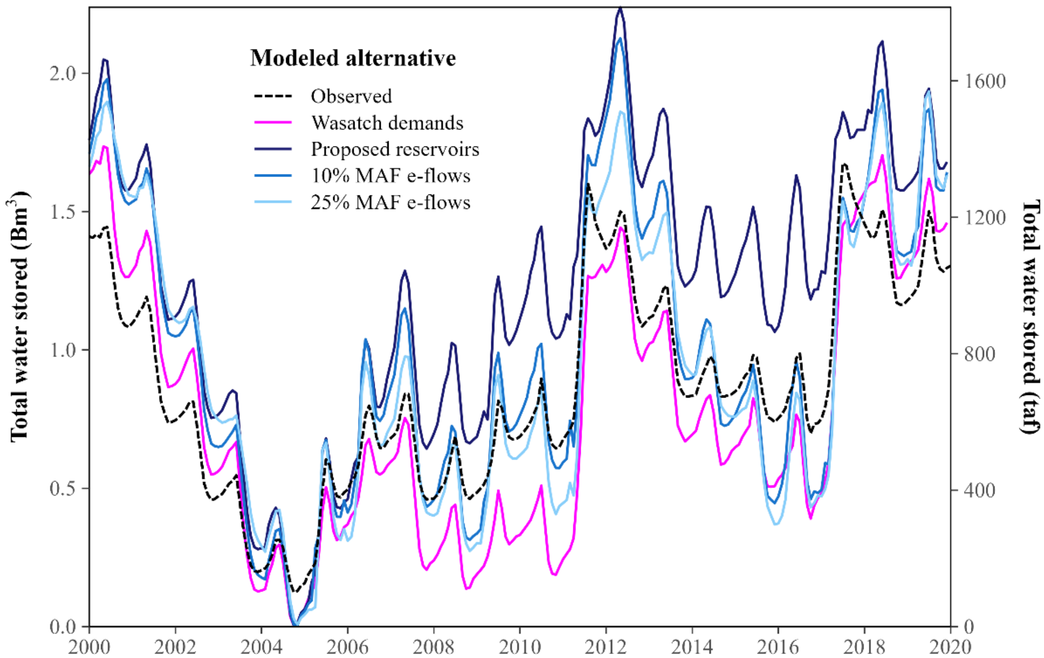

Figure 2.5 Monthly total water storage in Lower Bear River reservoirs under observed conditions and modeled alternatives. Proposed reservoir, 10% MAF e-flow, and 25% MAF e-flow alternatives include an additional 0.4 Bm^3 of storage capacity created by proposed reservoirs.

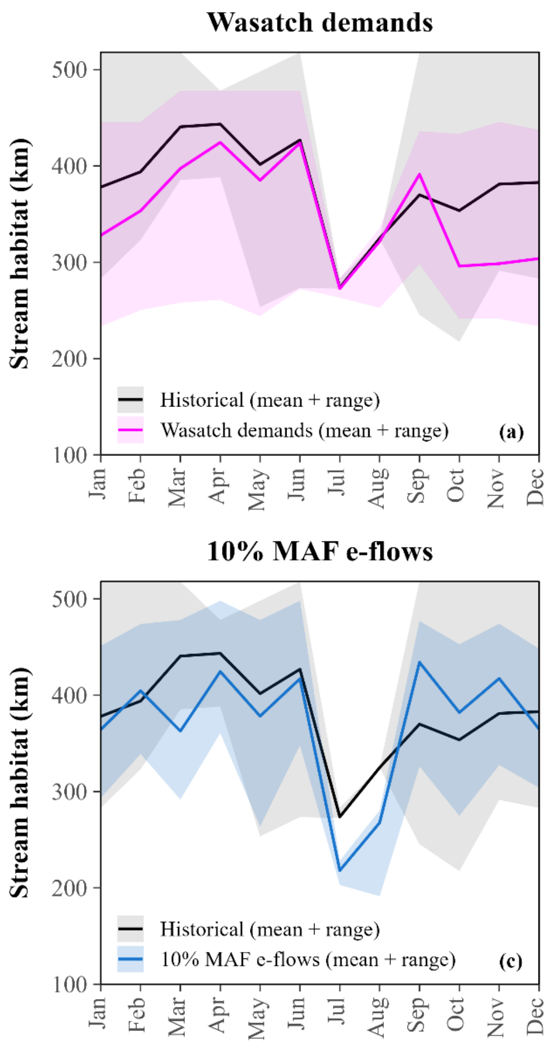

Figure 2.6. Monthly average and range of stream habitat for Bonneville Cutthroat Trout in the Lower Bear River under historical conditions and modeled alternatives from 2000-2020. Panels show the mean (lines) and range (shaded area) of suitability-weighted stream habitat for historical conditions and (a) Wasatch demands, (b) proposed reservoirs, (c) 10% MAF e-flow, and (d) 25% MAF e-flow.

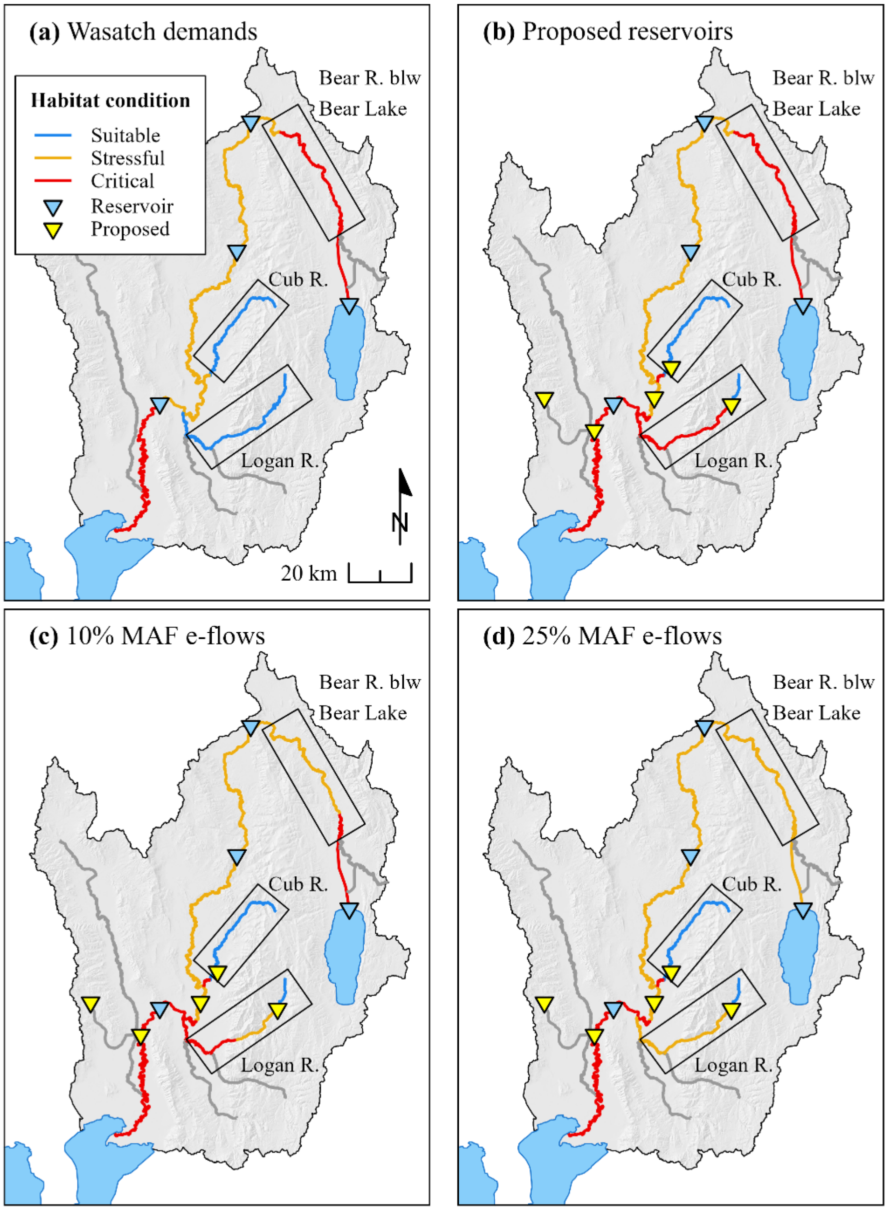

Figure 2.7. Most restrictive habitat condition for modeled stream reaches in the Lower Bear River for the (a) Wasatch Demand, (b) Proposed Reservoirs, (c) 10% MAF E-Flow, and (d) 25% MAF E-Flow modeled alternatives. Suitable reaches maintain sufficient streamflow and temperature conditions throughout the year, while impaired reaches expose fish to at least one month of stressful or critical habitat conditions.

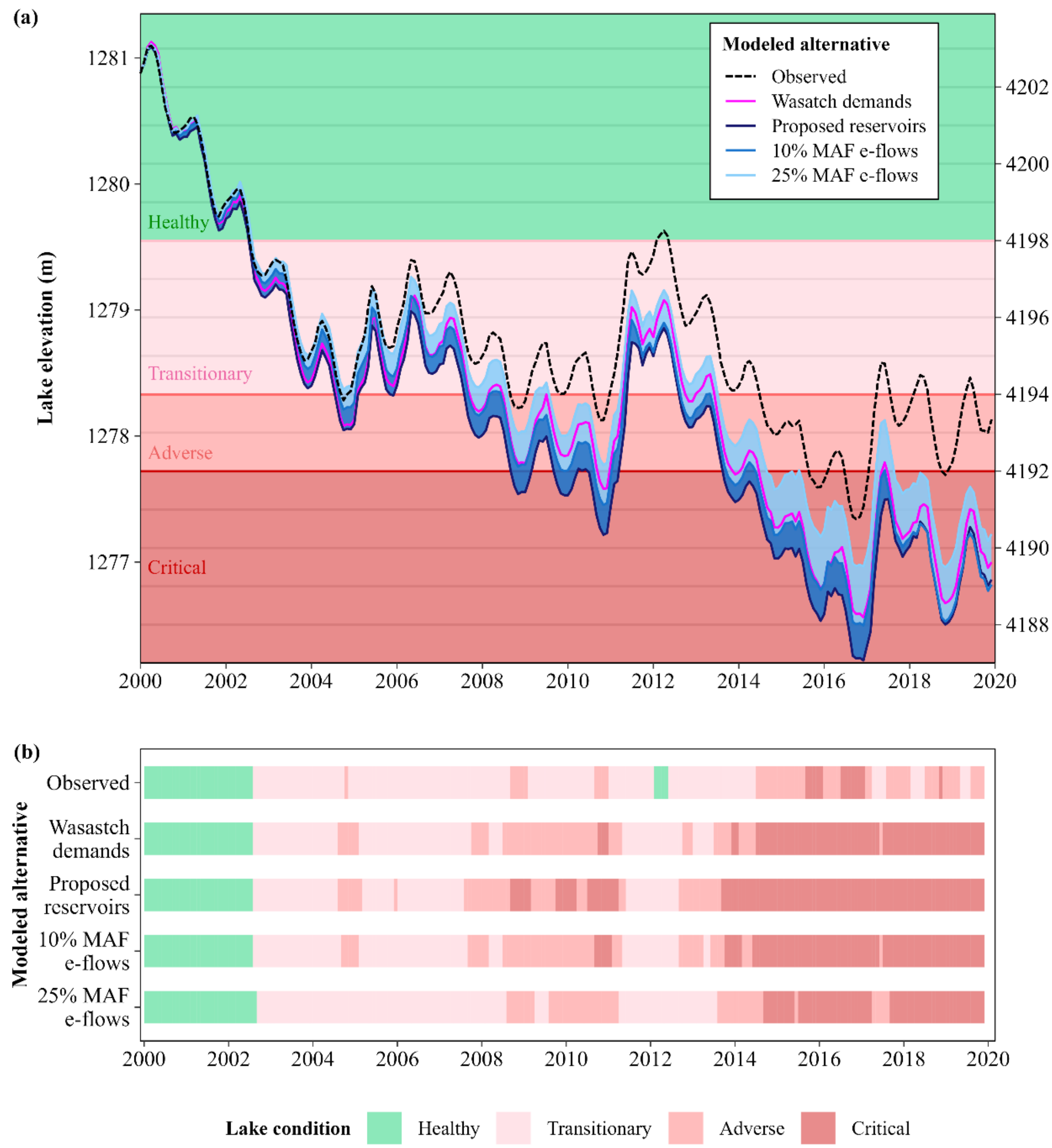

Figure 2.8. Monthly Great Salt Lake (a) elevation and (b) lake condition from observed lake conditions and with Wasatch demand, proposed reservoir, and e-flow modeled alternatives. Lake conditions reflect declining lake level and increasing salinity effects on brine shrimp viability, mineral production, air quality, recreation, and ecosystem health (FFSL, 2013).

CHAPTER 3

ROBUST INSTREAM BARRIER REMOVAL FOR RESTORING FISH HABITAT CONNECTIVITY

Abstract

Robust decision-making uses analytical frameworks to identify model solutions that remain effective in the presence of uncertainty. Habitat suitability models are often used to represent environmental objectives for barrier removal and other river restoration actions. These models are sensitive to input data and suitability function uncertainty, but how uncertainties in habitat suitability estimates affect barrier removal optimizations has not been evaluated. I used stream temperature data and habitat suitability modeling to estimate growth and summer thermal refugia habitat suitability under uncertain conditions and uncertain species-habitat relationships for Bonneville Cutthroat Trout (*Oncorhynchus clarkii utah)* in the Weber River Basin, Utah (USA). I used Monte-Carlo random sampling to represent uncertain habitat suitability estimates in a barrier removal optimization model to identify robust barrier removal decisions reconnecting aquatic habitats. Thermal habitat suitability estimates were more sensitive to stream temperature input data and suitability function uncertainty than growth habitat. Input data uncertainty influenced habitat suitability estimates more than suitability function uncertainty. Growth habitat and thermal refugia barrier removals were largely robust to stream temperature input data and suitability function uncertainty. Out of 50 barriers that were selected for removal across all model runs, five were robust to input data and suitability function uncertainties. My findings demonstrate that input data and suitability function uncertainties influence habitat suitability and barrier removal optimization models, but

that differences between habitat objectives may provide more information for robust barrier removal decision-making. My work highlights the importance of incorporating uncertainty in barrier removal analysis and identifies pathways for improving decision robustness to aquatic habitat uncertainty in river management and conservation.

1. Introduction

Robust decision-making uses analytical frameworks to identify choices that remain effective given uncertainty (Lempert et al., 2006). Robust decision-making frameworks expand on optimization techniques, which identify the best solution across a range of possible conditions (Cohon, 2013). However, the output of optimization models may be sensitive to changes in input data and model assumptions, and optimal solutions may not perform well when input data and model formulations are uncertain (Lempert and Collins, 2007). Alternatively, robust decision-making frameworks, such as Monte-Carlo simulation, evaluate stable, rather than optimal, solutions that perform well given model uncertainty (Mavrotas et al., 2015). Monte-Carlo approaches use random sampling of model inputs to represent uncertainties in our knowledge of variable and complex systems and processes (Hung, 2024). For water resources management, Monte-Carlo simulation approaches have been used to evaluate the robustness of infrastructure changes and operations with economic, hydrologic, and climatic uncertainty (Cahill et al., 2013; Goharian et al., 2018; Maia et al., 2024). Robust decision-making frameworks may also be used to incorporate environmental and ecological uncertainty for river restoration actions such as instream barrier removal (Schindler and Hilborn, 2015). However, little research has focused on quantifying uncertainty and identifying decisions that are robust to change for river restoration and ecosystem management (Null et al., 2021).

Habitat suitability index models (HSI, hereafter habitat suitability models) predict the quality of habitat for target species from environmental conditions that influence the species' growth, survival, and reproductive success (Brooks, 1997). Habitat suitability models use suitability functions to quantify habitat quality from 0 (poor habitat conditions) to 1 (ideal habitat conditions). Suitability functions represent species-habitat relationships with parameters that describe organisms' ability to tolerate a specific range of instream conditions such as water velocity, oxygen availability, and stream temperature for species that inhabit streams (Guay et al., 2000). However, habitat suitability models rely on input data and species-habitat relationships that are often measured and modeled with uncertainty. Environmental data are typically represented as uniform values throughout river reaches in one-dimensional river models, but in reality they vary across space and time (Guo et al., 2019). Environmental measurements also have errors and uncertainty (Hamilton and Moore, 2012), with stream temperature errors often exceeding ± 2°C when modeled from atmospheric conditions (Luce et al., 2014). In addition, suitability function parameters are often based on species-habitat relationships observed in controlled laboratory experiments which are sensitive to experimental conditions and often differ from observed habitats (Galbraith et al., 2016; Lin et al., 2015; Schrank et al., 2003). These uncertainties compound in habitat suitability estimates (Roloff and Kernohan, 1999; Van Der Lee et al., 2006).

Habitat suitability indices are commonly used to represent environmental objectives for water management, conservation planning, and barrier removal (Nestler et al., 2019; Turney et al. 2025; Goodrum & Null 2023). For example, dams, diversions, and other instream infrastructure create barriers to movement for aquatic organisms that limit genetic exchange and block access to spawning, rearing, foraging, or thermal refuge habitats needed to ensure population survival (Cheng et al., 2016). Removing dams and other instream barriers to reconnect rivers has emerged as a priority for river restoration (Bellmore et al., 2017; O'Connor et al., 2015), and habitat suitability models are often applied to optimization models that identify barrier removals predicted to be most beneficial to fish and other aquatic organisms (Branco et al., 2014; Kemp and O'Hanley, 2010; Kraft et al., 2019). However, uncertainties in input data and species-habitat suitability functions can misrepresent habitat conditions, leading to barrier removal decisions that may appear optimal under certain environmental conditions but may yield poor results if specific conditions vary. Moreover, aquatic species often exhibit diverse life histories and complex species-habitat relationships (Hilborn et al., 2003; Winemiller and Rose, 1992), and the choice of which environmental variables and life history requirements to include in habitat representations can influence barrier removal optimization (McManamay et al., 2019).

While uncertainty analyses have been widely applied to evaluate the reliability of habitat suitability models, the implications of uncertain habitat suitability estimates for river management and conservation decisions have been largely ignored (Radinger et al., 2017). Numerous studies have explored how input data and suitability function uncertainties influence habitat suitability estimates (Ayllón et al., 2012; Fu and Guillaume, 2014; Turner et al., 2016; Van Der Lee et al., 2006), but they do not extend analyses to river management and restoration decisions. Alternatively, studies that have applied robust decision-making to aquatic ecosystem management have focused on climate change and stakeholder preference uncertainties while keeping aquatic habitat representations static or removing them all together (Conradt et al., 2024; Kim and Chung, 2014; Poff et al., 2016; Singh et al., 2015). Successful outcomes from river management require careful consideration of environmental and ecological uncertainties (Harris and Heathwaite, 2012), and the failure to adequately evaluate uncertainties is a factor in many unsuccessful river restorations (Wohl et al., 2015). To my knowledge, no studies have quantified uncertainty in habitat suitability estimates for barrier removal and river connectivity restoration.

The goal of this study was to evaluate the robustness of instream barrier removal decisions for restoring river connectivity to uncertainty in both habitat conditions and species-habitat relationships. I used a Monte-Carlo random sampling framework to estimate thermal habitat suitability for Bonneville Cutthroat Trout (*Oncorhynchus clarkii utah)* in Utah's Weber River Basin across a range of uncertainties in stream temperature data and temperature suitability function parameters. I focused on stream temperature because it influences many life-history requirements for fish (Barbarossa et al., 2021; Buisson et al., 2008; Dunham et al., 2003; Li et al., 2022). To identify alternative priorities for barrier removal, I estimated thermal habitat suitability for two conservation objectives: (a) maximizing growth and (b) providing summer thermal refugia. I then applied my range of habitat suitability estimates to a barrier removal optimization model to quantify how uncertainty in estimates of habitat suitability affects barrier removal decisions for restoring Cutthroat Trout habitat connectivity and identify those barrier removals that are robust to this uncertainty. As instream barrier removal is a primary focus for freshwater ecosystem conservation (Reid et al., 2019), my study helps identify barrier removals that best benefit fish and other aquatic organisms.

2. Methods

2.1. Study area and species

The Weber River drains 6,413 km^2 from its headwaters in the Uinta and Wasatch Mountains to its terminus at Great Salt Lake (Figure 3.1). The climate of the Weber River Basin is montane to semi-arid and characterized by hot, dry summers and cold, wet winters that deliver most of the basin's precipitation as snow. The river has a mean annual discharge of 14 m^3s^{-1} near its outlet at Great Salt Lake and is highly altered by dams and diversions (Wurtsbaugh et al., 2017). My study area encompassed the mainstem river and perennial tributaries and included 347 unnatural instream barriers that limit the movement of aquatic organisms. Instream barriers in the Weber River Basin include dams, diversions, and road crossing structures such as culverts. There are currently 65 barriers located along the main stem Weber River and 282 in tributaries.

The Weber River Basin supports a large metapopulation of threatened Bonneville Cutthroat Trout (Budy et al., 2020). Bonneville Cutthroat Trout are native to streams and lakes of the Bonneville Basin (Behnke, 1992), but they now occupy only 35-40% of their historical range and are managed for conservation in Utah (UDWR, 2019). Cutthroat Trout prefer streams with water temperatures between 10-20°C that maximize growth, survival, and reproductive success (Budy et al., 2012; Macnaughton et al., 2021). In order to exploit seasonal spatial variation in stream temperature, some Cutthroat Trout in the Weber River exhibit a fluvial life history involving movement between cool headwater tributaries in the summer and mainstem river and freshwater lake habitats in the winter (Bennett et al., 2014; Carlson and Rahel, 2010; Hillyard and Keeley, 2012). Habitat fragmentation caused by instream barriers restricts fish movement and limits access to preferred seasonal thermal habitats (Hilderbrand and Kershner, 2000), and hundreds of dams, diversions, and road-crossing barriers fragment the mainstem Weber River and its tributaries (Kraft et al., 2019). Restoring connectivity between seasonally variable thermal habitats is a goal to conserve Bonneville Cutthroat Trout in the Weber River Basin (Budy and Thiede, 2014; UDWR, 2019).

2.2. Conceptual overview

I used weekly and monthly stream temperature data and habitat suitability modeling in a Monte-Carlo random sampling framework to estimate stream temperature suitability under uncertain stream temperature estimates and species-habitat relationships. I then used my Monte-Carlo simulations of habitat suitability in a barrier removal optimization model to identify barrier removals that are robust to uncertainty for restoring thermal habitat connectivity for two conservation objectives (Figure 3.2). I represented uncertainty in habitat suitability estimates by randomly sampling stream temperature input data and suitability function parameters. I randomly sampled stream temperature input data from a normal distribution of measurement errors to represent the range of possible instream conditions. To represent uncertainty in habitat suitability models, I systematically adjusted the upper thermal limit of Bonneville Cutthroat Trout in a temperature dependence function to reflect the observed range of upper thermal limit estimates. I combined stream temperature input data and suitability function uncertainties to calculate habitat suitability for either annual growth or summer thermal refugia objectives. I then incorporated the range of habitat suitability estimate uncertainties into an optimization model that prioritizes barriers for removal to reconnect habitat patches. I used optimization model outputs across stochastic model iterations to identify barrier removals that are robust to uncertain stream temperature conditions and species-habitat relationships.

2.3. Stream temperature data

I obtained weekly and monthly modeled stream temperature data for the Weber River Basin from the NorWeST Regional Stream Temperature Database (Isaak et al., 2016). NorWeST datasets are based on spatial-stream-network models that predict mean monthly and maximum weekly maximum temperature (MWMT; defined as the highest seven-day moving average of maximum daily temperature) metrics. The spatial-stream-network models have 1 km stream segment resolution and include topographical, climatic, and hydrological covariates fit to over 220,000,000 stream temperature measurements from more than 22,000 stream and river monitoring locations in the western U.S. (Isaak et al., 2017a). Mean monthly and maximum weekly air temperature and streamflow data collected between 1993-2011. Mean monthly stream temperatures were unavailable for 12 km of the stream network. Missing temperatures were estimated as the difference between temperatures in contiguous upstream and downstream segments proportionally weighted by the distance from the upstream segment. Lake and reservoir temperatures are not modeled in NorWeST datasets, and stream segments representing lakes and reservoirs were omitted from habitat suitability calculations.

2.4. Stream temperature suitability function

For each 1 km stream segment, I calculated stream temperature habitat suitability index values using a temperature dependence function for coldwater fish species parameterized for Cutthroat Trout (Deslauriers et al., 2017). Temperature dependence functions model how temperature affects biological processes, such as metabolism, respiration, or consumption by estimating the proportion of the maximum rate an organism can achieve at a given temperature (Thornton and Lessem, 1978). Temperate dependence functions are advantageous for assessing thermal habitat suitability because they produce univariate outputs consistent with habitat suitability models where extremes denote fully unsuitable (0) or suitable (1) habitat based on well-studied physiological processes and temperature.

To estimate stream temperature suitability, I used the consumption temperature dependence function parameterized for Cutthroat Trout in the Fish Bioenergetics 4.0 modeling package available in the R computing environment (Deslauriers et al., 2017). I selected the consumption temperature dependence function because consumption rates reflect environmental constraints on organism growth which influence survival and reproductive success (Myrvold and Kennedy, 2020; Railsback and Rose, 1999). The temperature dependence function for coldwater species requires several temperature-related function parameters including the upper and lower thermal limits for consumption, the upper and lower optimal thermal limits for consumption where consumption exceeds 98% of the maximum rate, and the proportions of maximum consumption at the upper and lower thermal limits of consumption.

2.5. Uncertainty of stream temperature data and suitability function parameters

To represent uncertainty in stream temperature input data, I sampled mean monthly and MWMT temperature metrics for each stream segment from a normal distribution parameterized with the standard error measurement of each metric for each stream segment. I sampled from a normal distribution because mean monthly and

MWMT (weekly) metrics aggregate data, which smooths skewness and long tails from extreme values regardless of the distribution of the original data (Berthouex and Brow, 2002). I parameterized the spread of a normal distribution with stream temperature standard errors because standard errors provide an estimate of the uncertainty of the true value of the mean stream temperature (Curran-Everett, 2008). Random sampling was conducted using the stats package in R version 4.3.1 (R Core Team, 2023).

I represented uncertainty in the stream temperature suitability function by varying the upper thermal limit parameter of 24 ºC by +/- 3 ºC based on values derived from the literature. I focused on the upper thermal limit parameter because estimates of upper thermal limits from the literature vary more widely than for either the lower thermal limit (Chezik et al., 2014; Coleman and Fausch, 2007a) or thermal optima (Bear et al., 2007; Rogers et al., 2022). I set the minimum parameter estimate at 21°C consistent with the lowest temperatures that induce mortality in 30- to 60-day chronic exposure experiments of Cutthroat Trout (Bear et al., 2007; Zeigler et al., 2013). I considered 27°C the maximum thermal limit to reflect the highest temperatures tolerated by Cutthroat Trout for extended periods in observational habitat use studies (Hillyard and Keeley, 2012; Schrank et al., 2003). I used a uniform distribution for parameter values based on the assumption that any parameter value between the minimum and maximum estimates derived from the literature were equally likely to represent a 'true' upper thermal limit.

2.6. Habitat suitability and uncertainty estimates for conservation objectives

To analyze uncertainty in habitat suitability calculations, I generated 1,000 unique habitat suitability estimates with Monte-Carlo random sampling by concurrently sampling stream temperature distributions and systematically adjusting the upper thermal limit parameter in my stream temperature suitability function. Then I calculated stream segment habitat suitability for each conservation objective. I verified that 1,000 habitat suitability estimates were sufficient to represent habitat suitability variability in the barrier removal optimization model by confirming that both the total number of barriers selected for removal and the coefficient of variation for barrier removal selection frequency reached an asymptote (Figure A1). I compared uncertainty estimates with a base case scenario using reported NorWeST stream temperature metrics and published temperature dependence function parameter values.

My first conservation objective focused on restoring connectivity between stream segments that provide suitable habitat for fish growth. I calculated growth habitat suitability as the annual average of mean monthly stream temperature suitability for each reach. I used mean annual stream temperature suitability, rather than the suitability of the mean annual temperature, to capture the intra-annual upstream and downstream propagation of seasonal growth opportunities and represent the ability of warmer downstream habitats to fuel fish growth during shoulder seasons (Armstrong et al., 2021). Growth habitat suitability estimates emphasize sections of the stream network that maintain suitable thermal conditions throughout the year rather than providing seasonally optimal temperatures.

My second conservation objective emphasized habitats that provide thermal refugia during warm periods. I identified thermal refugia using MWMT for each stream segment. Extended exposure to stressful thermal conditions can be lethal and limit species distribution and habitat use (Isaak et al., 2017b; Moore et al., 2013; Turschwell et al., 2017). Weekly maximum stream temperatures are commonly used to identify thermal refugia habitats for conservation (Hubler et al., 2024; Isaak and Young, 2023; Null et al., 2013). Thermal refugia provide seasonally beneficial conditions and are sometimes the only habitable portions of the river system during periods of maximum thermal stress for aquatic organisms (Isaak et al., 2015).

2.7. Barrier removal optimization model

I evaluated barrier removals that are robust to habitat and model uncertainties with a modified barrier removal optimization model developed for the Weber River Basin by Kraft et al. (2019). The model quantifies longitudinal connectivity as the integral index of connectivity (IIC; Pascual-Hortal and Saura, 2006). IIC measures stream network connectivity at the watershed scale with values ranging from 1 (a fully connected network without barriers) to 0 (a network where all stream reaches are separated by impassable barriers). The objective function maximizes connectivity between stream reaches separated by instream barriers:

$$Maximize\ Z = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\frac{H_i H_j}{1+TL_{ij}} * CR_{ij} * P_i * P_j + H_i^2}{H_L^2}, i \neq j \qquad (1)$$

where Z is watershed IIC (unitless), H_i and H_j are the suitability-weighted stream length (km) above barriers i and j, TL_{ij} is the topological distance between the two barriers (unitless), CR_{ij} is the binary decision to remove all barriers between barriers i and j $\{0,1\}$, P_i and P_j are the unitless passability ratings for barriers i and j, and H_L is the total suitability-weighted stream length in the stream network (km) (Kraft et al., 2019; Pascual-Hortal and Saura, 2006). I used passability ratings of impassable (1), severe

(0.6), moderate (0.3), or passable (0.1) barriers to fish movement that characterized barrier passability in the Weber River Basin using expert opinion and structural and topographical criteria (Kraft et al. 2019).

The objective function is constrained by equations representing physical, habitat, and economic bounds. Stream reaches are reconnected only when all barriers between barriers i and j are removed (Equation 2). Reconnecting reaches and removing barriers are binary decisions where barriers either remain or are fully removed (Equations 3 and 4). The number of barriers removed is limited by the cost of removing barriers (Equation 5). Constraints are expressed mathematically as:

$$CR_{ij} \leq \frac{\sum_k Int_{i,j,k} * B_k}{\sum_k Int_{i,j,k}}, \forall i \neq j \tag{2}$$

$$CR_{ij} \in \{0,1\}, \forall_{i,j} \tag{3}$$

$$B_k \in \{0,1\}, \forall_k \tag{4}$$

$$TC \geq \sum_k C_k * B_k, \forall_k \tag{5}$$

where $Int_{i,j,k}$ is a binary parameter indicating that barrier k is located between barriers i and j, B_k is the binary decision to remove barrier k from the stream network, C_k is the cost to remove barrier k (USD), and TC is the barrier removal budget (USD).

I conducted optimization model runs using a $2M barrier removal budget. I chose a $2M budget as it approximates the midpoint range for most barrier removal projects that range from hundreds of thousands to millions of dollars (King and O'Hanley, 2016; Maitland et al., 2016). Kraft et al. (2019) also found that uncertainty in removal costs did not affect barrier removal prioritizations for budgets below $10M. My budget was sufficient to remove any barrier in the Weber River Basin except for the seven large water storage dams that were represented in the optimization model but not considered for removal.

I calculated suitability-weighted stream length as the sum of NorWeST stream segment lengths between barriers i and j multiplied by habitat suitability. Longitudinal lengths of stream segments were calculated in ArcGIS Pro version 3.1.2. For each stream reach between barriers i and j, suitability-weighted stream length is expressed as:

$$H_{i,j} = \sum_{i,j} L_s * HSI_s \, , \forall_{i,j,s} \quad (6)$$

where L is the longitudinal length (km) and HSI is the habitat suitability (unitless) of stream segments s between barriers i and j.

2.8. Assessment of habitat suitability estimate uncertainty and barrier removal robustness

To assess the relative influence of predicted stream temperature and suitability function uncertainties, I conducted three sets of 1,000 habitat suitability calculations derived from Monte-Carlo random sampling of input data and suitability function parameters for each conservation objective. First, I randomly sampled predicted stream temperature from NorWeST datasets while using published temperature dependence function parameters to isolate input data uncertainty. Secondly, I calculated habitat suitability function uncertainty by systematically varying the temperature dependence function upper thermal limit parameter while using NorWeST monthly mean and MWMT predicted stream temperatures to isolate parameter uncertainty. Finally, I concurrently sampled predicted stream temperature and varied the upper thermal limit parameter to integrate uncertainty. I evaluated the relative influence of input data and parameter uncertainties by comparing the mean and standard deviation of HSI values for each 1 km stream segment across all habitat suitability estimates to those of the total uncertainty.

I assessed the robustness of barrier removals to uncertain habitat suitability estimates by calculating the number of times a barrier was selected for removal across 1,000 optimization model runs for each conservation objective and Monte-Carlo simulation of habitat suitability. I also examined the robustness of barrier removals in the base case scenarios to evaluate whether barrier removal optimizations without uncertainty analysis provide robust removal recommendations. Finally, I calculated the robustness of barrier removals as the number of times a barrier was selected for removal across 2,000 model runs representing all habitat suitability estimates for both conservation objectives to highlight barrier removals that are robust to habitat suitability uncertainties for multiple conservation objectives.

3. Results

3.1. Habitat suitability estimates and uncertainty analysis

Thermal refugia habitat suitability was more sensitive to stream temperature input data and suitability function parameter uncertainties than was growth habitat suitability (Figure 3.3). There was also a spatial mismatch. Thermal refugia habitat suitability was highest in headwater reaches, whereas growth habitat suitability was highest in downstream reaches of large tributaries and the mainstem Weber River. Similarly, uncertainty, represented as standard deviation of habitat suitability, was highest for thermal refugia in headwaters and suitable tributaries, while it was highest for growth habitat in downstream tributaries and mainstem reaches. The standard deviation of habitat suitability for growth habitat was less than 0.1 across all reaches and less than 0.05 in over 90% of the stream network, indicating that growth habitat suitability estimates varied little with differences in stream temperature input data and estimates of suitability function parameters. Alternatively, habitat suitability estimates for thermal refugia varied considerably throughout the stream network from both stream temperature input data and suitability function uncertainty. Standard deviation of thermal refuge habitat suitability ranged between 0.03 and 0.4 and exceeded 0.2 in over 75% of the stream network. For both growth habitats and thermal refugia, standard deviation of habitat suitability varied spatially, with higher values in reaches that provided better habitat.

For both growth habitat and thermal refugia, input data uncertainty influenced habitat suitability more than suitability function uncertainty (Figure 3.4). Input data uncertainty was nearly four times greater than suitability function uncertainty for both conservation objectives. Uncertainty of habitat suitability indices did not amplify when stream temperature input data and suitability function uncertainties were combined, suggesting that input data and suitability function uncertainties did not propagate in habitat suitability estimates.

3.2 Sensitivity of optimal barrier removals

The uncertainty of stream temperature input data and suitability function parameters had little influence on optimal barrier removals for the growth habitat conservation objective (left panel in Figure 3.5). Barrier removal prioritizations that were selected in the base case were generally robust. Nine barriers were selected in all 1,000 randomizations. These barriers were concentrated in connected third- and fourth-order reaches of the Basin's northernmost tributaries. No barriers were selected where average habitat suitability in neighboring stream reaches was less than 0.5 or exceeded 0.65. An additional 14 barriers were selected to be removed in less than 1% of runs, suggesting that removing these barriers was worthwhile only under certain limited conditions. These barriers were distributed across discontinuous reaches throughout the Weber Basin.

Optimal barrier removals for the thermal refugia conservation objective were sensitive to uncertainties in habitat suitability estimates and varied more than those selected with the growth habitat conservation objective (right panel in Figure 3.5). Only one barrier was selected in all 1,000 thermal refugia suitability estimates and eight additional barriers were selected in more than half of all suitability estimates. Thirty-five barriers were occasionally selected to be removed, and eight were selected across more than 10% but less than 50% of suitability estimates, whereas 11 were selected in less than 1% of suitability estimates. Of the barriers selected in more than half of all suitability estimates, six were grouped along contiguous third- and fourth-order reaches, whereas the remaining three were located on discontinuous first- and second-order reaches in the basin. The robust barrier removals selected in over half of suitability estimates commonly connected reaches with highly suitable habitat (>0.6), which presumably enables organisms to access some of the highest quality habitat patches in the stream network.

Barrier removals in base case scenarios were typically robust to uncertainty in habitat suitability (Figure 3.5). The nine barriers removed in the base case scenario for the growth habitat objective were selected across all habitat suitability estimates, indicating that the growth habitat base scenario was robust to stream temperature input data and suitability function uncertainty. The base scenario for thermal refugia objective was less robust to stream temperature input data and suitability function uncertainties than the base scenario for the growth habitat objective. For the thermal refugia conservation objective, nine barriers removed in the base scenario were selected from more than half of habitat suitability estimates. However, in the thermal refugia base scenario, three barriers were selected in fewer than half of the habitat suitability estimates. My analysis found that two alternative barrier removals were more robust to uncertainty, making them reliably good choices for removal. Prioritizing robust decisions over optimal ones could lead to better outcomes when species-habitat relationships are not well understood or when input data contain errors.

Few barrier removals were robust to stream temperature input data and suitability function uncertainty for both conservation objectives (Figure 3.6). Out of 50 barrier removals selected across all habitat suitability estimates and objectives, sixteen barriers were selected in model runs for both growth habitat or thermal refugia conservation objectives. Only one barrier was selected in all model runs and four additional barriers were selected in more than half of model runs for both objectives. Four additional barriers were selected across all growth habitat suitability estimates but were selected in less than 10% of thermal refugia suitability estimates. Seven additional barriers were selected for both objectives but in less than 10% of model runs for either objective. The five robust barriers removals selected for both objectives in more than half of all habitat suitability runs would cost an estimated $940k to remove. They would reconnect 95 km, or 8%, of the stream network in the Weber River Basin.

Barriers removed under optimal models with uncertain habitat suitability consistently included non-passable barriers of all types (Figure 3.7). Dams, diversions, and road crossing barriers were all commonly removed in optimal solutions, with each type representing 3-5 barriers in removal prioritizations. Completely impassable barriers represent 43% of all barriers and disproportionately affect stream network connectivity (Goodrum et al., 2025). They were most frequently selected for removal for both conservation objectives. Severely impassable and moderately passable barriers that partially limit fish movement were also consistently prioritized for removal for both objectives despite representing only 12% and 23% of all barriers, respectively. No passable barriers were selected for removal for any alternatives.

4. Discussion

4.1. Robust barrier removals with uncertain habitat suitability

My study demonstrated that uncertainty in environmental data and suitability functions influences habitat suitability and barrier removal optimization models. Overall, thermal refugia habitat suitability estimates were more sensitive to stream temperature input data and suitability function uncertainty than growth habitat estimates, and input data influenced habitat suitability estimates more than did suitability function uncertainties. Similarly, barrier removal selections were largely robust to stream temperature input data and suitability function uncertainty for the growth habitat objective but were less robust for the thermal refugia objective. I identified only 5 barriers that were robust to uncertainty and to management objective, being consistently selected for both growth habitat and thermal refugia objectives. Optimal barrier removals primarily targeted impassable barriers to fish movement.

My findings suggest that intra-annual habitat suitability estimates and data corresponding to species-specific life-history requirements may provide more informative measures of habitat suitability than annual averages and improve robust decision-making for habitat conservation and barrier removal. Thermal refugia habitat suitability and barrier removal robustness were more sensitive to stream temperature input data and suitability function uncertainties than those of growth habitat due to annual averaging of monthly suitability estimates. Season-specific and extreme conditions influence ecological processes and often affect species distribution and habitat use (Gaines and Denny, 1993; Katz et al., 2005; Ledger and Milner, 2015). However, stream temperature and other instream conditions are often represented as weekly, monthly, or annual averages that reduce variability and suppress extreme events in environmental data (Thompson et al., 2013). Habitat representations should focus on seasonal and extreme habitat conditions to better represent uncertainties in species-habitat relationships and improve outcomes from barrier removal and other conservation decisions.

Stream temperature input data uncertainties had a greater influence on habitat suitability index values than suitability function uncertainties because the magnitude of stream temperature measurement error exceeded uncertainty in the temperature dependence function. My findings did not support previous studies that demonstrated uncertainty in suitability function parameters can generate significant variability in habitat suitability estimates (Ayllón et al., 2012; Fu and Guillaume, 2014; Vilizzi et al., 2004). Uncertainty in habitat suitability index models depends on the number of habitat variables included in the index, the certainty of suitability functions, and the variability of habitat variable measurements (Turner et al., 2016; Van Der Lee et al., 2006). Stream temperature influence on biological rates for salmonids is well studied and may produce more certain suitability functions than for other habitat variables or organisms (Railsback, 2022). Users should consider robust decision frameworks or uncertainty analyses when either input data or suitability functions are uncertain.

My study examined uncertainty in stream temperature suitability because stream temperature influences many life-history requirements for fish (Barbarossa et al., 2021; Buisson et al., 2008; Dunham et al., 2003). However, many abiotic aspects of rivers, including streamflow (Bradford and Heinonen, 2008; Kiernan et al., 2012), physical habitat conditions (Morrisett et al., 2023), dissolved oxygen concentration (Null et al., 2017), spawning substrate availability (Rosenfeld, 2003), and water quality (Railsback, 2016) interact with stream temperature to determine the suitability of instream habitats. Biotic conditions such as food availability (Naman et al., 2020) and nonnative species presence (Nemec et al., 2021) also influence habitat suitability but are unavailable as watershed-scale datasets, which make them challenging to incorporate in habitat suitability indices or barrier removal optimization models (Milt et al., 2018). While some studies have included multi-variate habitat suitability models in barrier removal optimization (Kraft et al., 2019; Zheng et al., 2009), uncertainty among multiple habitat variables, and how they affect barrier removal prioritization, remains unknown.

4.2. Limitations

I represented uncertainty in a stream temperature suitability function by varying the upper thermal limit of Cutthroat Trout and keeping all other thermal tolerance parameters constant. While optimal thermal conditions maximizing metabolic performance and upper thermal limits that induce mortality for Cutthroat Trout have been extensively studied (Bear et al., 2007; Dickerson and Vinyard, 1999; Johnstone and Rahel, 2003; Rogers et al., 2022; Zeigler et al., 2013), few studies have examined lower thermal tolerance for Cutthroat Trout and other coldwater species. Like unsuitably warm instream conditions, unsuitably cold stream temperatures decrease species growth and survival (Coleman and Fausch, 2007a, 2007b; Macnaughton et al., 2021). Headwater tributaries that occur in high-elevation areas of the watershed and expose fish to stressful cold conditions make up the majority of stream length in montane river systems (Wohl, 2017). Over- or under-estimating lower thermal suitability in seasonally cold habitats may influence habitat suitability estimates and optimal barrier removals similarly to uncertainty in upper thermal limits, but lower thermal tolerance data are unavailable for most species.

4.3. Implications for barrier removal and habitat restoration

Impassable barriers were the most common type selected for removal in all model runs. Nine of the thirteen barriers selected for removal for either objective were impassable barriers, as were three of the five barrier removals robust across both objectives. The remaining barriers that were robust to uncertain habitat suitability were partially passable and contiguous with impassable barriers, suggesting that connectivity benefits may depend on the concurrent removal of impassable barriers. While small, impassable barriers to fish movement are relatively rare, they play a disproportionate role in river system fragmentation (Goodrum et al., 2025; Januchowski-Hartley et al., 2013;

Perkin et al., 2020). My results suggest that selecting small impassable barriers for removal may be an effective choice for river restoration under uncertainty.

Evaluating the robustness of barrier removals across a gradient of plausible habitat suitabilities and life history-based conservation objectives is critical to enhancing ecological outcomes of river restoration and barrier removal (de Leaniz and O'Hanley, 2022). However, uncertainty in environmental data and habitat suitability functions are rarely considered in barrier removal analysis and optimization (McManamay et al., 2019). While I demonstrated that barrier removals can be robust to uncertainty in estimates of growth habitat suitability, my findings support incorporating uncertainty analysis for summer thermal refuge habitats. Species-habitat relationships are not clearly defined for many organisms and stream habitat variables, and additional studies of biological response to changing instream conditions would improve our ability to bound uncertainty in habitat suitability functions and barrier removal optimization models. I recommend uncertainty analysis to identify barrier removals that satisfy many life-history objectives to maximize the ecological benefits across a range of alternatives. My findings provide an approach to improve robustness to ecological and environmental uncertainty in barrier removal planning and river connectivity restoration.

Acknowledgments

This work was supported by the Agriculture and Food Research Initiative, project award number 2021-69012-35916, from the US Department of Agriculture National Institute of Food and Agriculture. It was also supported by the National Sciences Foundation Grant #1653452. Any opinions, findings, and conclusions or recommendations expressed are those of the authors and do not necessarily reflect the views of the National Science Foundation.

References

Armstrong, J.B., Fullerton, A.H., Jordan, C.E., Ebersole, J.L., Bellmore, J.R., Arismendi, I., Penaluna, B.E., Reeves, G.H., 2021. The importance of warm habitat to the growth regime of cold-water fishes. Nat. Clim. Change 11, 354–361. https://doi.org/10.1038/s41558-021-00994-y

Ayllón, D., Almodóvar, A., Nicola, G.G., Elvira, B., 2012. The influence of variable habitat suitability criteria on PHABSIM habitat index results. River Res. Appl. 28, 1179–1188. https://doi.org/10.1002/rra.1496

Barbarossa, V., Bosmans, J., Wanders, N., King, H., Bierkens, M.F.P., Huijbregts, M.A.J., Schipper, A.M., 2021. Threats of global warming to the world's freshwater fishes. Nat. Commun. 12, 1701. https://doi.org/10.1038/s41467-021-21655-w

Barry, S., Elith, J., 2006. Error and uncertainty in habitat models. J. Appl. Ecol. 43, 413–423. https://doi.org/10.1111/j.1365-2664.2006.01136.x

Bear, E.A., McMahon, T.E., Zale, A.V., 2007. Comparative Thermal Requirements of Westslope Cutthroat Trout and Rainbow Trout: Implications for Species Interactions and Development of Thermal Protection Standards. Trans. Am. Fish. Soc. 136, 1113–1121. https://doi.org/10.1577/T06-072.1

Behnke, R.J., 1992. Native trout of western North America, American Fisheries Society Monograph. American Fisheries Society.

Belletti, B., Garcia De Leaniz, C., Jones, J., Bizzi, S., Börger, L., Segura, G., Castelletti, A., Van De Bund, W., Aarestrup, K., Barry, J., Belka, K., Berkhuysen, A., Birnie-Gauvin, K., Bussettini, M., Carolli, M., Consuegra, S., Dopico, E., Feierfeil, T., Fernández, S., Fernandez Garrido, P., Garcia-Vazquez, E., Garrido, S., Giannico, G., Gough, P., Jepsen, N., Jones, P.E., Kemp, P., Kerr, J., King, J., Łapińska, M., Lázaro, G., Lucas, M.C., Marcello, L., Martin, P., McGinnity, P., O'Hanley, J., Olivo Del Amo, R., Parasiewicz, P., Pusch, M., Rincon, G., Rodriguez, C., Royte, J., Schneider, C.T., Tummers, J.S., Vallesi, S., Vowles, A., Verspoor, E., Wanningen, H., Wantzen, K.M., Wildman, L., Zalewski, M., 2020. More than one million barriers fragment Europe's rivers. Nature 588, 436–441. https://doi.org/10.1038/s41586-020-3005-2

Bellmore, J.R., Duda, J.J., Craig, L.S., Greene, S.L., Torgersen, C.E., Collins, M.J., Vittum, K., 2017. Status and trends of dam removal research in the United States. WIREs Water 4, e1164. https://doi.org/10.1002/wat2.1164

Bennett, S., Al-Chokhachy, R., Roper, B.B., Budy, P., 2014. Annual Variation of Spawning Cutthroat Trout in a Small Western USA Stream: A Case Study with Implications for the Conservation of Potamodromous Trout Life History Diversity. North Am. J. Fish. Manag. 34, 1033–1046. https://doi.org/10.1080/02755947.2014.938139

Berthouex, P.M., Brow, L.C., 2002. Statistics for Environmental Engineers, Second Edition. ed. CRC Press, Boca Raton, Florida, USA.

Bradford, M.J., Heinonen, J.S., 2008. Low Flows, Instream Flow Needs and Fish Ecology in Small Streams. Can. Water Resour. J. 33, 165–180. https://doi.org/10.4296/cwrj3302165

Branco, P., Segurado, P., Santos, J.M., Ferreira, M.T., 2014. Prioritizing barrier removal to improve functional connectivity of rivers. J. Appl. Ecol. 51, 1197–1206. https://doi.org/10.1111/1365-2664.12317

Brooks, R.P., 1997. Improving Habitat Suitability Index Models. Wildl. Soc. Bull. 25, 163–167.

Budy, P., Thompson, P.D., McKell, M.D., Thiede, G.P., Walsworth, T.E., Conner, M.M., 2020. A Multifaceted Reconstruction of the Population Structure and Life History Expressions of a Remnant Metapopulation of Bonneville Cutthroat Trout: Implications for Maintaining Intermittent Connectivity. Trans. Am. Fish. Soc. 149, 443–461. https://doi.org/10.1002/tafs.10240

Budy, P., Wood, S., Roper, B., 2012. A Study of the Spawning Ecology and Early Life History Survival of Bonneville Cutthroat Trout. North Am. J. Fish. Manag. 32, 436–449. https://doi.org/10.1080/02755947.2012.675945

Budy, P.E., Thiede, G.P., 2014. Weber River metapopulation and source-sink dynamics of native and nongame fishes (Performance Report to the Utah Division of Wildlife Resources No. Sport Fish Restoration, Grant Number: F-135-R, Segment 2. UTCFWRU).

Buisson, L., Blanc, L., Grenouillet, G., 2008. Modelling stream fish species distribution in a river network: the relative effects of temperature versus physical factors. Ecol. Freshw. Fish 17, 244–257. https://doi.org/10.1111/j.1600-0633.2007.00276.x

Cahill, R., R. Lund, J., DeOreo, B., & Medellín-Azuara, J. (2013). Household water use and conservation models using Monte Carlo techniques. *Hydrology and Earth System Sciences*, *17*(10), 3957–3967. https://doi.org/10.5194/hess-17-3957-2013

Carlson, A.J., Rahel, F.J., 2010. Annual Intrabasin Movement and Mortality of Adult Bonneville Cutthroat Trout among Complementary Riverine Habitats. Trans. Am. Fish. Soc. 139, 1360–1371. https://doi.org/10.1577/T09-010.1

Cheng, S.-T., Herricks, E.E., Tsai, W.-P., Chang, F.-J., 2016. Assessing the natural and anthropogenic influences on basin-wide fish species richness. Sci. Total Environ. 572, 825–836. https://doi.org/10.1016/j.scitotenv.2016.07.120

Chezik, K.A., Lester, N.P., Venturelli, P.A., 2014. Fish growth and degree-days I: selecting a base temperature for a within-population study. Can. J. Fish. Aquat. Sci. 71, 47–55. https://doi.org/10.1139/cjfas-2013-0295

Cohon, J.L., 2013. Multiobjective programming and planning. Courier Corporation.

Coleman, M.A., Fausch, K.D., 2007a. Cold Summer Temperature Limits Recruitment of Age-0 Cutthroat Trout in High-Elevation Colorado Streams. Trans. Am. Fish. Soc. 136, 1231–1244. https://doi.org/10.1577/T05-244.1

Coleman, M.A., Fausch, K.D., 2007b. Cold Summer Temperature Regimes Cause a Recruitment Bottleneck in Age-0 Colorado River Cutthroat Trout Reared in Laboratory Streams. Trans. Am. Fish. Soc. 136, 639–654. https://doi.org/10.1577/T05-288.1

Conradt, J., Funk, S., Sguotti, C., Voss, R., Blenckner, T., Möllmann, C., 2024. Robust fisheries management strategies under deep uncertainty. Sci. Rep. 14, 16863. https://doi.org/10.1038/s41598-024-68006-5

Curran-Everett, D., 2008. Explorations in statistics: standard deviations and standard errors. Adv. Physiol. Educ. 32, 203–208. https://doi.org/10.1152/advan.90123.2008

de Leaniz, C.G., O’Hanley, J.R., 2022. Operational methods for prioritizing the removal of river barriers: Synthesis and guidance. Sci. Total Environ. 848, 157471. https://doi.org/10.1016/j.scitotenv.2022.157471

Deslauriers, D., Chipps, S.R., Breck, J.E., Rice, J.A., Madenjian, C.P., 2017. Fish Bioenergetics 4.0: An R-Based Modeling Application. Fisheries 42, 561–604. https://doi.org/10.1080/03632415.2017.1377558

Dickerson, B.R., Vinyard, G.L., 1999. Effects of High Chronic Temperatures and Diel Temperature Cycles on the Survival and Growth of Lahontan Cutthroat Trout. Trans. Am. Fish. Soc. 128, 385–550. https://doi.org/10.1577/1548-8659(1999)128<0516:EOHCTA>2.0.CO;2

Dunham, J., Rieman, B., Chandler, G., 2003. Influences of Temperature and Environmental Variables on the Distribution of Bull Trout within Streams at the Southern Margin of Its Range. North Am. J. Fish. Manag. 23, 894–904. https://doi.org/10.1577/M02-028

Fu, B., Guillaume, J.H.A., 2014. Assessing certainty and uncertainty in riparian habitat suitability models by identifying parameters with extreme outputs. Environ. Model. Softw. 60, 277–289. https://doi.org/10.1016/j.envsoft.2014.06.015

Gaines, S.D., Denny, M.W., 1993. The Largest, Smallest, Highest, Lowest, Longest, and Shortest: Extremes in Ecology. Ecology 74, 1677–1692. https://doi.org/10.2307/1939926

Galbraith, H.S., Blakeslee, C.J., Cole, J.C., Talbert, C.A., Maloney, K.O., 2016. Evaluating Methods to Establish Habitat Suitability Criteria: A Case Study in the Upper Delaware River Basin, USA. River Res. Appl. 32, 1765–1775. https://doi.org/10.1002/rra.3025

Goharian, E., Zahmatkesh, Z., & Sandoval-Solis, S. (2018). Uncertainty Propagation of Hydrologic Modeling in Water Supply System Performance: Application of Markov Chain Monte Carlo Method. *Journal of Hydrologic Engineering*, *23*(5). https://doi.org/10.1061/(asce)he.1943-5584.0001646

Goodrum, G.C., Hawkins, C.P., Walsworth, T.E., Null, S.E., 2025. Predicting Road-Crossing Passability for River Connectivity Analysis. River Res. Appl. rra.4434. https://doi.org/10.1002/rra.4434

Guay, J.C., Boisclair, D., Rioux, D., Leclerc, M., Lapointe, M., Legendre, P., 2000. Development and validation of numerical habitat models for juveniles of Atlantic salmon (*Salmo salar*). Can. J. Fish. Aquat. Sci. 57, 2065–2075. https://doi.org/10.1139/f00-162

Guo, D., Lintern, A., Webb, J.A., Ryu, D., Liu, S., Bende-Michl, U., Leahy, P., Wilson, P., Western, A.W., 2019. Key Factors Affecting Temporal Variability in Stream Water Quality. Water Resour. Res. 55, 112–129. https://doi.org/10.1029/2018WR023370

Hamilton, A.S., Moore, R.D., 2012. Quantifying Uncertainty in Streamflow Records. Can. Water Resour. J. Rev. Can. Ressour. Hydr. 37, 3–21. https://doi.org/10.4296/cwrj3701865

Harris, G.P., Heathwaite, A.L., 2012. Why is achieving good ecological outcomes in rivers so difficult? Freshw. Biol. 57, 91–107. https://doi.org/10.1111/j.1365-2427.2011.02640.x

Hilborn, R., Quinn, T.P., Schindler, D.E., Rogers, D.E., 2003. Biocomplexity and fisheries sustainability. Proc. Natl. Acad. Sci. 100, 6564–6568. https://doi.org/10.1073/pnas.1037274100

Hilderbrand, R.H., Kershner, J.L., 2000. Movement Patterns of Stream-Resident Cutthroat Trout in Beaver Creek, Idaho–Utah. Trans. Am. Fish. Soc. 129, 1160–1170. https://doi.org/10.1577/1548-8659(2000)129<1160:MPOSRC>2.0.CO;2

Hillyard, R.W., Keeley, E.R., 2012. Temperature-Related Changes in Habitat Quality and Use by Bonneville Cutthroat Trout in Regulated and Unregulated River Segments. Trans. Am. Fish. Soc. 141, 1649–1663. https://doi.org/10.1080/00028487.2012.717517

Hubler, S., Stamp, J., Sullivan, S.P., Fernandez, M., Larson, C., Macneale, K., Wisseman, R.W., Plotnikoff, R., Bierwagen, B., 2024. Improved thermal preferences and a stressor index derived from modeled stream temperatures and regional taxonomic standards for freshwater macroinvertebrates of the Pacific Northwest, USA. Ecol. Indic. 160, 111869. https://doi.org/10.1016/j.ecolind.2024.111869

Hung, Y. (2024). A review of Monte Carlo and quasi-Monte Carlo sampling techniques. *WIREs Computational Statistics*, *16*(1). https://doi.org/10.1002/wics.1637

Isaak, D.J., Wenger, S.J., Peterson, E.E., Ver Hoef, J.M., Hostetler, S.W., Luce, C.H., Dunham, J.B., Kershner, J.L., Roper, B.B., Nagel, D.E., Chandler, G.L., Wollrab, S.P., Parkes, S.L., Horan, D.L., 2016. NorWeST modeled summer stream temperature scenarios for the western U.S. https://doi.org/10.2737/RDS-2016-0033

Isaak, D.J., Wenger, S.J., Peterson, E.E., Ver Hoef, J.M., Nagel, D.E., Luce, C.H., Hostetler, S.W., Dunham, J.B., Roper, B.B., Wollrab, S.P., Chandler, G.L., Horan, D.L., Parkes-Payne, S., 2017a. The NorWeST Summer Stream Temperature Model and Scenarios for the Western U.S.: A Crowd-Sourced Database and New Geospatial Tools Foster a User Community and Predict Broad Climate Warming of Rivers and Streams. Water Resour. Res. 53, 9181–9205. https://doi.org/10.1002/2017WR020969

Isaak, D.J., Wenger, S.J., Young, M.K., 2017b. Big biology meets microclimatology: defining thermal niches of ectotherms at landscape scales for conservation planning. Ecol. Appl. 27, 977–990. https://doi.org/10.1002/eap.1501

Isaak, D.J., Young, M.K., 2023. Cold-water habitats, climate refugia, and their utility for conserving salmonid fishes. Can. J. Fish. Aquat. Sci. 80, 1187–1206. https://doi.org/10.1139/cjfas-2022-0302

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. Gloabl Change Biol. 21, 2465–2828. https://doi.org/10.1111/gcb.12879

Januchowski-Hartley, S.R., McIntyre, P.B., Diebel, M., Doran, P.J., Infante, D.M., Joseph, C., Allan, J.D., 2013. Restoring aquatic ecosystem connectivity requires expanding inventories of both dams and road crossings. Front. Ecol. Environ. 11, 211–217. https://doi.org/10.1890/120168

Johnstone, H.C., Rahel, F.J., 2003. Assessing Temperature Tolerance of Bonneville Cutthroat Trout Based on Constant and Cycling Thermal Regimes. Trans. Am. Fish. Soc. 132, 1–175. https://doi.org/10.1577/T05-244.1

Jones-Farrand, D.T., Fearer, T.M., Thogmartin, W.E., Iii, F.R.T., Nelson, M.D., Tirpak, J.M., 2011. Comparison of statistical and theoretical habitat models for conservation planning: the benefit of ensemble prediction. Ecol. Appl. 21, 2269–2282. https://doi.org/10.1890/10-1047.1

Katz, R.W., Brush, G.S., Parlange, M.B., 2005. STATISTICS OF EXTREMES: MODELING ECOLOGICAL DISTURBANCES. Ecology 86, 1124–1134. https://doi.org/10.1890/04-0606

Kemp, P.S., O’Hanley, J.R., 2010. Procedures for evaluating and prioritising the removal of fish passage barriers: a synthesis. Fish. Manag. Ecol. 17, 297–322. https://doi.org/10.1111/j.1365-2400.2010.00751.x

Kiernan, J.D., Moyle, P.B., Crain, P.K., 2012. Restoring native fish assemblages to a regulated California stream using the natural flow regime concept. Ecol. Appl. 22, 1472–1482. https://doi.org/10.1890/11-0480.1

Kim, Y., Chung, E.-S., 2014. An index-based robust decision making framework for watershed management in a changing climate. Sci. Total Environ. 473–474, 88–102. https://doi.org/10.1016/j.scitotenv.2013.12.002

King, S., O’Hanley, J.R., 2016. Optimal Fish Passage Barrier Removal-Revisited. River Res. Appl. 32, 418–428. https://doi.org/10.1002/rra.2859

Kraft, M., Rosenberg, D.E., Null, S.E., 2019. Prioritizing Stream Barrier Removal to Maximize Connected Aquatic Habitat and Minimize Water Scarcity. JAWRA J. Am. Water Resour. Assoc. 55, 382–400. https://doi.org/10.1111/1752-1688.12718

Ledger, M.E., Milner, A.M., 2015. Extreme events in running waters. Freshw. Biol. 60, 2455–2460. https://doi.org/10.1111/fwb.12673

Lempert, R.J., Collins, M.T., 2007. Managing the Risk of Uncertain Threshold Responses: Comparison of Robust, Optimum, and Precautionary Approaches. Risk Anal. 27, 1009–1026. https://doi.org/10.1111/j.1539-6924.2007.00940.x

Lempert, R.J., Groves, D.G., Popper, S.W., Bankes, S.C., 2006. A General, Analytic Method for Generating Robust Strategies and Narrative Scenarios. Manag. Sci. 52, 514–528. https://doi.org/10.1287/mnsc.1050.0472

Li, D., Dorber, M., Barbarossa, V., Verones, F., 2022. Global characterization factors for quantifying the impacts of increasing water temperature on freshwater fish. Ecol. Indic. 142, 109201. https://doi.org/10.1016/j.ecolind.2022.109201

Lin, Y.-P., Lin, W.-C., Wu, W.-Y., 2015. Uncertainty in Various Habitat Suitability Models and Its Impact on Habitat Suitability Estimates for Fish. Water 7, 4088–4107. https://doi.org/10.3390/w7084088

Luce, C., Staab, B., Kramer, M., Wenger, S., Isaak, D., McConnell, C., 2014. Sensitivity of summer stream temperatures to climate variability in the Pacific Northwest. Water Resour. Res. 50, 3428–3443. https://doi.org/10.1002/2013WR014329

Macnaughton, C.J., Durhack, T.C., Mochnacz, N.J., Enders, E.C., 2021. Metabolic performance and thermal preference of westslope cutthroat trout (Oncorhynchus clarkii lewisi) and non-native trout across an ecologically relevant range of temperatures. Can. J. Fish. Aquat. Sci. 78, 1247–1256. https://doi.org/10.1139/cjfas-2020-0173

Maia, A. G., Camargo-Valero, M. A., Trigg, M. A., & Khan, A. (2024). Uncertainty and Sensitivity Analysis in Reservoir Modeling: a Monte Carlo Simulation Approach. *Water Resources Management*, *38*(8), 2835–2850. https://doi.org/10.1007/s11269-024-03794-z

Maitland, B.M., Poesch, M., Anderson, A.E., 2016. Prioritising culvert removals to restore fish habitat for at-risk salmonids in the boreal forest. Fish. Manag. Ecol. 23, 489–502. https://doi.org/10.1111/fme.12188

Mavrotas, G., Pechak, O., Siskos, E., Doukas, H., & Psarras, J. (2015). Robustness analysis in Multi-Objective Mathematical Programming using Monte Carlo simulation. *European Journal of Operational Research*, *240*(1), 193–201. https://doi.org/10.1016/j.ejor.2014.06.039

McManamay, R.A., Perkin, J.S., Jager, H.I., 2019. Commonalities in stream connectivity restoration alternatives: an attempt to simplify barrier removal optimization. Ecosphere 10. https://doi.org/10.1002/ecs2.2596

Milt, A.W., Diebel, M.W., Doran, P.J., Ferris, M.C., Herbert, M., Khoury, M.L., Moody, A.T., Neeson, T.M., Ross, J., Treska, T., O'Hanley, J.R., Walter, L., Wangen, S.R., Yacobson, E., McIntyre, P.B., 2018. Minimizing opportunity costs to aquatic connectivity restoration while controlling an invasive species: Cost of Invasive Control. Conserv. Biol. 32, 894–904. https://doi.org/10.1111/cobi.13105

Moore, R.D., Nelitz, M., Parkinson, E., 2013. Empirical modelling of maximum weekly average stream temperature in British Columbia, Canada, to support assessment of fish habitat suitability. Can. Water Resour. J. 38, 135–147. https://doi.org/10.1080/07011784.2013.794992

Morrisett, C.N., Van Kirk, R.W., Null, S.E., 2023. Assessing downstream aquatic habitat availability relative to headwater reservoir management in the Henrys Fork Snake River. River Res. Appl. 39, 1749–1762. https://doi.org/10.1002/rra.4175

Myrvold, K.M., Kennedy, B.P., 2020. Seasonal variation in growth, consumption and growth efficiency in overwintering juvenile steelhead. Ecol. Freshw. Fish 29, 450–464. https://doi.org/10.1111/eff.12526

Naman, S.M., Rosenfeld, J.S., Neuswanger, J.R., Enders, E.C., Hayes, J.W., Goodwin, E.O., Jowett, Ian.G., Eaton, B.C., 2020. Bioenergetic Habitat Suitability Curves for Instream Flow Modeling: Introducing User-Friendly Software and its Potential Applications. Fisheries 45, 605–613. https://doi.org/10.1002/fsh.10489

Nemec, Z.C., Lee, L.N., Bonar, S.A., 2021. Development and Evaluation of Habitat Suitability Criteria for Native Fishes in Three Arizona Streams. North Am. J. Fish. Manag. 41, 661–677. https://doi.org/10.1002/nafm.10575

Nestler, J.M., Milhous, R.T., Payne, T.R., Smith, D.L., 2019. History and review of the habitat suitability criteria curve in applied aquatic ecology. River Res. Appl. 35, 1155–1180. https://doi.org/10.1002/rra.3509

Null, S.E., Mouzon, N.R., Elmore, L.R., 2017. Dissolved oxygen, stream temperature, and fish habitat response to environmental water purchases. J. Environ. Manage. 197, 559–570. https://doi.org/10.1016/j.jenvman.2017.04.016

Null, S.E., Olivares, M.A., Cordera, F., Lund, J.R., 2021. Pareto Optimality and Compromise for Environmental Water Management. Water Resour. Res. 57, e2020WR028296. https://doi.org/10.1029/2020WR028296

Null, S.E., Viers, J.H., Deas, M.L., Tanaka, S.K., Mount, J.F., 2013. Stream temperature sensitivity to climate warming in California's Sierra Nevada: impacts to coldwater habitat. Clim. Change 116, 149–170. https://doi.org/10.1007/s10584-012-0459-8

O'Connor, J.E., Duda, J.J., Grant, G.E., 2015. 1000 dams down and counting: Dam removals are reconnecting rivers in the United States. Science 348, 496–497. https://doi.org/10.1126/science.aaa9204

Pascual-Hortal, L., Saura, S., 2006. Comparison and development of new graph-based landscape connectivity indices: towards the priorization of habitat patches and corridors for conservation. Landsc. Ecol. 21, 959–967. https://doi.org/10.1007/s10980-006-0013-z

Perkin, J.S., Acre, M.R., Graham, J., Hoenke, K., 2020. An integrative conservation planning framework for aquatic landscapes fragmented by road-stream crossings. Landsc. Urban Plan. 202, 103860. https://doi.org/10.1016/j.landurbplan.2020.103860

Poff, N.L., Brown, C.M., Grantham, T.E., Matthews, J.H., Palmer, M.A., Spence, C.M., Wilby, R.L., Haasnoot, M., Mendoza, G.F., Dominique, K.C., Baeza, A., 2016. Sustainable water management under future uncertainty with eco-engineering decision scaling. Nat. Clim. Change 6, 25–34. https://doi.org/10.1038/nclimate2765

R Core Team, 2023. R: A language and environment for statistical computing.

Radinger, J., Kail, J., Wolter, C., 2017. Differences among Expert Judgments of Fish Habitat Suitability and Implications for River Management. River Res. Appl. 33, 538–547. https://doi.org/10.1002/rra.3109

Railsback, S.F., 2022. What We Don't Know About the Effects of Temperature on Salmonid Growth. Trans. Am. Fish. Soc. 151, 3–12. https://doi.org/10.1002/tafs.10338

Railsback, S.F., 2016. Why It Is Time to Put PHABSIM Out to Pasture. Fisheries 41, 720–725. https://doi.org/10.1080/03632415.2016.1245991

Railsback, S.F., Rose, K.A., 1999. Bioenergetics Modeling of Stream Trout Growth: Temperature and Food Consumption Effects. Trans. Am. Fish. Soc. 128, 193–384. https://doi.org/10.1577/1548-8659(1999)128<0241:BMOSTG>2.0.CO;2open_in_newISSN0002-8487

Reid, A.J., Carlson, A.K., Creed, I.F., Eliason, E.J., Gell, P.A., Johnson, P.T.J., Kidd, K.A., MacCormack, T.J., Olden, J.D., Ormerod, S.J., Smol, J.P., Taylor, W.W., Tockner, K., Vermaire, J.C., Dudgeon, D., Cooke, S.J., 2019. Emerging threats and persistent conservation challenges for freshwater biodiversity. Biol. Rev. 94, 849–873. https://doi.org/10.1111/brv.12480

Ren, K., Huang, S., Huang, Q., Wang, H., Leng, G., Wu, Y., 2019. Defining the robust operating rule for multi-purpose water reservoirs under deep uncertainties. J. Hydrol. 578, 124134. https://doi.org/10.1016/j.jhydrol.2019.124134

Rogers, K.B., Sucher, B.J., Hodge, B.W., Myrick, C.A., 2022. Thermal tolerance in cutthroat trout of the southern Rocky Mountains. Can. J. Fish. Aquat. Sci. 79, 2043–2055. https://doi.org/10.1139/cjfas-2021-0352

Roloff, G.J., Kernohan, B.J., 1999. Evaluating reliability of habitat suitability index models. Wildl. Soc. Bull. 27, 973–985.

Rosenfeld, J., 2003. Assessing the Habitat Requirements of Stream Fishes: An Overview and Evaluation of Different Approaches. Trans. Am. Fish. Soc. 132, 953–968. https://doi.org/10.1577/T01-126

Schindler, D. E., & Hilborn, R., 2015. Prediction, precaution, and policy under global climate change. Science. 347, 953-954. https://doi.org/ https://doi.org/10.1126/science.1261824

Schrank, A.J., Rahel, F.J., Johnstone, H.C., 2003. Evaluating Laboratory-Derived Thermal Criteria in the Field: An Example Involving Bonneville Cutthroat Trout. Trans. Am. Fish. Soc. 132, 100–109. https://doi.org/10.1577/1548-8659(2003)132<0100:ELDTCI>2.0.CO;2

Singh, R., Reed, P.M., Keller, K., 2015. Many-objective robust decision making for managing an ecosystem with a deeply uncertain threshold response. Ecol. Soc. 20, art12. https://doi.org/10.5751/ES-07687-200312

Sun, J., Du, W., Lucas, M.C., Ding, C., Chen, J., Tao, J., He, D., 2023. River fragmentation and barrier impacts on fishes have been greatly underestimated in the upper Mekong River. J. Environ. Manage. 327, 116817. https://doi.org/10.1016/j.jenvman.2022.116817

Sun, J., Galib, S.M., Lucas, M.C., 2020. Are national barrier inventories fit for stream connectivity restoration needs? A test of two catchments. Water Environ. J. 34, 791–803. https://doi.org/10.1111/wej.12578

Thompson, R.M., Beardall, J., Beringer, J., Grace, M., Sardina, P., 2013. Means and extremes: building variability into community-level climate change experiments. Ecol. Lett. 16, 799–806. https://doi.org/10.1111/ele.12095

Thornton, K.W., Lessem, A.S., 1978. A Temperature Algorithm for Modifying Biological Rates. Trans. Am. Fish. Soc. 284–287. https://doi.org/10.1577/1548-8659(1978)107<284:ATAFMB>2.0.CO;2

Turner, D., Bradford, M.J., Venditti, J.G., Peterman, R.M., 2016. Evaluating Uncertainty in Physical Habitat Modelling in a High-Gradient Mountain Stream. River Res. Appl. 32, 1106–1115. https://doi.org/10.1002/rra.2915

Turschwell, M.P., Balcombe, S.R., Steel, E.A., Sheldon, F., Peterson, E.E., 2017. Thermal habitat restricts patterns of occurrence in multiple life-stages of a headwater fish. Freshw. Sci. 36, 402–414. https://doi.org/10.1086/691553

UDWR, 2019. Bonneville cutthroat trout range-wide conservation agreement and strategy (No. Publication Number 18-11). Utah Division of Wildlife Resources, Salt Lake City, UT.

Van Der Lee, G.E.M., Van Der Molen, D.T., Van Den Boogaard, H.F.P., Van Der Klis, H., 2006. Uncertainty analysis of a spatial habitat suitability model and implications for ecological management of water bodies. Landsc. Ecol. 21, 1019–1032. https://doi.org/10.1007/s10980-006-6587-7

Vilizzi, L., Copp, G.H., Roussel, J., 2004. Assessing variation in suitability curves and electivity profiles in temporal studies of fish habitat use. River Res. Appl. 20, 605–618. https://doi.org/10.1002/rra.767

Winemiller, K.O., Rose, K.A., 1992. Patterns of Life-History Diversification in North American Fishes: implications for Population Regulation. Can. J. Fish. Aquat. Sci. 49, 2196–2218. https://doi.org/10.1139/f92-242

Wohl, E., 2017. The significance of small streams. Front. Earth Sci. 11, 447–456. https://doi.org/10.1007/s11707-017-0647-y

Wohl, E., Lane, S.N., Wilcox, A.C., 2015. The science and practice of river restoration. Water Resour. Res. 51, 5974–5997. https://doi.org/10.1002/2014WR016874

Wurtsbaugh, W.A., Miller, C., Null, S.E., DeRose, R.J., Wilcock, P., Hahnenberger, M., Howe, F., Moore, J., 2017. Decline of the world's saline lakes. Nat. Geosci. 10, 816–821. https://doi.org/10.1038/ngeo3052

Zeigler, M.P., Brinkman, S.F., Caldwell, C.A., Todd, A.S., Recsetar, M.S., Bonar, S.A., 2013. Upper Thermal Tolerances of Rio Grande Cutthroat Trout under Constant and Fluctuating Temperatures. Trans. Am. Fish. Soc. 142, 1395–1405. https://doi.org/10.1080/00028487.2013.811104

Zheng, P.Q., Hobbs, B.F., Koonce, J.F., 2009. Optimizing multiple dam removals under multiple objectives: Linking tributary habitat and the Lake Erie ecosystem. Water Resour. Res. 45, 2008WR007589. https://doi.org/10.1029/2008WR007589

Tables and Figures

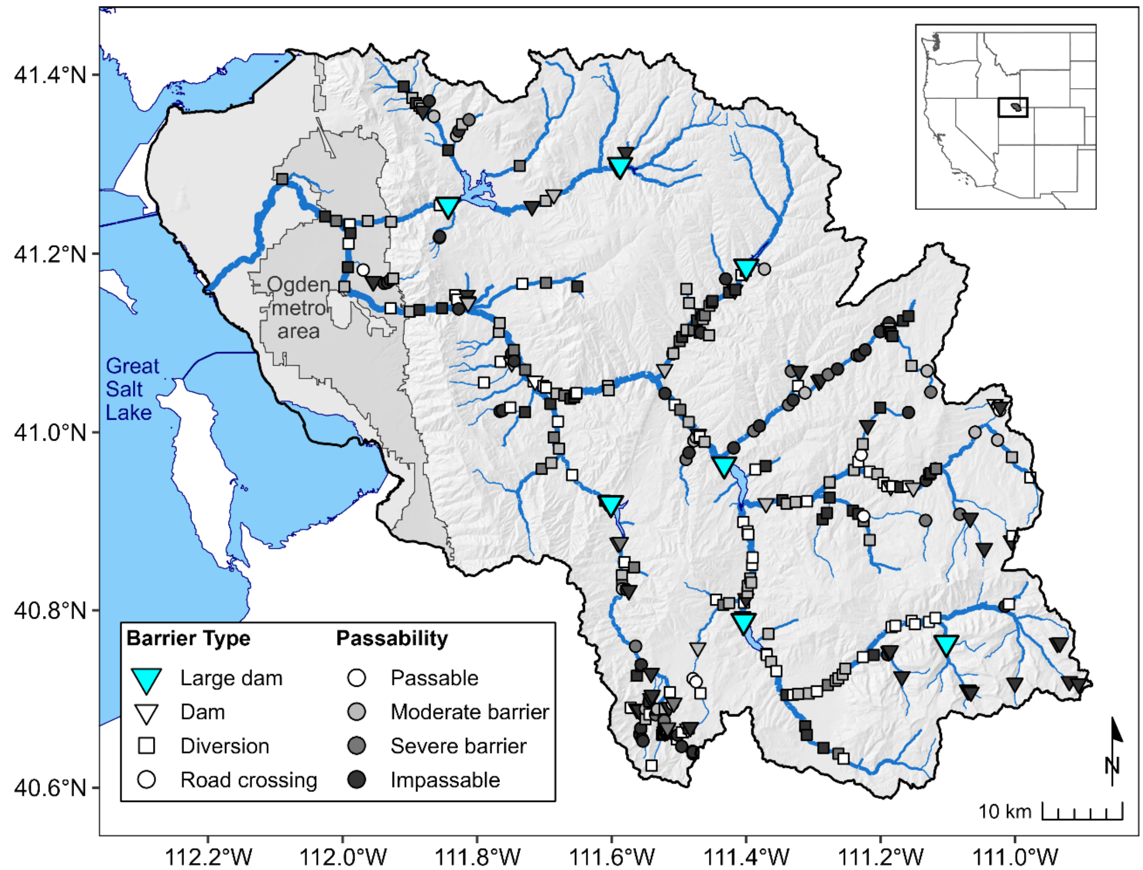

Figure 3.1 Weber River Basin study area showing the location, type, and passability of 347 instream barriers. Large dams are greater than 1.5 m tall and are not considered for removal in this study. All large dams are impassable barriers to fish movement.

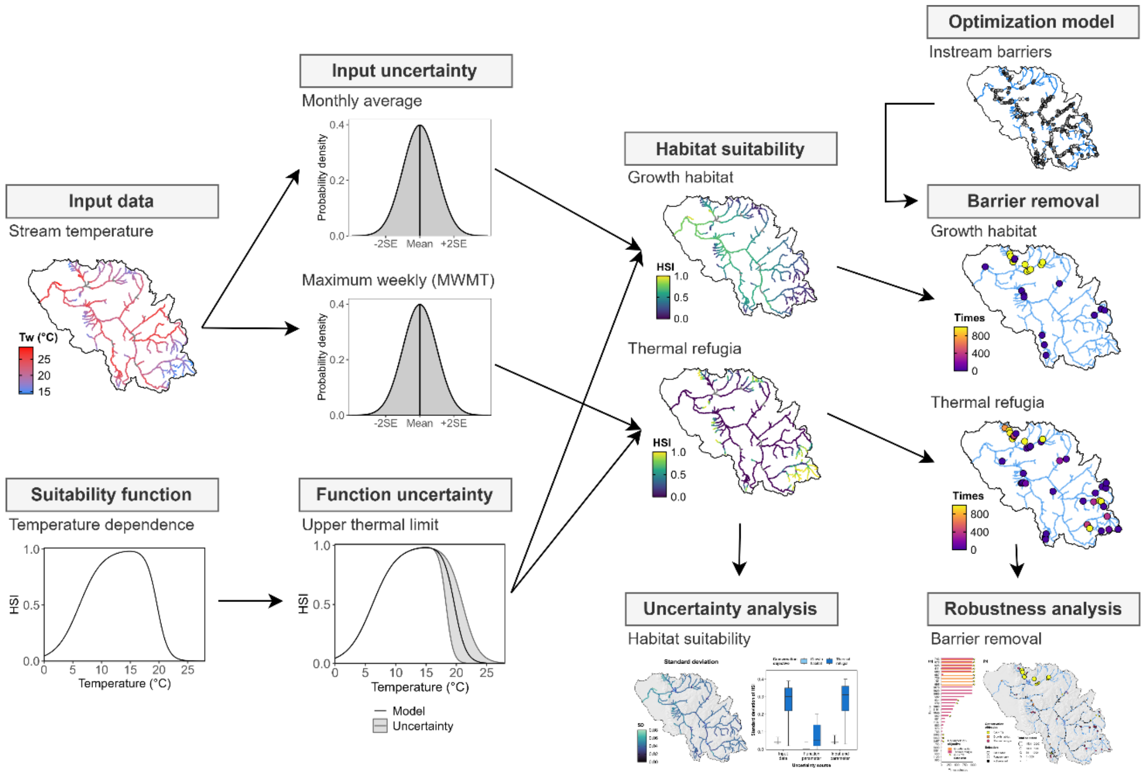

Figure 3.2. Conceptual diagram of data and models, including stream temperature uncertainty, suitability function uncertainty, habitat suitability variability, and barrier removal optimization to analyze uncertainty in habitat suitability estimates and robustness of instream barrier removal prioritization.

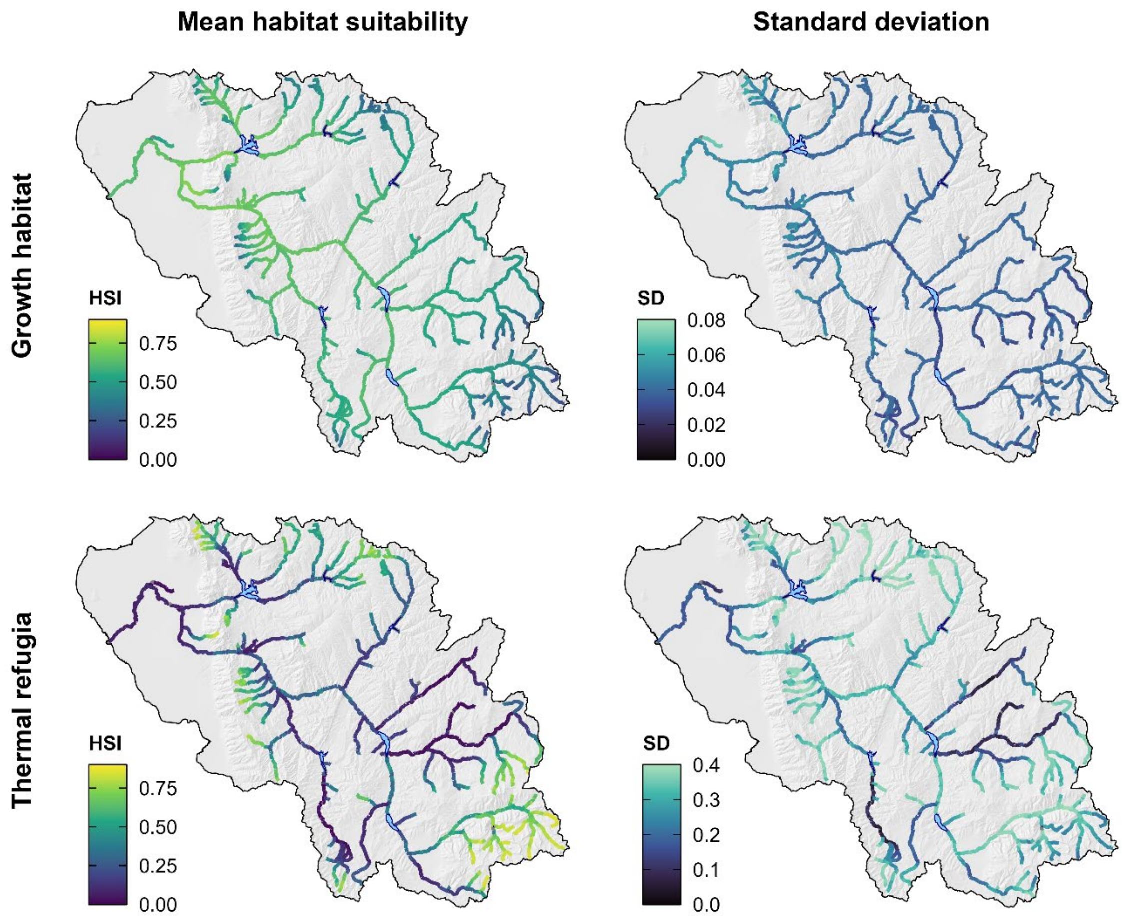

Figure 3.3. Mean and standard deviation of habitat suitability index (HSI) values, calculated across 1,000 habitat suitability estimates that varied stream temperature input data and suitability function parameter for growth habitat and thermal refugia conservation objectives. Note that colorbar scales for standard deviation differ between growth habitat and thermal refugia conservation objectives.

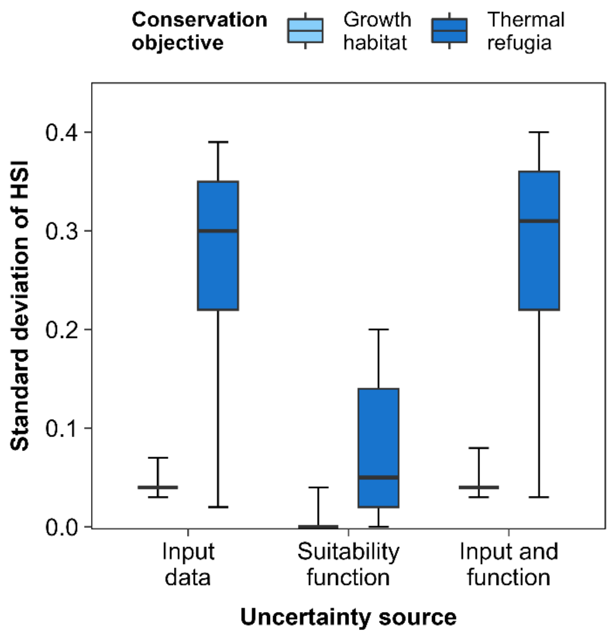

Figure 3.4. Habitat suitability index (HSI) standard deviation range from uncertainty in stream temperature input data, suitability function parameter, and combined input data and suitability function uncertainty for each conservation objective. Boxes show the interquartile range, lines the median, and whiskers the minimum and maximum of standard deviations.

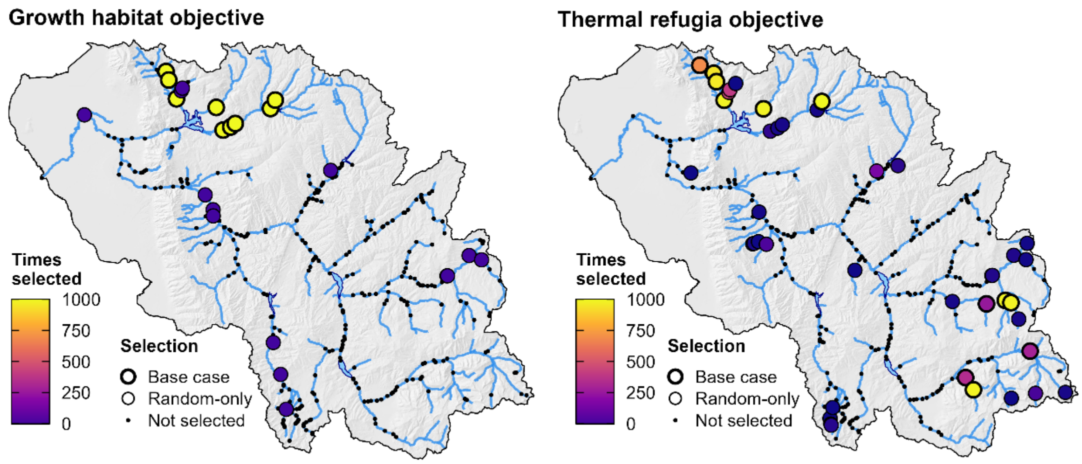

Figure 3.5. Locations and selection frequency of barriers removed in optimal solutions for growth habitat and thermal refugia conservation objectives. Colors show the frequency that barriers were selected for removal across 1,000 habitat suitability model runs. Bold outlines show barriers removed in the base scenario using published stream temperature metric and suitability function parameter values.

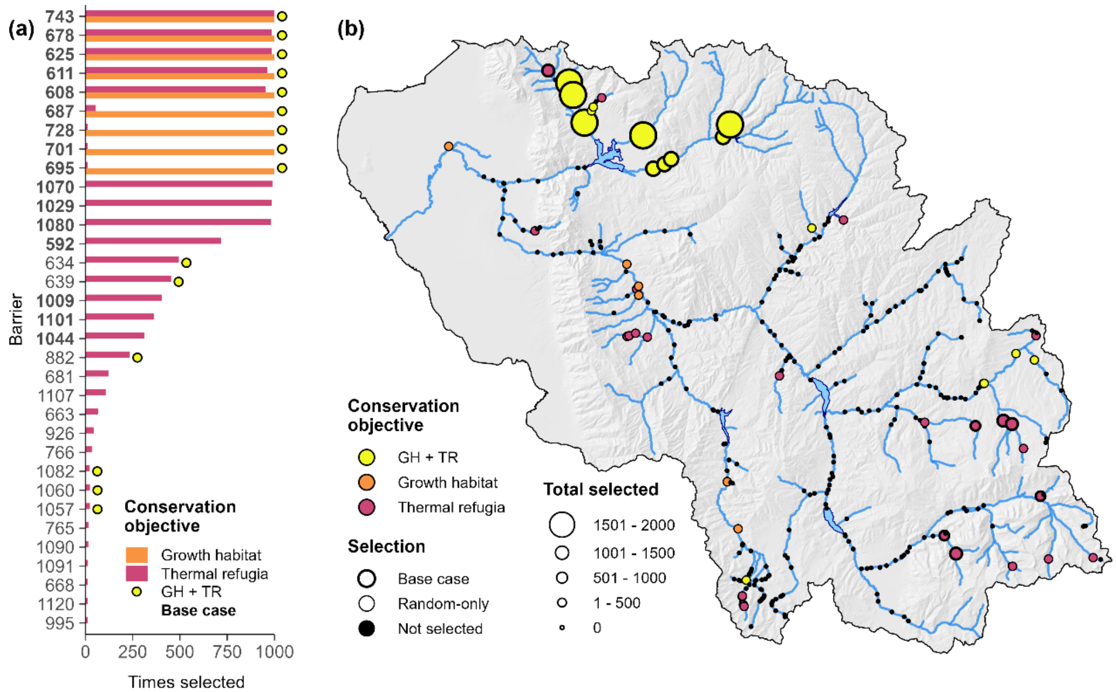

Figure 3.6. Robust barrier removals in the Weber River Basin. (a) The number of times barriers were selected for removal by conservation objective and (b) the spatial distribution of barriers removed for growth habitat and thermal refugia conservation objectives. Colors show the conservation objective and bolding indicates selection in the base alternative that did not consider uncertainty. Panel (a) is limited to barriers selected at least 10 times with uncertain habitat suitability.

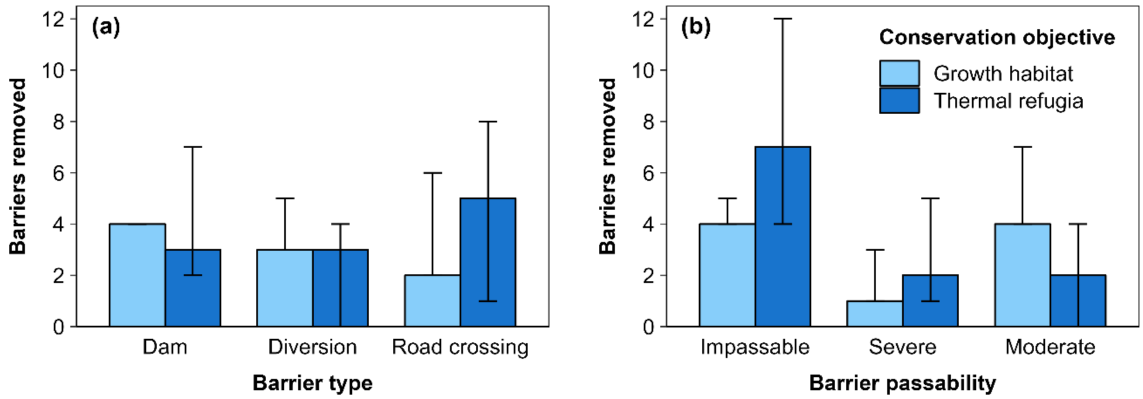

Figure 3.7. The number of barriers removed in model runs grouped by (a) barrier type and (b) passability rating for growth habitat and thermal refugia conservation objectives. Bars show the mode and whiskers show variability in the number of barriers removed across 1,000 habitat suitability runs.

CHAPTER 4

PREDICTING ROAD-CROSSING BARRIER PASSABILITY FOR RIVER CONNECTIVITY ANALYSIS

Abstract

Road-crossing structures limit organism movement but their passabilities are rarely measured because they are numerous and time-consuming to survey. Instead, road crossing passability could be treated in one of four ways: assuming equal passability at all locations (uniform method), assigning random passability values sample from barrier surveys (random sample method), or using remote sensing data to infer presence (presence/absence method) or rate passability (rating category method). Each prediction method produces different passability estimates for individual barriers, but how these differences affect river connectivity estimates has not been systematically evaluated. I compared river connectivity estimates from these four road-crossing passability prediction methods in the Bear River Basin, USA. I parameterized barrier passability methods with Bonneville Cutthroat Trout *Oncorhynchus clarkii utah* passage survey data at 140 road crossings. Road crossings blocked fish passage at 37% of survey locations. Those road-crossing barriers that obstructed fish movement also decreased the proportion of connected reaches in the river network from 12% (with dams and all road crossings assumed to be passable), to just 3%. All passability prediction methods produced similar results and had considerable uncertainty predicting passability for individual barriers. My findings suggest that more simple methods, like uniform or random sample road-crossing passability predictions are sufficient to characterize river connectivity. My work highlights the importance of identifying road crossings that act as barriers to organism

passage and identifies critical limitations to predicting barrier status for connectivity analysis and conservation planning.

1. Introduction

River fragmentation caused by instream barriers is a global threat to freshwater biodiversity (Fuller et al., 2015). Instream barriers such as dams and road-crossing structures limit the movement of aquatic organisms, causing populations to become genetically isolated or blocking access to spawning, rearing, and foraging habitats (Cheng et al., 2016). Fragmentation is particularly threatening to migratory fish species, which require connected streams to move between habitats (Barbarossa et al., 2020). Connectivity indices quantify stream network connectivity as the cumulative probability of an organism's ability to move between any section of stream within the network (Cote et al., 2009; Grill et al., 2014). Connectivity indices are often used to evaluate fragmentation caused by large dams in rivers (Buddendorf et al., 2017; Rodeles et al., 2021; Shaad et al., 2018) and increasingly used to assess fragmentation caused by road crossings (Baumgartner et al., 2022; Lehrter et al., 2024; Sun et al., 2023).

Accurate data for the location and passability of road-crossing barriers are needed to estimate how fragmentation affects populations of fish and other aquatic organisms (Bourne et al., 2011; O'Hanley, 2011). Typically, road-stream intersections are identified with geographic information systems (GIS) (Kroon & Phillips, 2016), yet determining whether road crossings represent a barrier to movement is challenging. Barrier passability is often based on species- and life stage-specific swimming and jumping abilities (King et al., 2017; Vowles et al., 2024), but passability estimates require knowledge of the structural and hydraulic characteristics of potential barriers that are not widely available or standardized in databases (Briggs & Galarowicz, 2013; Wang & Chanson, 2018; Warren & Pardew, 1998). Passability also varies temporally as flow conditions affect passability of road-crossing barriers (Belford & Gould, 1989; Kelson et al., 2020; Reiser et al., 2006), requiring that passability surveys be matched to hydrologic conditions (Shaw et al., 2016). Road crossings are ubiquitous in watersheds, which make passability surveys of all road crossings costly, time-consuming, and hence infeasible (Hrodey et al., 2021; Januchowski-Hartley et al., 2013).

As an alternative to passability surveys, passability prediction methods either assume barrier passability is constant, adequately characterized by a subsample of observed passabilities, or can be represented by generic relationships between fish passage, barrier design, and natural gradients in topography and stream size (McKay et al., 2017; Milt et al., 2018; Neeson et al., 2015). *Uniform* methods characterize all barriers of a given type with a single passability rating, such as assuming all culverts are impassable (Cote et al., 2009; Perkin & Gido, 2012). *Random sampling* methods assign passability values to unobserved barriers based on a representative sample of measured passage rates and barrier type but have not been applied to systematically predict barrier passability. Machine-learning models have been used to predict barrier presence (hereafter *presence/absence* methods) and passability ratings (hereafter *rating category* methods) for fish from commonly-available landscape and hydrologic features, such as stream slope and discharge (Collins, 2016; Januchowski-Hartley et al., 2014; Perkin et al., 2020). However, the reliability of machine-learning model predictions can be influenced by imbalance in the number of passable and impassable sites used to train models (Han et al., 2021; Johnson et al., 2012) or uncertain criteria used to evaluate barrier passability (Anderson et al., 2012; Januchowski-Hartley et al., 2019). The alternative passability prediction methods introduced above produce different passability estimates for instream barriers, yet no studies have systematically evaluated how uncertain road-crossing passability predictions affect connectivity estimates.

The goal of this study is to compare uniform, random sample, presence/absence, and rating category methods for predicting road-crossing passability and stream network connectivity for threatened Bonneville Cutthroat Trout *Oncorhynchus clarkii utah* in the Bear River Basin in Wyoming, Idaho, and Utah, USA. I address two primary research questions: (1) Does predictive accuracy vary among alternative barrier passability prediction methods? (2) How does uncertainty from barrier passability prediction methods affect stream network connectivity estimates? As removing instream barriers and improving habitat connectivity are ongoing conservation efforts (UDWR, 2019), understanding the impact of road crossings on stream connectivity is critical to informing barrier removal decisions.

2. Methods

2.1. Overview of approach

To estimate stream network connectivity with alternative barrier passability methods, I first examined geospatial datasets to identify the locations of known dams and potential road crossings within the Bear River Basin (Figure 4.1). I then visited a proportion of identified road crossings that could pose barriers to fish movement in two subbasins and measured outflow drop, structure slope, water velocity, and water depth. I used these measurements to characterize passability of surveyed road crossings and predict basin-wide road-crossing passability with uniform, random sample, presence/absence, and rating category methods. I quantified uncertainty by performing a sensitivity analysis where I systematically varied uniform passability assumptions and ran random sampling, presence/absence, and rating category methods with randomized subsets of my observed passability values to generate a range of passability models for each method. Finally, I estimated stream network connectivity in the Bear River Basin from the barrier passability models derived from each method. I also compared stream network connectivity using only dams as barriers and using dams and predicted road-crossing passability as barriers.

2.2. Study area

My study subbasins included the Logan River (4,107 km^2) and Upper Bear River (9,263 km^2) of the Bear River Basin (35,156 km^2), which span portions of Wyoming, Idaho, and Utah (Figure 4.2). Elevations within the subbasins ranged from 1343-3874 m above sea level, which captured most of the elevational gradient within the Bear River Basin (1280-3874 m). The Logan River Subbasin includes Logan, UT, the largest urban area in the Bear River Basin with a 2022 population of 113,927. The smallest urban area is Evanston, WY, in the Upper Bear River Subbasin, with a 2022 population of 11,416 (U.S. Census Bureau, 2022). About 10-12% of total subbasin area is irrigated agricultural land (Brandt et al., 2021), representative of widespread agricultural land use throughout the Bear River Basin (Downard & Endter-Wada, 2013).

The Bear River Basin supports the largest remaining metapopulation of Bonneville Cutthroat Trout *Oncorhynchus clarkii utah* (Budy et al., 2012). This species is native to streams and lakes of the Bonneville Basin (Behnke, 1992) and is managed for conservation in Utah, Idaho, and Wyoming (Budy et al., 2020). Bonneville Cutthroat

Trout migrate during spring runoff from mainstem river and lake habitats to spawn throughout summer in headwater tributaries before returning to lower-elevation foraging habitat as flows decline (Bennett et al., 2014; Schrank & Rahel, 2004). Bonneville Cutthroat Trout now occupy as little as 35-40% of their historical range, in part due to barriers that fragment habitat and inhibit fish movement (Budy et al., 2020; Hilderbrand & Kershner, 2000).

2.3. Barrier data and detection

I intersected road geospatial data with perennial and intermittent streams to identify 2,144 potential road-crossing barriers. It was unknown if the potential barriers were culverts, which could be partially or fully impassable, or bridges, which could be partially impassable or fully passable. I identified 317 additional waterfalls, dams, culverts, and bridges from geospatial infrastructure datasets (UDOT, 2022; UDWRi, 2023; USACE, 2023; USFHA, 2020; Utah Division of Wildlife Resources, 2020, unpublished data). I compiled all potential instream barriers and removed duplicate barriers to identify 2,379 total potential instream barriers to Bonneville Cutthroat Trout movement in the Bear River Basin, including 6 waterfalls, 82 dams, and 2,291 road crossings (Figure 4.2) (Table 4.1).

2.4. Barrier surveys

I visited 10 randomly selected bridges, 10 culverts, and 50 unknown types of potential road crossings in each subbasin (total n = 140 for both subbasins) to identify whether the type of road crossing identified using geospatial data was accurate and to assess passability. When a randomly selected road crossing was inaccessible, I surveyed the nearest accessible road crossing of the same type. During surveys, I characterized road crossings as bridges (bridges, fords, fill or puncheon crossings), culverts (four-sided or piped road-crossing structures), or absent when no structure was found within 500m of the potential road-crossing barrier location (WDFW, 2019).

Passability estimates reflect the degree to which a barrier restricts fish movement (McKay et al., 2013; WDFW, 2019). Road crossings were assigned passabilities of 0% (impassable), 33% (severe barrier), 67% (moderate barrier), or 100% (fully passable) based on Washington Department of Fish and Wildlife (WDFW) passability rating categories for adult salmonids, including Coastal Cutthroat Trout (*Oncorhynchus clarkii clarkii*) (WDFW, 2019). Passability values were assigned based on structural (water surface drop, structure slope, structure width) and hydraulic (water depth, velocity) criteria described in WDFW (2019) and measured at each barrier (Figure B1, Table B1).

The X, Y, and Z coordinates of barrier upstream and downstream position were measured with a Leica GS14 RTK-GPS (baseline accuracy of 8mm for horizontal displacements and 15mm for vertical displacements) and structure slope was later calculated in a GIS. Water depth and velocity were measured at the barrier thalweg with a Hach FH950 velocity flow meter. The fastest velocities in culverts occur in the thalweg, so my method produced a conservative estimate of passability. I surveyed structural criteria from August - October 2022 during annual low flow when road crossings were most accessible and hydraulic criteria surveys during June 2023 annual peak flows that coincide with seasonal Bonneville Cutthroat Trout upstream migration movements. Survey periods included a dry year in 2022 and a wet year in 2023.

2.5. Passability prediction methods

I used my survey data to predict passability for all unobserved road crossings in the Bear River Basin using four alternative passability prediction methods: uniform, random sample, presence/absence, and rating category (Figure 4.1). The simplest method is uniform passability prediction, which assigns all road crossings a single passability value. Uniform prediction can provide data for connectivity estimates when barrier passability data are unavailable (Cote et al., 2009; Perkin & Gido, 2012). I considered four uniform passability sets where all road crossings were considered passable (100%), moderate (67%), severe (33%), or impassable (0%) barriers to fish movement (WDFW, 2019).

The random sample prediction method randomly assigns road-crossing passability values drawn from the distribution of observed passabilities to each unsurveyed road crossing. I extrapolated my survey results to unsampled road crossings by categorizing each crossing's listed type (bridge, culvert, or unknown), then randomly assigned a passability based on the observed frequency that the listed type was a passable (100%), moderate (67%), severe (33%), or impassable (0%) barrier to fish movement (WDFW, 2019). Random sampling provides a simple approach for spatially extrapolating sampled barrier passabilities to unsampled road crossings across large geospatial datasets.

My presence/absence prediction method fit boosted regression tree models with binary presence/absence data to predict the existence of barriers. I modeled road-crossing barrier presence/absence by converting survey results into binary values where all passable and absent barriers were assigned a value of 100% and moderate, severe, and impassable barriers were assigned a value of 0%. Presence/absence approaches have previously been used to predict road-crossing passability (Januchowski-Hartley et al., 2014), and may improve accuracy over multinomial classifications by aggregating rare classes in small and skewed datasets (Han et al., 2021).

Rating category prediction estimates the passability of each potential road-crossing barrier by fitting boosted regression tree models with multinomial rating category data. I modeled categorical road-crossing passability by splitting sampled road crossings into impassable (0%), severe (33%), moderate (67%), or passable (100%) ratings (WDFW, 2019) for each road crossing. Rating category passability models improve specificity by directly predicting partial and impassable barriers instead of inferring passability from binary presence/absence, and have been used to predict road-crossing passability in the southeastern U.S. (Collins, 2016).

2.7. Uncertainty of passability prediction methods

I estimated uncertainty for each passability prediction method by analyzing method sensitivity to input data and assumptions to generate a range of possible passability models for each method. For uniform prediction, I generated four models of uniform barrier passabilities, with each of the four models assuming that all road crossings were one of the following: passable (100%), moderately impassable (33%), severely impassable (67%) or impassable (0%) barriers to fish movement. I assessed uncertainty in the random sample method by randomly drawing passability ratings for each unsurveyed barrier from a multinomial distribution based on the frequency of observed passability by barrier type, assessing the predictive accuracy, and repeating this randomization procedure 100 times. I explored draw sizes of up to 1,000 random samples for random assignment in preliminary analysis but found that a draw size of 100 was sufficient to characterize the distribution of connectivity estimates. For both presence/absence and rating category methods, I split observed road-crossing passabilities into 100 randomly seeded train/test datasets, then fit individual boosted regression tree models to each dataset.

2.8. Evaluation of passability predictions

I evaluated predictive performance for all passability prediction methods using the true skill statistic (TSS), relative influence of predictor variables, and the area under the receiver operating characteristic curve (AUROC). TSS is a prevalence-independent performance metric that equally weights sensitivity and specificity defined as:

$$TSS = sensitivity + specificity - 1 \tag{1}$$

where $sensitivity$ is the true positive classification rate and $specificity$ is the true negative classification rate. TSS values range from -1 (all wrong predictions) to 1 (all correct predictions), with values > 0 indicating models that predict better than random. TSS's prevalence-independence is advantageous when prevalence among classes varies (Allouche et al., 2006; Freeman & Moisen, 2008), and it is often used to evaluate ecological models with rare classes and imbalanced datasets (Akosa, 2017; Fourcade et al., 2018; Somodi et al., 2017). Relative influence is the percentage contribution of each predictor variable to model fit, calculated as the improvement to classification accuracy made by each variable averaged across all trees. Relative influence was extracted from each fitted model. I quantified uncertainty of predictive performance as the 95% prediction interval of TSS and AUROC across all passability models for each passability prediction method.

I reported AUROC for comparison to previous machine-learning models predicting barrier passability (Collins, 2016; Januchowski-Hartley et al., 2014, 2019). AUROC is a scalar measure of classification accuracy where 1 is perfect classification and 0.5 implies classification accuracy no better than random (Johnson et al., 2012). AUROC has been criticized for ignoring prevalence among classes and being insensitive to rare class mis-classification (Leroy et al., 2018; Lobo et al., 2008), but it remains a useful indicator of predictive performance due to its high agreement with independent validation data (Konowalik & Nosol, 2021) and widespread application enabling model comparison (Ramazi et al., 2021).

2.9. Stream network connectivity

I calculated stream network connectivity of the Bear River Basin using the dendritic connectivity index (DCI) (Cote et al., 2009). DCI quantifies the connectedness of a stream network by dividing it into segments separated by confluences and barriers, then calculates the probability that an individual fish can move freely among segments throughout the network. A value of 100 indicates a fully connected watershed and 0 indicates that all stream segments are separated by impassable barriers. I used the potamodromous DCI formulation (DCI_p) for riverine and lacustrine life histories involving repeated movements throughout the stream network (Cote et al., 2009) to reflect the migratory life history of Bonneville Cutthroat Trout, defined as:

$$DCI_p = 100 * \sum_{i=1}^{n}\sum_{j=1}^{n} \left[\left(\frac{l_i}{L}\right)\left(\frac{l_j}{L}\right)\left(\prod_{m=1}^{M} p_m^u p_m^d\right)\right] \tag{2}$$

where L is the total length of the stream network, l_i and l_j are the length of segments i and j, M is the total number of barriers between segments i and j, and p^u is the upstream and p^d the downstream passability for each barrier m (Cote et al., 2009).

I assumed equivalent upstream and downstream passability for each barrier consistent with my survey methods. I calculated DCI_p using the R version 4.3.1 riverconn package (Baldan et al., 2022). For all connectivity calculations, I rated dams and waterfalls as impassable (0%) and set passability for surveyed road crossings to their observed values. I calculated DCI_p for all passability prediction methods and passability models, creating a distribution of possible connectivity values for each road-crossing passability prediction method. I quantified uncertainty in connectivity estimates for each passability prediction method as the 95% prediction interval of DCI_p across all barrier passability models.

3. Results

3.1. Barrier surveys

From surveying 140 potential road-crossing barrier locations, I found the most common road-crossing structures were culverts (n = 54), which slightly outnumbered bridges (n = 50) (Table 4.2). All listed bridges and 75% of culverts were correctly attributed in geospatial datasets. Unknown road crossings were most often culverts (n = 47), which occurred more than twice as frequently as bridges (n = 21). No road-crossing structures were found at nearly one quarter of culvert and unknown road-crossing locations (n = 31) listed in the National Bridge Inventory, National Transportation Dataset, or Utah Division of Wildlife Resources instream barrier database. Three surveyed road crossings were located on ephemeral stream segments and two sites were dry during both structural and hydraulic sampling and were not included in passability predictions or connectivity analysis.

Thirty-seven percent (n = 50) of 135 surveyed road crossings were partial or complete barriers to fish movement (Figure 4.3). Bridges were rated as fully passable at all sample locations within the Logan River Subbasin and Upper Bear River Subbasin. Culverts were most commonly moderate (67%, n = 21) or severe (33%, n = 17) barriers, and less commonly impassable barriers (0%, n = 12) or fully passable (100%, n = 12). Culvert passability was most often limited by structure slope (n = 33), and less often by water surface drop (n = 9), water velocity (n = 5), or water depth (n = 3). Impassable barriers were limited by either structure slope (n = 11) or depth (n =1).

3.2. Passability prediction method performance

The performance of all passability prediction methods as assessed with TSS was variable and ranged from outperforming to slightly underperforming random predictions (Figure 4.4a). Presence/absence boosted regression tree models performed best, on average, among passability prediction methods (mean TSS = 0.15), but their performance was also the most variable (95% TSS prediction interval: -0.11 to 0.42). Random sample passability prediction followed with lower average predictive performance (mean TSS = 0.07) and variability (95% TSS prediction interval: -0.03 to 0.17). Uniform and rating category boosted regression tree models performed poorly among passability prediction methods with average performance no better than random (mean TSS = 0 and 0.04, respectively). All 95% prediction intervals spanned 0, indicating that any method could perform no better or worse than random. Average predictive performance and variability increased slightly when measured with AUROC, but they showed similar trends between passability prediction methods to TSS measurements (Figure 4.4b).

Among boosted regression tree models, elevation was the most influential predictor for both presence/absence and rating category models (Figure 4.5), but it was more influential for rating category models (28%) than presence/absence models (23%). Site slope, reach slope, and discharge were similarly important predictors in both presence/absence and rating category models. Segment slope was more influential in presence/absence (21%) than rating category (14%) models. Relative influence for the five landscape predictors was variable across all models, ranging between 2% to 41% for predictors in presence/absence models and 4% to 42% for predictors in rating category models. Road class was an uninformative predictor in both methods.

Road-crossing barriers to fish movement tended to occur in streams at elevations > 2000 m, with mean annual discharge < 1 $m^3 s^{-1}$, reach slope between 2-4%, and segment slope > 2% (Figure 4.5a). Passability rating categories showed few clear relationships to predictor variables, although increasing road-crossing passability coincided with decreasing slope (Figure 4.5c-d). Road crossings that were severe barriers (33%) were most common at locations with site slopes > 10% (Figure 4.5c). Moderately passable road-crossings (67%) occurred at reach slopes < 4% and at segment slopes between 2.5-5% (Figure 4.5d). Passable road-crossings (1) were ubiquitous throughout the study area (Figure 4.3) and across all predictor variable values (Figure 4.5e).

3.3. Stream network connectivity

The Bear River Basin was 95.4% connected based only on natural waterfalls as barriers. Accounting for dams reduced connectivity to 12.2%, an 87% drop in connectivity from natural conditions. Road-crossing barriers further fragmented the stream network regardless of passability prediction method (Figure 4.6). Uniform passability estimates provided the highest estimate of connectivity, reducing average connectivity to 2.88%, a 76% decrease from dam only connectivity. Rating category prediction similarly reduced connectivity on average by 80% to 2.4%. Random sample and presence/absence prediction alternatives estimated minimal connectivity values of 0.94% and 0.88% respectively, a 92-93% decrease from dam-only connectivity.

While mean connectivity estimates were similar for all passability prediction methods, 95% confidence intervals showed that connectivity could vary considerably across barrier passability models for each method (Figure 4.7). Uniformly assigning road-crossing passability produced the most variable connectivity estimates, ranging from 0.19% to 12.15%, although connectivity only exceeded 0.34% when all road crossings were considered passable (1). Randomly sampling road-crossing passability according to observed passability led to connectivity ranging from 0.72% to 1.32%. Variability among presence/absence and rating category boosted regression tree models was larger compared to random sample models. Presence/absence model connectivity ranged from 0.19% to 9.84% and rating category connectivity ranged from 0.23% to 9.84%. Overall, presence/absence models estimated similar connectivity (95% confidence interval = 0.62%-1.14%) as random sample barrier passabilities (95% confidence interval = 0.91%-0.96%) and lower connectivity than rating category models (95% confidence interval = 1.89%-2.93%). Rating category models, on average, estimated similar connectivity to uniform models with the lowest predictive accuracy equivalent to random chance.

4. Discussion

4.1 Road crossings and stream network connectivity

Road crossings substantially reduced stream network connectivity in the Bear River Basin, despite considerable uncertainty surrounding barrier location and passability. I identified 2,291 potential barriers at road-stream crossings and found that fewer than half were likely barriers to fish movement. Road-crossing barriers were most commonly culverts, though culverts were rarely impassable to Cutthroat Trout. While random sampling and boosted regression tree passability predictions were more accurate than uniform passability assumptions, no method significantly out-performed random. Nonetheless, all passability prediction methods estimated that road-crossing barriers reduced stream network connectivity. My study demonstrates that uncertainty surrounding road-crossing barrier presence and passability predictions propagates in connectivity indices and influence measures of stream network connectivity.

Ignoring road-crossing barriers to fish movement overestimates watershed connectivity. Dams reduced stream connectivity to 12.2%, then road crossings reduced it further to less than 3% on average for all prediction methods. My finding that road-crossing barriers decreased connectivity supports other studies that found road crossings collectively reduce connectivity at the basin-scale (Baumgartner et al., 2022; Diebel et al., 2015; Sun et al., 2023). While dams fragment rivers (Belletti et al., 2020; Graf, 1999; Lehner et al., 2011), road-crossing barriers far outnumber dams on smaller streams (Januchowski-Hartley et al., 2013; Perkin et al., 2013) and in sparsely populated areas (Sethi et al., 2017). Small streams constitute most of the channel length in river networks and influence downstream physical and ecological processes through longitudinal transport of water, sediment, nutrients, and organisms (Ferreira et al., 2023; Wohl, 2017). Connectivity analyses should incorporate road-crossing barriers to better estimate and mitigate river fragmentation, and in particular, include small streams that are critical to maintaining downstream habitat for fish and other aquatic organisms.

Connectivity indices are sensitive to uncertain passability estimates for road crossings and other instream barriers. To my knowledge, ours is the first study to evaluate the robustness of connectivity indices by systematically comparing connectivity under different passability prediction methods and passability condition assumptions. Connectivity estimates varied by up to 12% within methods representing considerable uncertainty based on the location and passability of individual barriers. However, averaging across plausible passability conditions mitigated the effects of uncertain road crossing passability and produced robust connectivity estimates that varied by less than 3% among prediction methods. These findings suggest that choice of barrier passability estimation method may be less influential than uncertainty within estimation methods when considering basin scale connectivity.

Rating category boosted regression trees performed poorly due to weak relationships between landscape variables and barrier passability ratings that over-estimated the number of passable barriers. My surveys showed that moderate, severe, and impassable barriers commonly co-occurred throughout the Logan River and Upper Bear River study areas (Figure 4.3) and that my topographical and hydrological landscape predictors did not demonstrate clear relationships to barrier passability ratings (Figure 4.5b-e). These weak predictive relationships and the ubiquity of passable road crossings meant rating category models predicted that most road crossings were passable and commonly misclassified listed culverts that were often barriers (Figure 4.3). Alternatively, random assignments were more likely to correctly identify listed culverts as moderate, severe, or impassable barriers based on their sample distribution. Since TSS is prevalence-independent, misclassifications in minority classes influence TSS to a greater degree than correct classifications of the majority class (Wunderlich et al., 2019). Rating category models often miscategorized barriers as passable (the majority class), which decreased performance relative to random assignments that more often correctly classified moderate, severe, and impassable barriers (minority classes).

Passability prediction methods used in my study represent tradeoffs between method complexity and predictive accuracy. While passability prediction methods did not greatly affect connectivity estimates on average, both the most data-intensive (rating category) and simplest (uniform) methods predicted barrier passability no better than random assignments. Presence/absence models most accurately predicted road-crossing barrier status, yet random sampling models provided similar connectivity estimates without the additional complexity and data requirements of boosted regression trees. These findings suggest that reduced-complexity approaches, including limited barrier surveys and random sampling barrier prediction, are sufficient to characterize stream network connectivity when precise passability estimates for individual barriers are unavailable. However, limited predictive accuracy across all methods may preclude their use when connectivity analyses depend on precise passability estimates for barrier removal planning (King & O’Hanley, 2016; Kraft et al., 2019) or siting proposed infrastructure (Barbarossa et al., 2020; Frankiewicz et al., 2021).

4.2 Limitations

My study focused on uncertainty of road-crossing passability prediction for connectivity analysis but did not consider uncertainty in barrier passability assessment. Road-crossing passability estimates are often uncertain whether assessed using field surveys (Anderson et al., 2012), hydraulic models (Bourne et al., 2011; Mahlum et al., 2014) or professional judgment (McKay et al., 2013). Fish passage success through culverts and other small instream barriers is difficult to estimate because of complex interactions between the physiological abilities and behavior of individual fish and temporally-variable hydraulic characteristics used to determine passability (Anderson et al., 2012; Goerig et al., 2016). In particular, assessments often underestimate passability during high-flow conditions that cue many species migratory life history expressions or overestimate passability when hydraulic criteria do not reflect species swimming and jumping abilities (Burford et al., 2009; Price et al., 2010). Bourne et al. (2011) found that individual culvert passability varied by up to 100% under alternative physiological and hydrological assessment criteria for Brook Trout *Salvelinus fontinalis* and Atlantic Salmon *Salmo salar* in Canada’s Terra Nova National Park, and that subsequent watershed connectivity estimates varied by up to 20% across different culvert passabilities. My approach complements these studies by establishing that passability prediction methods introduce further variability into barrier passability and subsequent connectivity estimates.

4.3 Implications for barrier removal and habitat conservation

I found that impassable road crossings that most severely reduce stream network connectivity are relatively rare, although they could present cost-effective opportunities to improve river connectivity. Only 12 of 135 (~9%) of the structures I surveyed were impassable to fish. Perkin et al. (2020) found that approximately 10% of 1,200 surveyed road crossings strongly affected aquatic organism passage in six Florida sub-basins. Januchowski-Hartley et al. (2013) similarly found 13% of road crossings impassable to fish in Wisconsin's Duck-Pensaukee Watershed, though impassable road crossings accounted for up to 58% of barriers in three other Great Lake watersheds (Januchowski-Hartley et al. 2013). Dam removal is often a focus for habitat restoration but is typically expensive with costs ranging from hundreds of thousands to hundreds of millions of dollars, even for small dams (Duda et al., 2023; Magilligan et al., 2016). Alternatively, removing impassable culverts and other road-crossing barriers is typically less costly and may be advantageous within dam-fragmented stream systems when sufficient habitats remain for species and populations to complete migratory life history expressions (Kraft et al., 2019; Maitland et al., 2016).

Quantifying connectivity across stream networks provides critical information for protecting and restoring freshwater ecosystems (Thieme et al., 2023). However, limitations imposed by uncertain or unavailable data are rarely considered when allocating resources for conservation projects (Ioannidou et al., 2023). My approach of first evaluating uncertainty within and across barrier passability prediction methods and then generating many possible barrier passability combinations allowed us to bound uncertainty in connectivity estimates. This highlighted the best- and worst-case range for fish passage. While I demonstrate that average stream network connectivity estimates are robust to uncertainty in road-crossing passability and the choice of passability prediction method, accurately predicting individual barrier passability remains a challenge. Future analysis examining the sensitivity of connectivity indices to passability at individual locations, while accounting for uncertainty at the basin scale, would improve my ability to prioritize those barriers most necessary to correctly classify for connectivity indices to be accurate. I recommend that users consider the relative importance of individual barriers when deciding whether predictive methods are sufficient to characterize connectivity. My work improves our understanding of how barrier passage prediction uncertainty impacts connectivity index estimates frequently used to inform conservation planning and infrastructure removal efforts, and my findings highlight critical limitations that need to be considered by restoration practitioners implementing such approaches.

Acknowledgments

Funding for this study was provided by the Agriculture and Food Research Initiative Competitive Grant number 2021-69012-35916 from the USDA National Institute of Food and Agriculture and the National Sciences Foundation Grant #1653452.

Data availability statement

Data and code that support the findings of this study are available on Hydroshare in the following repository:

https://doi.org/10.4211/hs.90e9ae2832334b5395499545788886bc.

References

Akosa, J. S. (2017). Predictive accuracy: A misleading performance measure for highly imbalanced data. *Proceedings of the SAS Global Forum*, *Paper 924-2017*, 2–5.

Allouche, O., Tsoar, A., & Kadmon, R. (2006). Assessing the accuracy of species distribution models: Prevalence, kappa and the true skill statistic (TSS): Assessing the accuracy of distribution models. *Journal of Applied Ecology*, *43*(6), 1223–1232. https://doi.org/10.1111/j.1365-2664.2006.01214.x

Anderson, G. B., Freeman, M. C., Freeman, B. J., Straight, C. A., Hagler, M. M., & Peterson, J. T. (2012). Dealing With Uncertainty When Assessing Fish Passage Through Culvert Road Crossings. *Environmental Management*, *50*(3), 462–477. https://doi.org/10.1007/s00267-012-9886-6

Baldan, D., Cunillera-Montcusí, D., Funk, A., & Hein, T. (2022). Introducing 'riverconn': An R package to assess river connectivity indices. *Environmental Modelling & Software*, *156*, 105470. https://doi.org/10.1016/j.envsoft.2022.105470

Barbarossa, V., Schmitt, R. J. P., Huijbregts, M. A. J., Zarfl, C., King, H., & Schipper, A. M. (2020). Impacts of current and future large dams on the geographic range connectivity of freshwater fish worldwide. *Proceedings of the National Academy of Sciences*, *117*(7), 3648–3655. https://doi.org/10.1073/pnas.1912776117

Baumgartner, L. J., Marsden, T., Duffy, D., Horta, A., & Ning, N. (2022). Optimizing efforts to restore aquatic ecosystem connectivity requires thinking beyond large dams. *Environmental Research Letters*, *17*(1), 014008. https://doi.org/10.1088/1748-9326/ac40b0

Behnke, R. J. (1992). *Native trout of western North America*. American Fisheries Society.

Belford, D. A., & Gould, W. R. (1989). An Evaluation of Trout Passage through Six Highway Culverts in Montana. *North American Journal of Fisheries Management*, *9*(4), 437–445. https://doi.org/10.1577/1548-8675(1989)009<0437:AEOTPT>2.3.CO;2

Belletti, B., Garcia De Leaniz, C., Jones, J., Bizzi, S., Börger, L., Segura, G., Castelletti, A., Van De Bund, W., Aarestrup, K., Barry, J., Belka, K., Berkhuysen, A., Birnie-Gauvin, K., Bussettini, M., Carolli, M., Consuegra, S., Dopico, E., Feierfeil, T., Fernández, S., … Zalewski, M. (2020). More than one million barriers fragment Europe's rivers. *Nature*, *588*(7838), 436–441. https://doi.org/10.1038/s41586-020-3005-2

Benkendorf, D. J., Schwartz, S. D., Cutler, D. R., & Hawkins, C. P. (2023). Correcting for the effects of class imbalance improves the performance of machine-learning based species distribution models. *Ecological Modelling*, *483*, 110414. https://doi.org/10.1016/j.ecolmodel.2023.110414

Bennett, S., Al-Chokhachy, R., Roper, B. B., & Budy, P. (2014). Annual Variation of Spawning Cutthroat Trout in a Small Western USA Stream: A Case Study with Implications for the Conservation of Potamodromous Trout Life History Diversity. *North American Journal of Fisheries Management*, *34*(5), 1033–1046. https://doi.org/10.1080/02755947.2014.938139

Bourne, C. M., Kehler, D. G., Wiersma, Y. F., & Cote, D. (2011). Barriers to fish passage and barriers to fish passage assessments: The impact of assessment methods and assumptions on barrier identification and quantification of watershed connectivity. *Aquatic Ecology*, *45*(3), 389–403. https://doi.org/10.1007/s10452-011-9362-z

Brandt, J. T., Caldwell, R. R., Haynes, J. V., Painter, J. A., & Read, A. L. (2021). *Verified Irrigated Agricultural Lands for the United States, 2002–17* [Dataset]. https://doi.org/10.5066/P9NAWU1U

Briggs, A. S., & Galarowicz, T. L. (2013). Fish Passage through Culverts in Central Michigan Warmwater Streams. *North American Journal of Fisheries Management*, *33*(3), 652–664. https://doi.org/10.1080/02755947.2013.788589

Buddendorf, W. B., Malcolm, I. A., Geris, J., Wilkinson, M. E., & Soulsby, C. (2017). Metrics to assess how longitudinal channel network connectivity and in-stream Atlantic salmon habitats are impacted by hydropower regulation. *Hydrological Processes*, *31*(12), 2132–2142. https://doi.org/10.1002/hyp.11159

Budy, P., Thompson, P. D., McKell, M. D., Thiede, G. P., Walsworth, T. E., & Conner, M. M. (2020). A Multifaceted Reconstruction of the Population Structure and Life History Expressions of a Remnant Metapopulation of Bonneville Cutthroat Trout: Implications for Maintaining Intermittent Connectivity. *Transactions of the American Fisheries Society*, *149*(4), 443–461. https://doi.org/10.1002/tafs.10240

Budy, P., Wood, S., & Roper, B. (2012). A Study of the Spawning Ecology and Early Life History Survival of Bonneville Cutthroat Trout. *North American Journal of Fisheries Management*, *32*(3), 436–449. https://doi.org/10.1080/02755947.2012.675945

Burford, D. D., McMahon, T. E., Cahoon, J. E., & Blank, M. (2009). Assessment of Trout Passage through Culverts in a Large Montana Drainage during Summer Low Flow. *North American Journal of Fisheries Management*, *29*(3), 739–752. https://doi.org/10.1577/M07-175.1

Cheng, S.-T., Herricks, E. E., Tsai, W.-P., & Chang, F.-J. (2016). Assessing the natural and anthropogenic influences on basin-wide fish species richness. *Science of The Total Environment*, *572*, 825–836. https://doi.org/10.1016/j.scitotenv.2016.07.120

Collins, E. R. (2016). *Evaluating connectivity in three watersheds in the southeastern United States* [M.S. Thesis]. University of Georgia.

Cote, D., Kehler, D. G., Bourne, C., & Wiersma, Y. F. (2009). A new measure of longitudinal connectivity for stream networks. *Landscape Ecology*, *24*(1), 101–113. https://doi.org/10.1007/s10980-008-9283-y

De'ath, G. (2007). Boosted regression trees for ecological modeling and prediction. *Ecology*, *88*(1), 243–251. https://doi.org/10.1890/0012-9658(2007)88[243:BTFEMA]2.0.CO;2

Diebel, M. W., Fedora, M., Cogswell, S., & O'Hanley, J. R. (2015). Effects of road crossings on habitat connectivity for stream-resident fish. *River Research and Applications*, *31*(10), 1251–1261. https://doi.org/10.1002/rra.2822

Downard, R., & Endter-Wada, J. (2013). Keeping wetlands wet in the western United States: Adaptations to drought in agriculture-dominated human-natural systems. *Journal of Environmental Management*, *131*, 394–406. https://doi.org/10.1016/j.jenvman.2013.10.008

Duda, J. J., Jumani, S., Wieferich, D. J., Tullos, D., McKay, S. K., Randle, T. J., Jansen, A., Bailey, S., Jensen, B. L., Johnson, R. C., Wagner, E., Richards, K., Wenger, S. J., Walther, E. J., & Bountry, J. A. (2023). Patterns, drivers, and a predictive model of dam removal cost in the United States. *Frontiers in Ecology and Evolution*, *11*, 1215471. https://doi.org/10.3389/fevo.2023.1215471

Elith, J., Leathwick, J. R., & Hastie, T. (2008). A working guide to boosted regression trees. *Journal of Animal Ecology*, *77*(4), 802–813. https://doi.org/10.1111/j.1365-2656.2008.01390.x

Ferreira, V., Albariño, R., Larrañaga, A., LeRoy, C. J., Masese, F. O., & Moretti, M. S. (2023). Ecosystem services provided by small streams: An overview. *Hydrobiologia*, *850*(12–13), 2501–2535. https://doi.org/10.1007/s10750-022-05095-1

Fourcade, Y., Besnard, A. G., & Secondi, J. (2018). Paintings predict the distribution of species, or the challenge of selecting environmental predictors and evaluation statistics. *Global Ecology and Biogeography*, *27*(2), 245–256. https://doi.org/10.1111/geb.12684

Frankiewicz, P., Radecki-Pawlik, A., Wałęga, A., Łapińska, M., & Wojtal-Frankiewicz, A. (2021). Small hydraulic structures, big environmental problems: Is it possible to mitigate the negative impacts of culverts on stream biota? *Environmental Reviews*, *29*(4), 510–528. https://doi.org/10.1139/er-2020-0126

Freeman, E. A., & Moisen, G. G. (2008). A comparison of the performance of threshold criteria for binary classification in terms of predicted prevalence and kappa. *Ecological Modelling*, *217*(1–2), 48–58. https://doi.org/10.1016/j.ecolmodel.2008.05.015

Friedman, J. H. (2002). Stochastic gradient boosting. *Computational Statistics & Data Analysis*, *38*(4), 367–378. https://doi.org/10.1016/S0167-9473(01)00065-2

Fuller, M. R., Doyle, M. W., & Strayer, D. L. (2015). Causes and consequences of habitat fragmentation in river networks. *Annals of the New York Academy of Sciences*, *1355*(1).

Goerig, E., Castro-Santos, T., & Bergeron, N. É. (2016). Brook trout passage performance through culverts. *Canadian Journal of Fisheries and Aquatic Sciences*, *73*(1), 94–104. https://doi.org/10.1139/cjfas-2015-0089

Graf, W. L. (1999). Dam nation: A geographic census of American dams and their large-scale hydrologic impacts. *Water Resources Research*, *35*(4), 1305–1311. https://doi.org/10.1029/1999WR900016

Grill, G., Ouellet Dallaire, C., Fluet Chouinard, E., Sindorf, N., & Lehner, B. (2014). Development of new indicators to evaluate river fragmentation and flow regulation at large scales: A case study for the Mekong River Basin. *Ecological Indicators*, *45*, 148–159. https://doi.org/10.1016/j.ecolind.2014.03.026

Han, S., Williamson, B. D., & Fong, Y. (2021). Improving random forest predictions in small datasets from two-phase sampling designs. *BMC Medical Informatics and Decision Making*, *21*(1), 322. https://doi.org/10.1186/s12911-021-01688-3

Hilderbrand, R. H., & Kershner, J. L. (2000). Movement Patterns of Stream-Resident Cutthroat Trout in Beaver Creek, Idaho–Utah. *Transactions of the American Fisheries Society*, *129*(5), 1160–1170. https://doi.org/10.1577/1548-8659(2000)129<1160:MPOSRC>2.0.CO;2

Hrodey, P. J., Lewandoski, S. A., Sullivan, W. P., Barber, J. M., Mann, K. A., Paudel, B., & Symbal, M. J. (2021). Evolution of the sea lamprey control barrier program: The importance of lowermost barriers. *Journal of Great Lakes Research*, *47*, S285–S296. https://doi.org/10.1016/j.jglr.2021.10.006

Ioannidou, C. T., Neeson, T. M., & O'Hanley, J. R. (2023). Boosting large-scale river connectivity restoration by planning for the presence of unrecorded barriers. *Conservation Biology*, *37*(3), e14093. https://doi.org/10.1111/cobi.14093

Januchowski-Hartley, S. R., Diebel, M., Doran, P. J., & McIntyre, P. B. (2014). Predicting road culvert passability for migratory fishes. *Diversity and Distributions*, *20*(12), 1414–1424. https://doi.org/10.1111/ddi.12248

Januchowski-Hartley, S. R., Jézéquel, C., & Tedesco, P. A. (2019). Modelling built infrastructure heights to evaluate common assumptions in aquatic conservation. *Journal of Environmental Management*, *232*, 131–137. https://doi.org/10.1016/j.jenvman.2018.11.040

Januchowski-Hartley, S. R., McIntyre, P. B., Diebel, M., Doran, P. J., Infante, D. M., Joseph, C., & Allan, J. D. (2013). Restoring aquatic ecosystem connectivity requires expanding inventories of both dams and road crossings. *Frontiers in Ecology and the Environment*, *11*(4), 211–217. https://doi.org/10.1890/120168

Johnson, R. A., Chawla, N. V., & Hellmann, J. J. (2012). Species distribution modeling and prediction: A class imbalance problem. *2012 Conference on Intelligent Data Understanding*, 9–16. https://doi.org/10.1109/CIDU.2012.6382186

Kelson, S. J., Miller, M. R., Thompson, T. Q., O'Rourke, S. M., & Carlson, S. M. (2020). Temporal dynamics of migration-linked genetic variation are driven by streamflows and riverscape permeability. *Molecular Ecology*, *29*(5), 870–885. https://doi.org/10.1111/mec.15367

King, S., & O'Hanley, J. R. (2016). Optimal Fish Passage Barrier Removal-Revisited. *River Research and Applications*, *32*(3), 418–428. https://doi.org/10.1002/rra.2859

King, S., O'Hanley, J. R., Newbold, L. R., Kemp, P. S., & Diebel, M. W. (2017). A toolkit for optimizing fish passage barrier mitigation actions. *Journal of Applied Ecology*, *54*(2), 599–611. https://doi.org/10.1111/1365-2664.12706

Konowalik, K., & Nosol, A. (2021). Evaluation metrics and validation of presence-only species distribution models based on distributional maps with varying coverage. *Scientific Reports*, *11*(1), 1482. https://doi.org/10.1038/s41598-020-80062-1

Kraft, M., Rosenberg, D. E., & Null, S. E. (2019). Prioritizing Stream Barrier Removal to Maximize Connected Aquatic Habitat and Minimize Water Scarcity. *JAWRA Journal of the American Water Resources Association*, *55*(2), 382–400. https://doi.org/10.1111/1752-1688.12718

Kroon, F. J., & Phillips, S. (2016). Identification of human-made physical barriers to fish passage in the Wet Tropics region, Australia. *Marine and Freshwater Research*, *67*(5), 677. https://doi.org/10.1071/MF14397

Kuhn, M. (2008). Building Predictive Models in *R* Using the **caret** Package. *Journal of Statistical Software*, *28*(5). https://doi.org/10.18637/jss.v028.i05

Lehner, B., Liermann, C. R., Revenga, C., Vörösmarty, C., Fekete, B., Crouzet, P., Döll, P., Endejan, M., Frenken, K., Magome, J., Nilsson, C., Robertson, J. C., Rödel, R., Sindorf, N., & Wisser, D. (2011). High-resolution mapping of the world's reservoirs and dams for sustainable river-flow management. *Frontiers in Ecology and the Environment*, *9*(9), 494–502. https://doi.org/10.1890/100125

Lehrter, R. J., Rutherford, T. K., Dunham, J. B., Johnston, A. N., Wood, D. J. A., Haby, T. S., & Carter, S. K. (2024). *Effects of culverts on habitat connectivity in streams: A science synthesis to inform National Environmental Policy Act analyses* (U.S. Geological Survey Scientific Investigations Report 2023–5132; Scientific Investigations Report). U.S. Geological Survey. https://doi.org/10.3133/sir20235132

Leroy, B., Delsol, R., Hugueny, B., Meynard, C. N., Barhoumi, C., Barbet-Massin, M., & Bellard, C. (2018). Without quality presence-absence data, discrimination metrics such as TSS can be misleading measures of model performance. *Journal of Biogeography*, *45*(9), 1994–2002. https://doi.org/10.1111/jbi.13402

Lobo, J. M., Jiménez-Valverde, A., & Real, R. (2008). AUC: A misleading measure of the performance of predictive distribution models. *Global Ecology and Biogeography*, *17*(2), 145–151. https://doi.org/10.1111/j.1466-8238.2007.00358.x

Magilligan, F. J., Graber, B. E., Nislow, K. H., Chipman, J. W., Sneddon, C. S., & Fox, C. A. (2016). River restoration by dam removal: Enhancing connectivity at watershed scales. *Elementa: Science of the Anthropocene*, *4*, 000108. https://doi.org/10.12952/journal.elementa.000108

Mahlum, S., Cote, D., Wiersma, Y. F., Kehler, D., & Clarke, K. D. (2014). Evaluating the Barrier Assessment Technique Derived from FishXing Software and the Upstream Movement of Brook Trout through Road Culverts. *Transactions of the American Fisheries Society*, *143*(1), 39–48. https://doi.org/10.1080/00028487.2013.825641

Maitland, B. M., Poesch, M., & Anderson, A. E. (2016). Prioritising culvert removals to restore fish habitat for at-risk salmonids in the boreal forest. *Fisheries Management and Ecology*, *23*(6), 489–502. https://doi.org/10.1111/fme.12188

McKay, S. K., Cooper, A. R., Diebel, M. W., Elkins, D., Oldford, G., Roghair, C., & Wieferich, D. (2017). Informing Watershed Connectivity Barrier Prioritization Decisions: A Synthesis: Synthesizing Barrier Prioritization. *River Research and Applications*, *33*(6), 847–862. https://doi.org/10.1002/rra.3021

McKay, S. K., Schramski, J. R., Conyngham, J. N., & Fischenich, J. C. (2013). Assessing upstream fish passage connectivity with network analysis. *Ecological Applications*, *23*(6), 1396–1409. https://doi.org/10.1890/12-1564.1

Milt, A. W., Diebel, M. W., Doran, P. J., Ferris, M. C., Herbert, M., Khoury, M. L., Moody, A. T., Neeson, T. M., Ross, J., Treska, T., O'Hanley, J. R., Walter, L., Wangen, S. R., Yacobson, E., & McIntyre, P. B. (2018). Minimizing opportunity costs to aquatic connectivity restoration while controlling an invasive species: Cost of Invasive Control. *Conservation Biology*, *32*(4), 894–904. https://doi.org/10.1111/cobi.13105

Moisen, G. G., Freeman, E. A., Blackard, J. A., Frescino, T. S., Zimmermann, N. E., & Edwards, T. C. (2006). Predicting tree species presence and basal area in Utah: A comparison of stochastic gradient boosting, generalized additive models, and tree-based methods. *Ecological Modelling*, *199*(2), 176–187. https://doi.org/10.1016/j.ecolmodel.2006.05.021

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

O'Hanley, J. R. (2011). Open rivers: Barrier removal planning and the restoration of free-flowing rivers. *Journal of Environmental Management*, *92*(12), 3112–3120. https://doi.org/10.1016/j.jenvman.2011.07.027

Perkin, J. S., Acre, M. R., Graham, J., & Hoenke, K. (2020). An integrative conservation planning framework for aquatic landscapes fragmented by road-stream crossings. *Landscape and Urban Planning*, *202*, 103860. https://doi.org/10.1016/j.landurbplan.2020.103860

Perkin, J. S., & Gido, K. B. (2012). Fragmentation alters stream fish community structure in dendritic ecological networks. *Ecological Applications*, *22*(8), 2176–2187. https://doi.org/10.1890/12-0318.1

Perkin, J. S., Gido, K. B., Al-Ta'ani, O., & Scoglio, C. (2013). Simulating fish dispersal in stream networks fragmented by multiple road crossings. *Ecological Modelling*, *257*, 44–56. https://doi.org/10.1016/j.ecolmodel.2013.02.021

Poplar-Jeffers, I. O., Petty, J. T., Anderson, J. T., Kite, S. J., Strager, M. P., & Fortney, R. H. (2009). Culvert Replacement and Stream Habitat Restoration: Implications from Brook Trout Management in an Appalachian Watershed, U.S.A. *Restoration Ecology*, *17*(3), 404–413. https://doi.org/10.1111/j.1526-100X.2008.00396.x

Price, D. M., Quinn, T., & Barnard, R. J. (2010). Fish Passage Effectiveness of Recently Constructed Road Crossing Culverts in the Puget Sound Region of Washington State. *North American Journal of Fisheries Management*, *30*(5), 1110–1125. https://doi.org/10.1577/M10-004.1

Ramazi, P., Kunegel-Lion, M., Greiner, R., & Lewis, M. A. (2021). Exploiting the full potential of Bayesian networks in predictive ecology. *Methods in Ecology and Evolution*, *12*(1), 135–149. https://doi.org/10.1111/2041-210X.13509

Reiser, D. W., Huang, C., Beck, S., Gagner, M., & Jeanes, E. (2006). Defining Flow Windows for Upstream Passage of Adult Anadromous Salmonids at Cascades and Falls. *Transactions of the American Fisheries Society*, *135*(3), 668–679. https://doi.org/10.1577/T05-169.1

Rodeles, A. A., Galicia, D., & Miranda, R. (2021). A simple method to assess the fragmentation of freshwater fish meta-populations: Implications for river management and conservation. *Ecological Indicators*, *125*, 107557. https://doi.org/10.1016/j.ecolind.2021.107557

Schrank, A. J., & Rahel, F. J. (2004). Movement patterns in inland cutthroat trout (Oncorhynchus clari utah): Management and conservation implications. *Canadian Journal of Fisheries and Aquatic Sciences*, *61*(8), 1528–1537. https://doi.org/10.1139/f04-097

Sethi, S. A., O'Hanley, J. R., Gerken, J., Ashline, J., & Bradley, C. (2017). High value of ecological information for river connectivity restoration. *Landscape Ecology*, *32*(12), 2327–2336. https://doi.org/10.1007/s10980-017-0571-2

Shaad, K., Souter, N. J., Farrell, T., Vollmer, D., & Regan, H. M. (2018). Evaluating the sensitivity of dendritic connectivity to fish pass efficiency for the Sesan, Srepok and Sekong tributaries of the Lower Mekong. *Ecological Indicators*, *91*, 570–574. https://doi.org/10.1016/j.ecolind.2018.04.034

Shaw, E. A., Lange, E., Shucksmith, J. D., & Lerner, D. N. (2016). Importance of partial barriers and temporal variation in flow when modelling connectivity in fragmented river systems. *Ecological Engineering*, *91*, 515–528. https://doi.org/10.1016/j.ecoleng.2016.01.030

Somodi, I., Lepesi, N., & Botta-Dukát, Z. (2017). Prevalence dependence in model goodness measures with special emphasis on true skill statistics. *Ecology and Evolution*, *7*(3), 863–872. https://doi.org/10.1002/ece3.2654

Sun, J., Du, W., Lucas, M. C., Ding, C., Chen, J., Tao, J., & He, D. (2023). River fragmentation and barrier impacts on fishes have been greatly underestimated in the upper Mekong River. *Journal of Environmental Management*, *327*, 116817. https://doi.org/10.1016/j.jenvman.2022.116817

Thieme, M., Birnie-Gauvin, K., Opperman, J. J., Franklin, P. A., Richter, H., Baumgartner, L., Ning, N., Vu, A. V., Brink, K., Sakala, M., O'Brien, G. C., Petersen, R., Tongchai, P., & Cooke, S. J. (2023). Measures to safeguard and restore river connectivity. *Environmental Reviews*, er-2023-0019. https://doi.org/10.1139/er-2023-0019

UDOT. (2022). *UDOT Structures Open Data* [Dataset]. https://data-uplan.opendata.arcgis.com/datasets/uplan::udot-structures-open-data-1/about

UDWR. (2019). *Bonneville cutthroat trout range-wide conservation agreement and strategy* (Publication Number 18-11). Utah Division of Wildlife Resources. https://westernnativetrout.org/wp-content/uploads/2020/01/Signed-Version-of-BCT-Plan-December-2019.pdf

UDWRi. (2023). *Utah Dam Inventory* [Dataset]. https://opendata.gis.utah.gov/datasets/utahDNR::utah-dam-inventory/explore

U.S. Census Bureau. (2022). *TIGER/Line Shapefile* [Dataset]. https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural.html

USACE. (2023). *National Inventory of Dams* [Dataset]. https://nid.sec.usace.army.mil/#/

USFHA. (2020). *National Bridge Inventory* [Dataset]. https://www.fhwa.dot.gov/bridge/nbi.cfm

USGS. (2023a). *National Hydrography Dataset (NHD)* [Dataset]. https://www.usgs.gov/national-hydrography/national-hydrography-dataset

USGS. (2023b). *National Transportation Dataset* [Dataset]. https://www.sciencebase.gov/catalog/item/4f70b1f4e4b058caae3f8e16

USGS. (2023c). *USGS National Map 3DEP 1/3rd arc-second Digital Elevation Models (DEMs)* [Dataset]. https://data.usgs.gov/datacatalog/data/USGS:3a81321b-c153-416f-98b7-cc8e5f0e17c3

Vowles, A. S., Kerr, J. R., & Kemp, P. S. (2024). Accuracy of coarse-resolution protocols for assessing fish passability at river infrastructure. *Ecological Informatics*, *81*, 102575. https://doi.org/10.1016/j.ecoinf.2024.102575

Wang, H., & Chanson, H. (2018). Modelling upstream fish passage in standard box culverts: Interplay between turbulence, fish kinematics, and energetics. *River Research and Applications*, *34*(3), 244–252. https://doi.org/10.1002/rra.3245

Warren, M. L., & Pardew, M. G. (1998). Road Crossings as Barriers to Small-Stream Fish Movement. *Transactions of the American Fisheries Society*, *127*(4), 637–644. https://doi.org/10.1577/1548-8659(1998)127<0637:RCABTS>2.0.CO;2

WDFW. (2019). *Fish Passage Inventory, Assessment, and Prioritization Manual*. Washington Department of Fish and Wildlife.

Wohl, E. (2017). The significance of small streams. *Frontiers of Earth Science*, *11*(3), 447–456. https://doi.org/10.1007/s11707-017-0647-y

Wunderlich, R. F., Lin, Y.-P., Anthony, J., & Petway, J. R. (2019). Two alternative evaluation metrics to replace the true skill statistic in the assessment of species distribution models. *Nature Conservation*, *35*, 97–116. https://doi.org/10.3897/natureconservation.35.33918

Tables and Figures

Table 4.1. Data sources and types of potential instream barriers in the Bear River Basin.

			Listed road-crossing type		
Source	Waterfall	Dam	Bridge	Culvert	Unknown
National Bridge Inventory	0	0	177	18	0
National Inventory of Dams	0	32	0	0	0
National Transportation Dataset	0	0	0	0	2,062
Utah Department of Transportation	0	0	14	0	0
Utah Division of Wildlife Resources	6	2	0	20	0
Utah Division of Water Rights	0	48	0	0	0
Total	6	82	191	38	2,062

Table 4.2. Listed and observed road-crossing barrier types in the Logan River and Upper Bear River Subbasins.

Subbasin	Listed road-crossing type	Observed road-crossing type						
		Absent		Bridge		Culvert		Total Sampled
		n	%	n	%	n	%	n
Logan River Subbasin	Bridge	0	0	10	100	0	0	10
	Culvert	2	20	0	0	8	80	10
	Unknown	15	33	13	28	18	39	46
Upper Bear River Subbasin	Bridge	0	0	10	100	0	0	10
	Culvert	2	20	1	10	7	70	10
	Unknown	12	24	8	16	29	59	49
Total	-	31	23	42	31	62	46	135

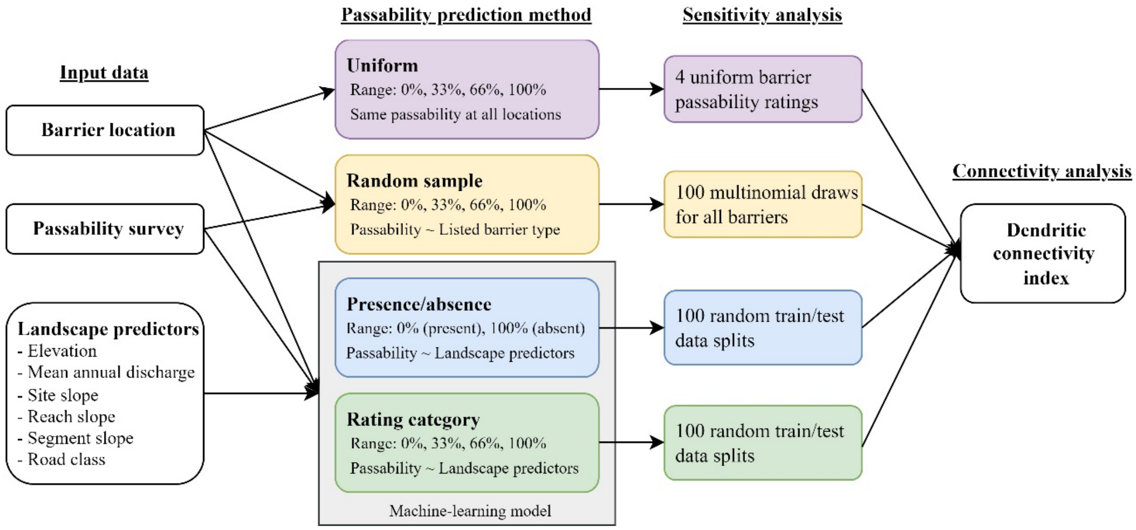

Figure 4.1. Conceptual diagram of input data, passability prediction methods, and sensitivity analyses used to estimate road-crossing passability and stream network connectivity.

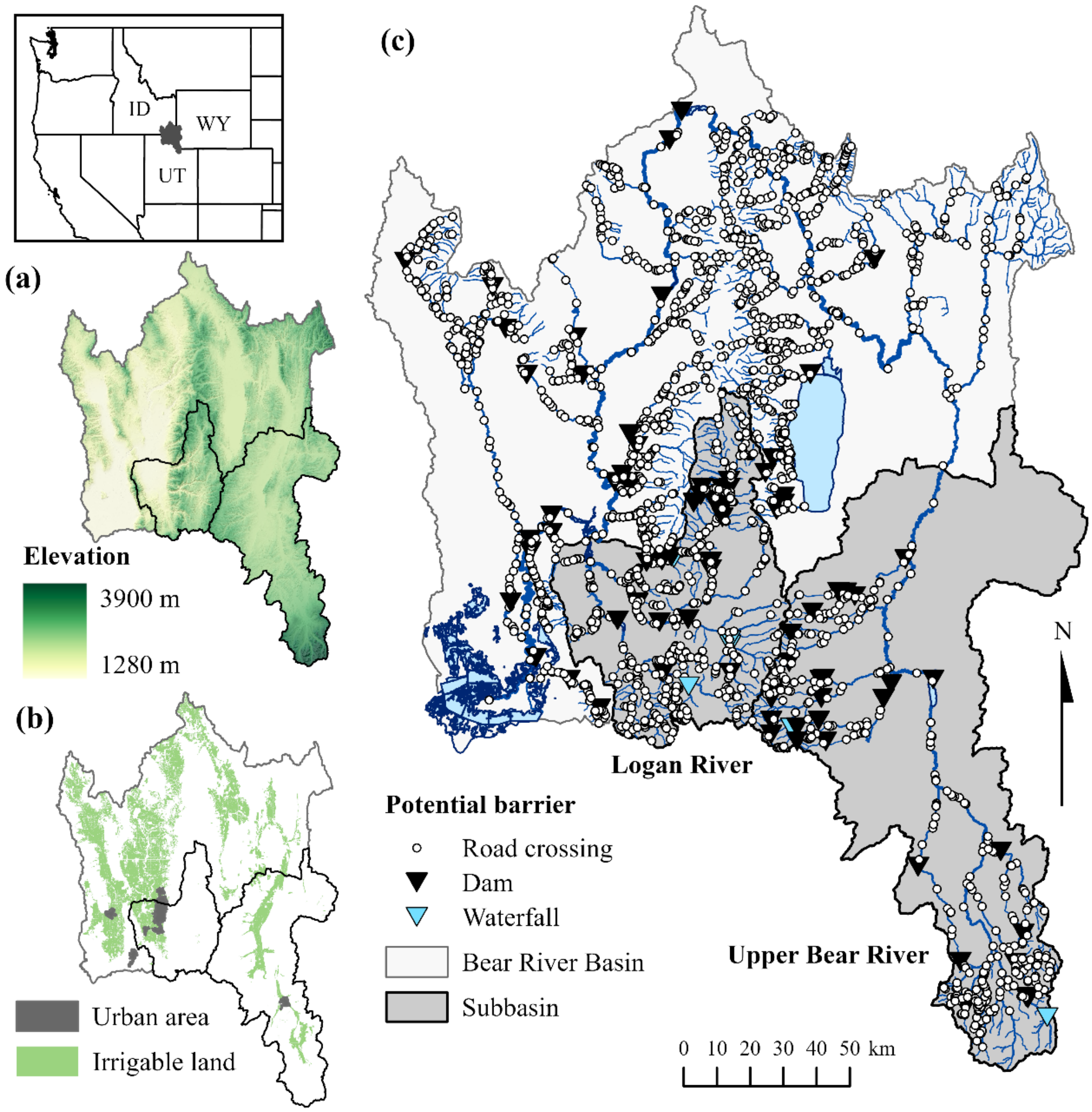

Figure 4.2. Bear River Basin study area showing study subbasins and (a) elevation, (b) irrigable and urban land, and (c) 2,379 potential instream barrier locations.

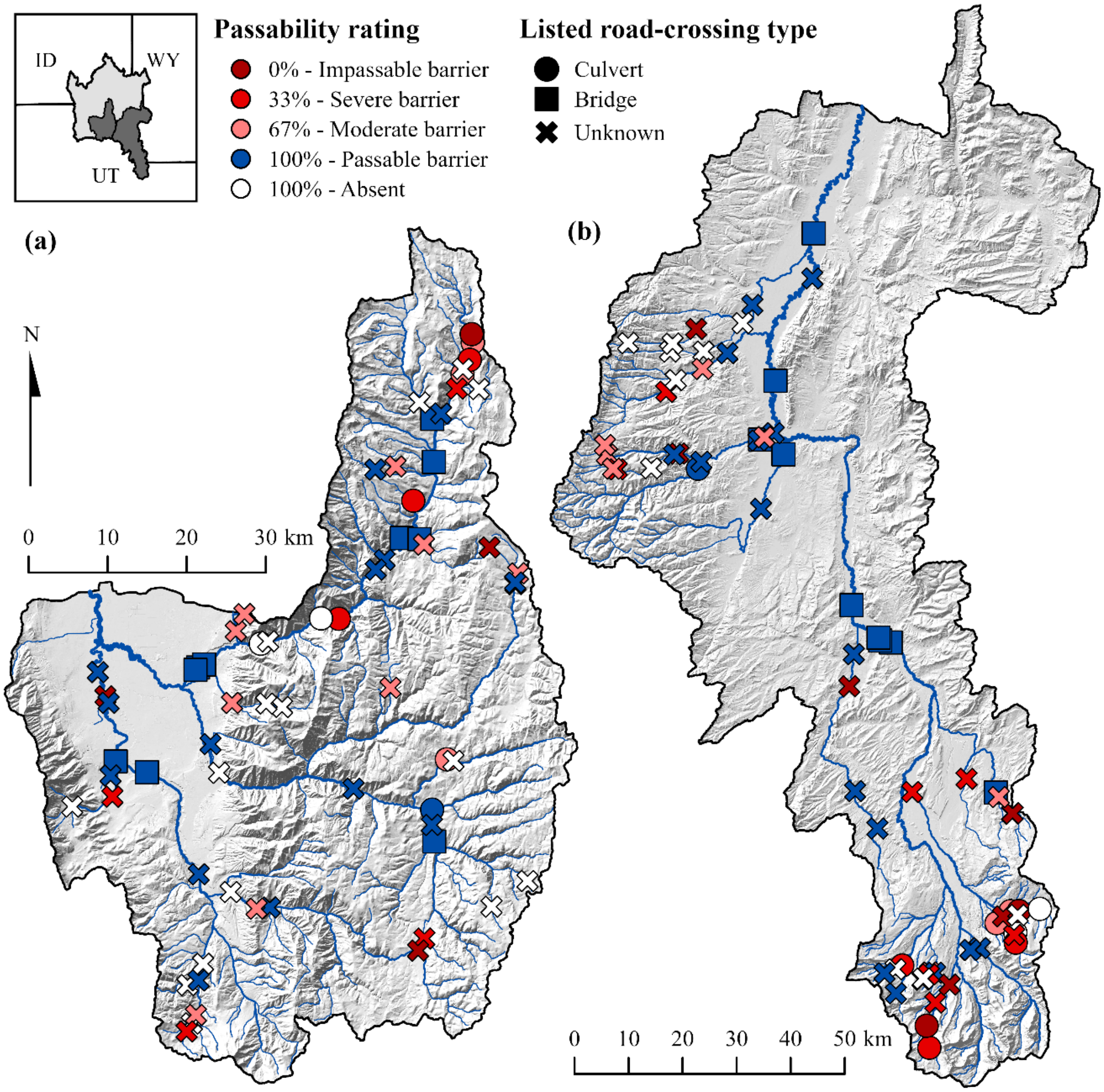

Figure 4.3. Road-crossing passability in the (a) Logan River and (b) Upper Bear River Subbasins for 135 surveyed road-stream intersections in the Bear River Basin. Shapes identify the listed road-crossing type. Colors show the observed passability rating determined through field surveys. See Appendix B1 and WDFW (2019) for definition of road-crossing types and passabilities.

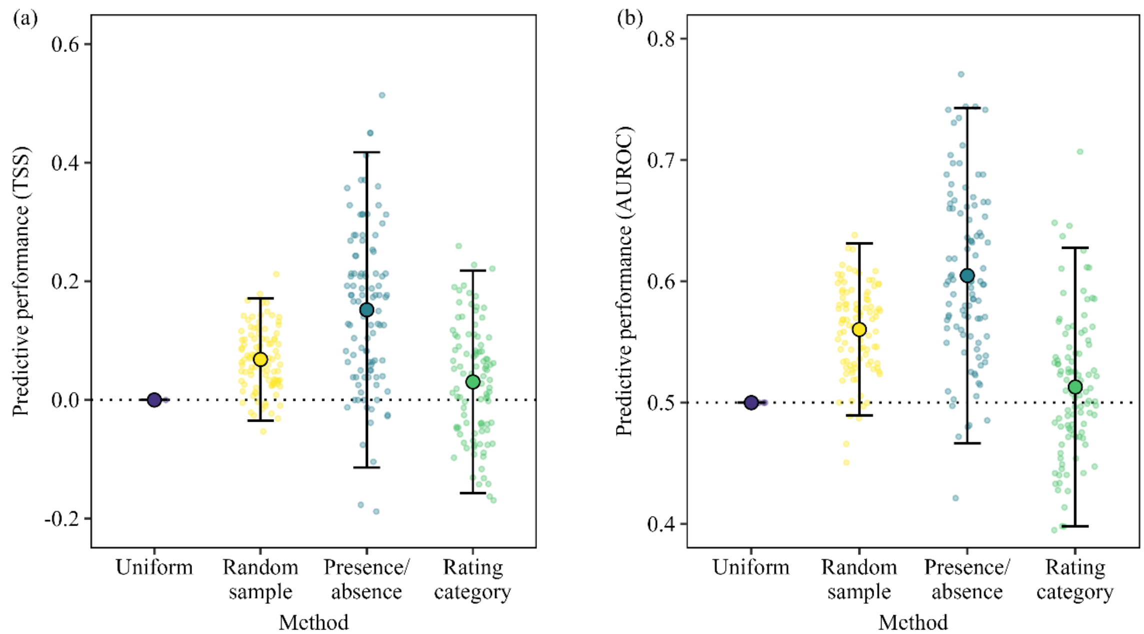

Figure 4.4. Mean and 95% prediction intervals of (a) TSS and (b) AUROC predictive performance measures by barrier passability prediction method. Background points show individual predictive performance for each passability model. The dotted line represents random predictive performance where correct and incorrect classification rates are equal.

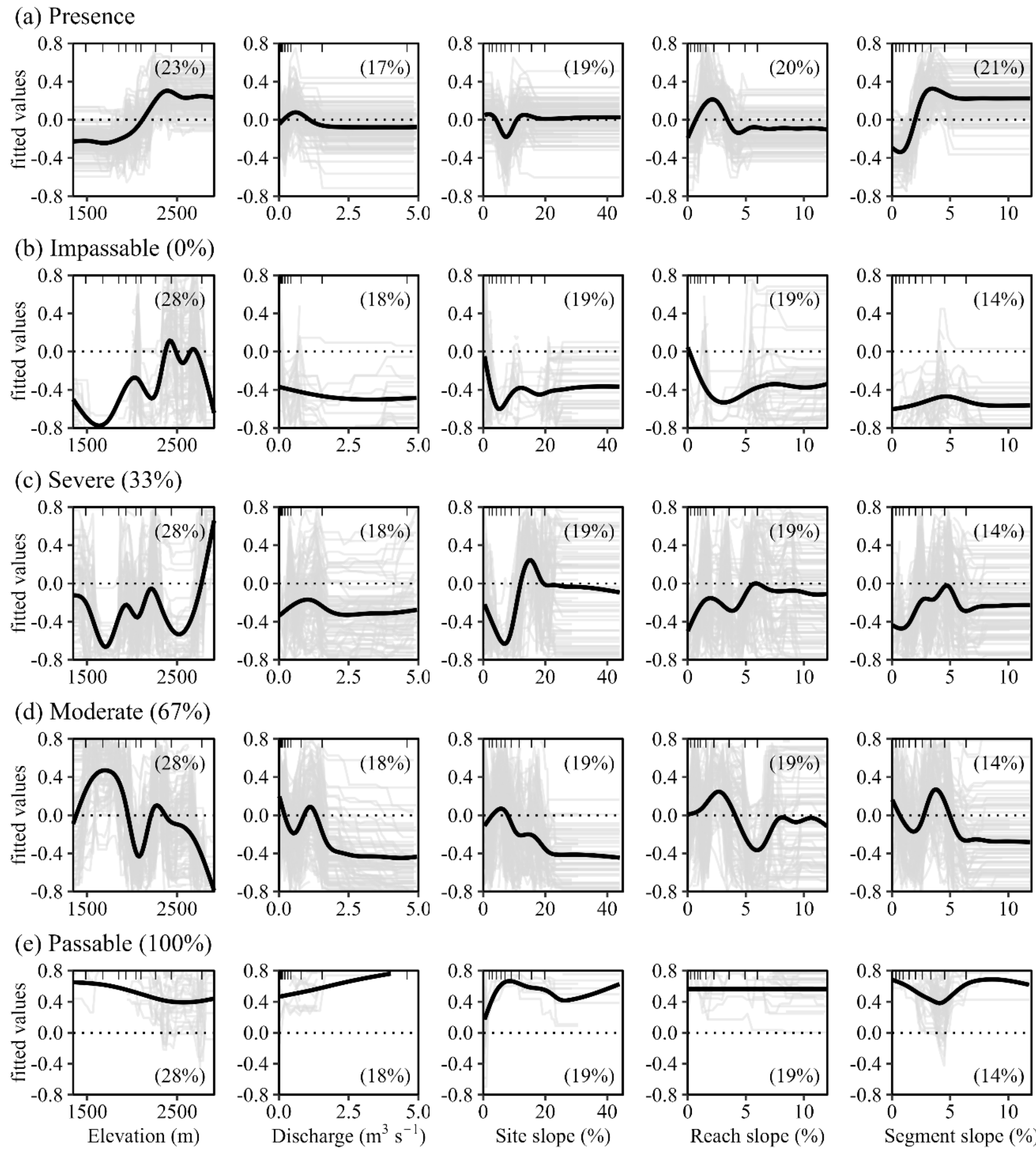

Figure 4.5. Partial dependency plots for predictor variables contributing >10% to (a) presence/absence and (b-e) rating category boosted regression tree model classification of road-crossing barrier passability. Gray lines show partial dependence plots for individual models and black lines show the mean across all models. Percentage values indicate the relative importance of the predictor variable averaged across all presence/absence or rating category models. Rug plots on the top axis show the distribution of observed variable values in deciles.

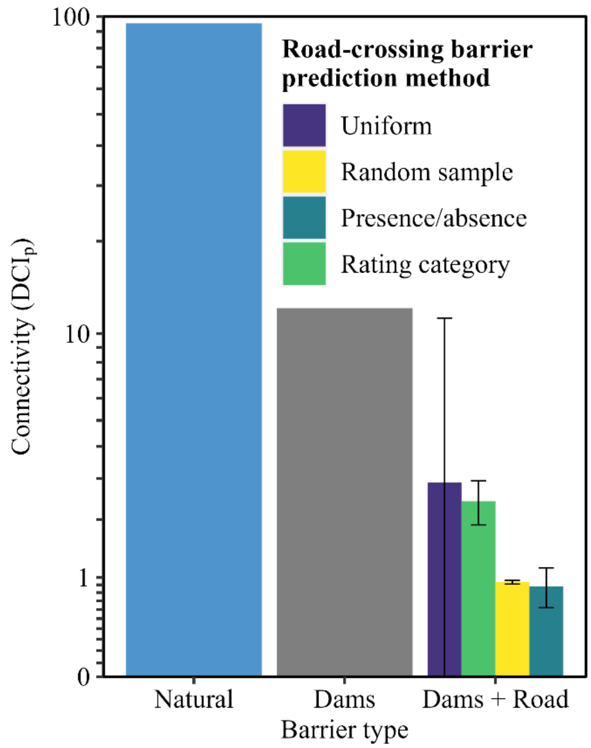

Figure 4.6. Bear River Basin connectivity (log10 scale) calculated with natural waterfalls, dams, and road-crossing barrier passability generated using uniform, random sample, presence/absence, and rating category methods. Error bars show the 95% confidence interval of the mean for each passability prediction method averaged across all passability models excepting uniform methods, which are shown individually.

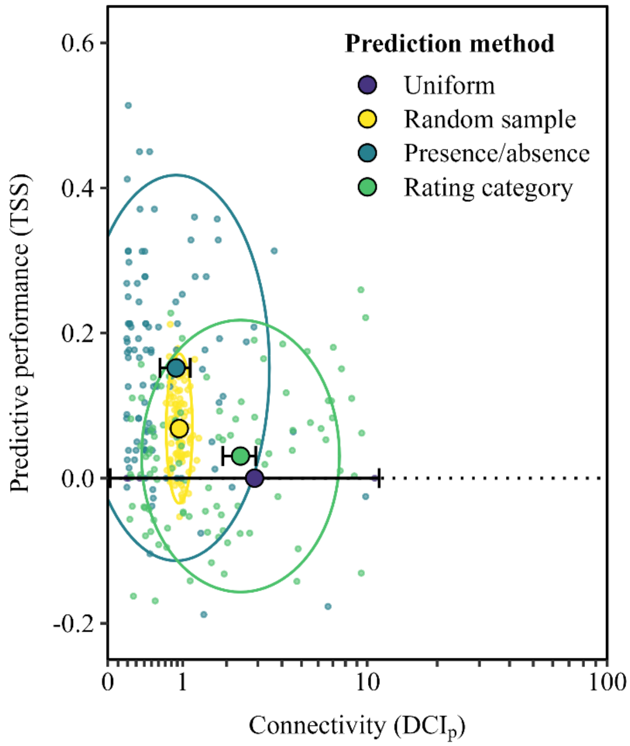

Figure 4.7. Bear River Basin connectivity (DCI$_p$, log10 scale) and predictive performance (TSS) calculated from road-crossing barrier passability generated using uniform, random sample, presence/absence, and rating category passability prediction methods. Points show connectivity and predictive performance for individual passability models. Large dots indicate mean connectivity, with error bars showing the 95% confidence interval of the mean averaged across all passability models. Ellipses show the 95% prediction interval for connectivity and predictive performance. The dotted line represents random predictive performance where correct and incorrect classification rates are equal.

CHAPTER 5

CONCLUSION

Freshwater ecosystems and species have declined worldwide due to the development of water resources to provide for human water demands (Harrison et al., 2018), and they risk further decline in the face of continued water resource development. Historically, dams and other river infrastructure were developed without consideration of their ecological impacts, leading to extensive and persistent biodiversity loss and habitat alternation (Poff et al., 2007; Wurtsbaugh et al., 2017). In response to the decline of freshwater ecosystems, minimizing environmental losses and restoring rivers have emerged as a focus for water resources management (Cosgrove & Loucks, 2015). However, rivers are highly complex systems that support diverse fauna with varied environmental needs and are subject to considerable environmental and ecological uncertainty (Thoms, 2006), making them difficult to represent alongside competing hydro-economic objectives of water resources management. Analysis techniques that address uncertainty in decision-making present a path for improving environmental objectives for water resources management. Despite this, little research has focused on quantifying uncertainty and identifying decisions that are robust to change for water resources and ecosystem management (Null et al., 2021).

In my second chapter, I used water resources systems modeling to evaluate tradeoffs between water supply for people, impacts to stream habitat, and changes to Great Salt Lake elevation under new water demands and proposed reservoir development alternatives. I found that new dams and reservoirs drive loss of summer stream habitat for Bonneville Cutthroat Trout, and that new water diversions to for agriculture and municipal use along Utah's metropolitan Wasatch Front lead to substantial decline in lake elevation at Great Salt Lake. My study provides important evidence for potential economic, environmental, and human health consequences from current diversion and reservoir proposals under Utah's Bear River Development Act. However, my study focused on the 2000-2020 historical period, and presents optimistic estimates for water availability, habitat conditions, and Great Salt Lake level. In the western US, climate change is leading to longer, warmer, and drier periods punctuated by more extreme storms and wet periods (Stevenson et al., 2022; Williams et al., 2022). These hydroclimatic shifts will change hydrological and thermal regimes in the Bear River Basin, reducing water available for human use and thermally suitable habitats for coldwater fish species (Dettinger et al., 2015; Isaak & Young, 2023). Reservoirs can exacerbate water shortages during dry periods (Di Baldassarre et al., 2018), and further reservoir development could amplify conflicts between water users and reduce water availability for the Bear River and Great Salt Lake. My study also assumed a healthy starting Great Salt Lake level, although Great Salt Lake recently reached its historic low level (Larsen, 2023; Great Salt Lake Strike Team, 2025). To understand the true environmental consequences of Bear River development, future research should evaluate development under likely future hydro-climatic conditions that could exacerbate economic, environmental, and human health risks for the Lower Bear River and Great Salt Lake Basin.

Removing dams, culverts, and other instream infrastructure that create barriers to movement for fish and other aquatic organisms has emerged as a strategy for reconnecting rivers and restoring freshwater ecosystems (Foley et al., 2017). Barrier removals are often prioritized to reconnect suitable habitats for fish (Branco et al., 2014; S. King & O'Hanley, 2016; Kraft et al., 2019), but habitat representations and habitat suitability functions are often uncertain (Roloff & Kernohan, 1999; Van Der Lee et al., 2006). In my third chapter, I used a Monte-Carlo random sampling framework to evaluate the robustness of barrier removal selection to environmental data and suitability function uncertainty for Bonneville Cutthroat Trout in the Weber River Basin. I determined that barrier removals to reconnect thermal refugia were sensitive to environmental data and suitability function uncertainty, and that few barrier removals were also robust for reconnecting growth habitat. My findings add to previous research that budget constraints (Maitland et al., 2016), uncertain barrier passage ratings (de Leaniz & O'Hanley, 2022), and different life histories (McManamay et al., 2019) all influence the robustness of decisions about barrier removals. I focused on thermal habitat suitability, but uncertainty in other instream variables influencing habitat suitability, such as stream temperature and dissolved oxygen content, have not been evaluated. Other studies also highlight that barrier removal risks expanding the scope of biological invasions (Dolan et al., 2025), yet barrier removal optimization rarely considers risks posed by nonnative species (Milt et al., 2018). My approach represents a flexible method for addressing environmental uncertainty in barrier removal optimization modeling that could be extended to other habitat variables and nonnative species.

Connectivity indices measure river fragmentation and are often used to guide dam and barrier removals to restore river connectivity (Diebel et al., 2015; M. King et al., 2023; Kraft et al., 2019). Connectivity indices rely on barrier passability estimates that are difficult to predict and often derived using different methods (Januchowski-Hartley et al., 2014; Perkin et al., 2020), rendering connectivity estimates uncertain. I investigated how uncertainty in passability prediction methods affects barrier passability ratings and stream network connectivity estimates. I found that different passability prediction methods produced similar estimates of stream network connectivity but had considerable uncertainty predicting passability for individual barriers. My findings demonstrate that passability prediction methods are sufficient to characterize river fragmentation at the network scale needed to support ecological analyses and conservation planning (Brown et al., 2011; McCluney et al., 2014). However, I highlight that current passability prediction methods are insufficient to guide specific barrier removal decision-making with connectivity analysis. Future work could explore solutions for overcoming passability prediction uncertainty to improve remote assessment of barrier status for barrier removal optimization modeling.

This dissertation explores approaches to improve aquatic habitat representation for water resources management and ecosystem conservation. My work demonstrates how environmental and ecological uncertainty influence models used to inform water management and river restoration decisions. I emphasize pathways for evaluating robustness to environmental uncertainties in water resources management needed to achieve better outcomes for aquatic organisms and mitigate impacts from water management on freshwater ecosystems. Overall, this work expands our knowledge of and solutions to freshwater ecosystem decline by identifying decisions that allow us to manage rivers for people and the environment.

References

Branco, P., Segurado, P., Santos, J. M., & Ferreira, M. T. (2014). Prioritizing barrier removal to improve functional connectivity of rivers. *Journal of Applied Ecology*, *51*(5), 1197–1206. https://doi.org/10.1111/1365-2664.12317

Brown, B. L., Swan, C. M., Auerbach, D. A., Campbell Grant, E. H., Hitt, N. P., Maloney, K. O., & Patrick, C. (2011). Metacommunity theory as a multispecies, multiscale framework for studying the influence of river network structure on riverine communities and ecosystems. *Journal of the North American Benthological Society*, *30*(1), 310–327. https://doi.org/10.1899/10-129.1

Cosgrove, W. J., & Loucks, D. P. (2015). Water management: Current and future challenges and research directions. *Water Resources Research*, *51*(6), 4823–4839. https://doi.org/10.1002/2014WR016869

de Leaniz, C. G., & O'Hanley, J. R. (2022). Operational methods for prioritizing the removal of river barriers: Synthesis and guidance. *Science of The Total Environment*, *848*, 157471. https://doi.org/10.1016/j.scitotenv.2022.157471

Dettinger, M., Udall, B., & Georgakakos, A. (2015). Western water and climate change. *Ecological Applications*, *25*(8), 2069–2093. https://doi.org/10.1890/15-0938.1

Di Baldassarre, G., Wanders, N., AghaKouchak, A., Kuil, L., Rangecroft, S., Veldkamp, T. I. E., Garcia, M., Van Oel, P. R., Breinl, K., & Van Loon, A. F. (2018). Water shortages worsened by reservoir effects. *Nature Sustainability*, *1*(11), 617–622. https://doi.org/10.1038/s41893-018-0159-0

Diebel, M. W., Fedora, M., Cogswell, S., & O'Hanley, J. R. (2015). Effects of road crossings on habitat connectivity for stream-resident fish. *River Research and Applications*, *31*(10), 1251–1261. https://doi.org/10.1002/rra.2822

Dolan, E. J., Soto, I., Dick, J. T. A., He, F., & Cuthbert, R. N. (2025). Riverine Barrier Removals Could Proliferate Biological Invasions. *Global Change Biology*, *31*(3), e70093. https://doi.org/10.1111/gcb.70093

Foley, M. M., Bellmore, J. R., O'Connor, J. E., Duda, J. J., East, A. E., Grant, G. E., Anderson, C. W., Bountry, J. A., Collins, M. J., Connolly, P. J., Craig, L. S., Evans, J. E., Greene, S. L., Magilligan, F. J., Magirl, C. S., Major, J. J., Pess, G. R., Randle, T. J., Shafroth, P. B., … Wilcox, A. C. (2017). Dam removal: Listening in. *Water Resources Research*, *53*(7), 5229–5246. https://doi.org/10.1002/2017WR020457

Great Salt Lake Strike Team. (2025). Great Salt Lake data and insights summary. Retrieved from https://d36oiwf74r1rap.cloudfront.net/wp-content/uploads/2025/01/GSL-Jan2025.pdf

Harrison, I., Abell, R., Darwall, W., Thieme, M. L., Tickner, D., & Timboe, I. (2018). The freshwater biodiversity crisis. *Science*, *362*(6421), 1369–1369. https://doi.org/10.1126/science.aav9242

Isaak, D. J., & Young, M. K. (2023). Cold-water habitats, climate refugia, and their utility for conserving salmonid fishes. *Canadian Journal of Fisheries and Aquatic Sciences*, *80*(7), 1187–1206. https://doi.org/10.1139/cjfas-2022-0302

Januchowski-Hartley, S. R., Diebel, M., Doran, P. J., & McIntyre, P. B. (2014). Predicting road culvert passability for migratory fishes. *Diversity and Distributions*, *20*(12), 1414–1424. https://doi.org/10.1111/ddi.12248

King, M., Van Zyll De Jong, M., & Cowx, I. G. (2023). A dynamic dendritic connectivity assessment tool for the planning and design of barrier mitigation strategies in river networks. *Landscape Ecology*, *38*(6), 1431–1446. https://doi.org/10.1007/s10980-023-01627-9

King, S., & O'Hanley, J. R. (2016). Optimal Fish Passage Barrier Removal-Revisited. *River Research and Applications*, *32*(3), 418–428. https://doi.org/10.1002/rra.2859

Kraft, M., Rosenberg, D. E., & Null, S. E. (2019). Prioritizing Stream Barrier Removal to Maximize Connected Aquatic Habitat and Minimize Water Scarcity. *JAWRA Journal of the American Water Resources Association*, *55*(2), 382–400. https://doi.org/10.1111/1752-1688.12718

Larsen, L. (2023, September 19). A year after Great Salt Lake's record low, half the lake is left for dead. *The Salt Lake Tribute*. https://www.sltrib.com/news/environment/2023/09/18/one-year-after-great-salt-lakes/

Maitland, B. M., Poesch, M., & Anderson, A. E. (2016). Prioritising culvert removals to restore fish habitat for at-risk salmonids in the boreal forest. *Fisheries Management and Ecology*, *23*(6), 489–502. https://doi.org/10.1111/fme.12188

McCluney, K. E., Poff, N. L., Palmer, M. A., Thorp, J. H., Poole, G. C., Williams, B. S., Williams, M. R., & Baron, J. S. (2014). Riverine macrosystems ecology: Sensitivity, resistance, and resilience of whole river basins with human alterations. *Frontiers in Ecology and the Environment*, *12*(1), 48–58. https://doi.org/10.1890/120367

McManamay, R. A., Perkin, J. S., & Jager, H. I. (2019). Commonalities in stream connectivity restoration alternatives: An attempt to simplify barrier removal optimization. *Ecosphere*, *10*(2). https://doi.org/10.1002/ecs2.2596

Milt, A. W., Diebel, M. W., Doran, P. J., Ferris, M. C., Herbert, M., Khoury, M. L., Moody, A. T., Neeson, T. M., Ross, J., Treska, T., O'Hanley, J. R., Walter, L., Wangen, S. R., Yacobson, E., & McIntyre, P. B. (2018). Minimizing opportunity costs to aquatic connectivity restoration while controlling an invasive species: Cost of Invasive Control. *Conservation Biology*, *32*(4), 894–904. https://doi.org/10.1111/cobi.13105

Null, S. E., Olivares, M. A., Cordera, F., & Lund, J. R. (2021). Pareto Optimality and Compromise for Environmental Water Management. *Water Resources Research*, *57*(10), e2020WR028296. https://doi.org/10.1029/2020WR028296

Perkin, J. S., Acre, M. R., Graham, J., & Hoenke, K. (2020). An integrative conservation planning framework for aquatic landscapes fragmented by road-stream crossings. *Landscape and Urban Planning*, *202*, 103860. https://doi.org/10.1016/j.landurbplan.2020.103860

Poff, N. L., Olden, J. D., Merritt, D. M., & Pepin, D. M. (2007). Homogenization of regional river dynamics by dams and global biodiversity implications. *Proceedings of the National Academy of Sciences*, *104*(14), 5732–5737. https://doi.org/10.1073/pnas.0609812104

Roloff, G. J., & Kernohan, B. J. (1999). Evaluating reliability of habitat suitability index models. *Wildlife Society Bulletin*, *27*(4), 973–985.

Stevenson, S., Coats, S., Touma, D., Cole, J., Lehner, F., Fasullo, J., & Otto-Bliesner, B. (2022). Twenty-first century hydroclimate: A continually changing baseline, with more frequent extremes. *Proceedings of the National Academy of Sciences*, *119*(12), e2108124119. https://doi.org/10.1073/pnas.2108124119

Thoms, M. C. (2006). Variability in riverine ecosystems. *River Research and Applications*, *22*(2), 115–121. https://doi.org/10.1002/rra.900

Van Der Lee, G. E. M., Van Der Molen, D. T., Van Den Boogaard, H. F. P., & Van Der Klis, H. (2006). Uncertainty analysis of a spatial habitat suitability model and implications for ecological management of water bodies. *Landscape Ecology*, *21*(7), 1019–1032. https://doi.org/10.1007/s10980-006-6587-7

Williams, A. P., Cook, B. I., & Smerdon, J. E. (2022). Rapid intensification of the emerging southwestern North American megadrought in 2020–2021. *Nature Climate Change*, *12*(3), 232–234. https://doi.org/10.1038/s41558-022-01290-z

Wurtsbaugh, W. A., Miller, C., Null, S. E., DeRose, R. J., Wilcock, P., Hahnenberger, M., Howe, F., & Moore, J. (2017). Decline of the world's saline lakes. *Nature Geoscience*, *10*(11), 816–821. https://doi.org/10.1038/ngeo3052

APPENDICES

APPENDIX A: SUPPLEMENTAL INFORMATION FOR CHAPTER 3

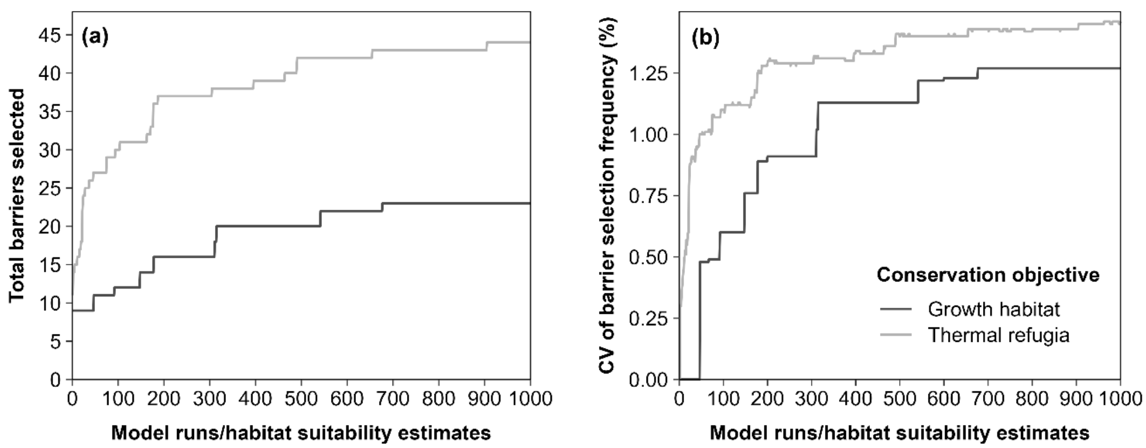

Figure A.1. Sensitivity of barrier removal optimization to the number of model runs and habitat suitability estimates for each conservation objective: (a) Total number of individual barriers selected and (b) the coefficient of variation (CV) of barrier selection frequency calculated iteratively across all optimization model solutions.

APPENDIX B: SUPPLEMENTAL INFORMATION FOR CHAPTER 4

1. Methods for assigning passability to instream barriers

Barrier passability was adapted from the Washington Department of Fish and Wildlife's (WDFW) fish passage assessment methodology and barrier standard (WDFW 2019). The assessment assigns a categorical passability to any instream barrier based on the swimming and leaping abilities of trout and salmon $\geq$ 15.24 cm (6 in) in length. Passability is a qualitative indicator of the limitation a barrier creates to fish movement and not a quantitative measure of the percentage of fish able to pass a barrier. The WDFW assessment evaluates barriers based on structural parameters (Level A analysis) and a hydraulic model (Level B analysis) to quantify the duration for which water velocity exceeds fish species swimming capability. The WDFW assessment also includes a gated barrier assessment key, which I removed because no gated barriers in my survey prevented water or fish movement. I adapted this approach into a single-level workflow (Figure S1) that assigned culvert passability using structural and hydraulic criteria (Table S1) but did not incorporate the WDFW Level B hydraulic model. Barriers were assigned the lowest passability (most limiting to fish movement) among all criteria to characterize overall passability.

Table B.1. Criteria to determine barrier passability. For more information describing criteria and data collection methods see (WDFW 2019).

Criteria type	Criteria	Barrier length	Value	Passability
Structural	Water surface drop	N/A	0.24 m - 0.49 m	67%
			0.50 m - 0.99 m	33%
			≥ 1.00m	0%
	Slope	< 18.3 m	1.01 % - 1.99%	67%
			2.00 % - 3.99 %	33%
			≥ 4.00 %	0%
		≥ 18.3 m	1.01 % - 1.99 %	33%
			≥ 2.00 %	0%
Hydraulic	Water depth	N/A	0.15 m - 0.30 m	67%
			0.05 m - 0.14 m	33%
			≤ 0.04 m	0%
	Velocity	≤ 30.4m	1.22 m s^{-1} - 1.82 m s^{-1}	67%
			≥ 1.83 m s^{-1}	33%
		30.5 m – 61 m	0.92 m s^{-1} - 1.52 m s^{-1}	67%
			≥ 1.53 m s^{-1}	33%
		> 61 m	0.61 m s^{-1} - 1.21 m s^{-1}	67%
			≥ 1.22 m s^{-1}	33%

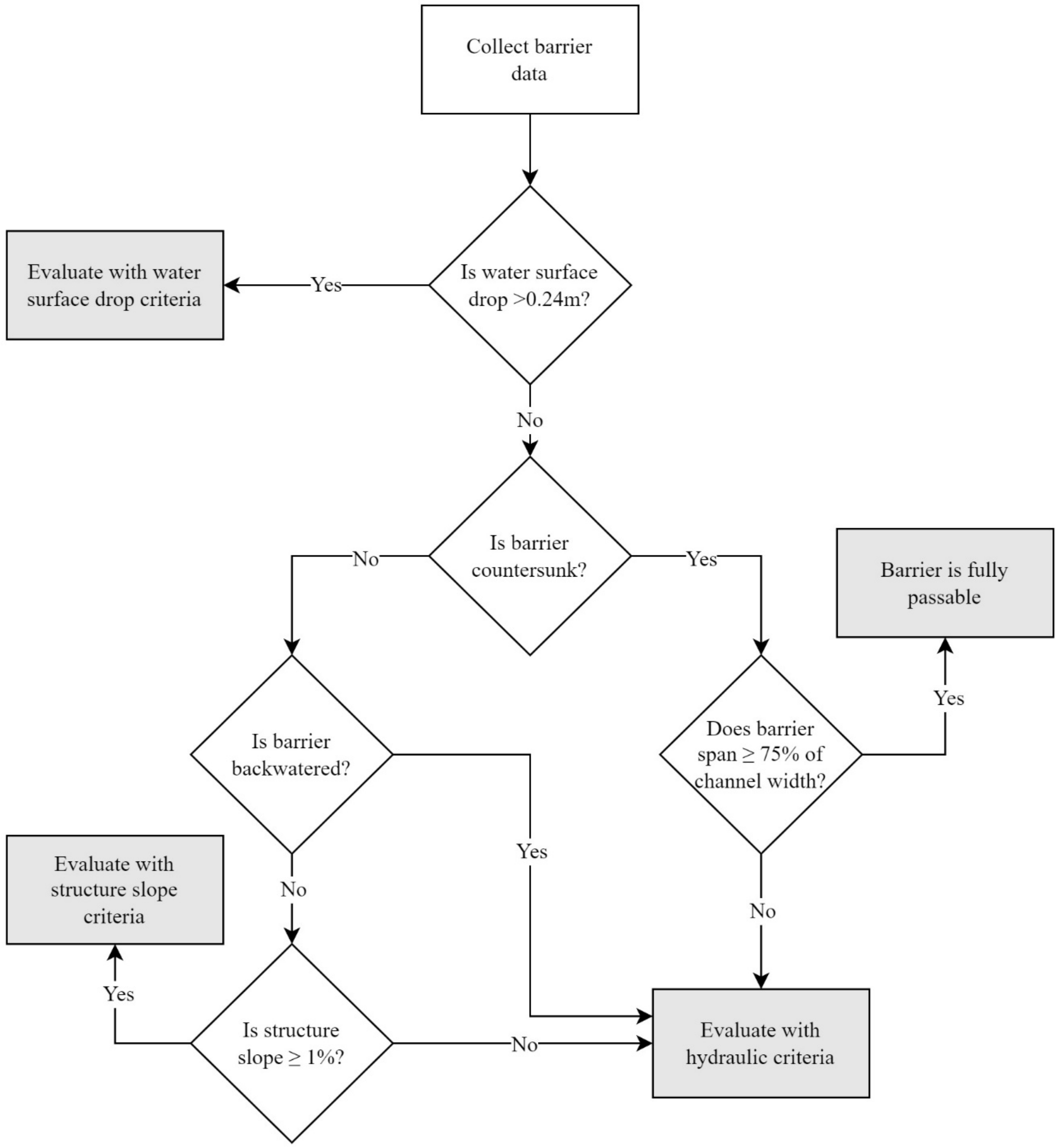

Figure B.1. Flow chart for determining passability for instream barriers adapted from (WDFW 2019). Barriers are countersunk if the depth of bed material at the barrier outlet is ≥ 20% of the total culvert rise and bed material covers the entire structure length. Barriers are backwatered if the average water velocity is visibly slower than velocity in the adjacent channel or there is little to no visible flow velocity through the barrier.

References

WDFW (Washington Department of Fish and Wildlife). 2019. "Fish Passage Inventory, Assessment, and Prioritization Manual." Olympia, WA: Washington Department of Fish and Wildlife.

CURRICULUM VITAE

Gregory C. Goodrum, Ph.D.
Utah State University
Department of Watershed Sciences
5230 Old Main Hill
Logan, Utah 84322-5230
Email: goodrum.greg@gmail.com

EDUCATION

2025 **Ph.D. in Watershed Sciences**
Utah State University, Department of Watershed Sciences
Aquatic habitat representation for robust water resources management and fish conservation decision-making
Major advisor: Dr. Sarah Null
Committee: Dr. Joanna Endter-Wada, Dr. Charles Hawkins, Dr. David Rosenberg, Dr. Timothy Walsworth

2020 **M.S. in Watershed Sciences**
Utah State University, Department of Watershed Sciences
Improving aquatic habitat representation in Utah using large spatial scale environmental datasets
Major Advisor: Dr. Sarah Null
Committee: Dr. Brett Roper, Dr. Jeff Horsburgh, Don Wiley

2010 **B.S. in Geography**, Geographic Information Science Option
University of Arizona, School of Geography, Development, and Environment

PROFESSIONAL EXPERIENCE

Graduate Research Assistant (Ph.D.), Department of Watershed Sciences, Utah State University, UT
August 2020- May 2025
40+ hrs/week
Supervisor: Sarah Null, Professor (sarah.null@usu.edu)
Selected duties/responsibilities

- Developed an economic-environmental water management optimization model to evaluate tradeoffs between water supply, fish habitat, and Great Salt Lake level from building new dams in Utah's Bear River Basin.

- Developed methods and code to evaluate uncertainty in barrier removal optimization modeling for dam, culvert, and diversion removal in Utah's Weber River Basin.
- Identified over 2,000 instream barriers (culverts, dams, road crossings) in the Bear River Basin (UT, WY, ID) using remote sensing and geospatial datasets.
- Conducted barrier passability assessments at 150 sites in the Bear River Basin using hydraulic and structural criteria to estimate fish passage for Bonneville Cutthroat Trout.
- Invited participant to study river processes and dam development in the Magdalena River Basin, Colombia as part of the Rivers of the Andes Field Training Program (Partner university: Universidad EAFIT, Medellin, Colombia).
- Coauthored meta-analysis of environmental tradeoffs for hydropower dams in the lower Mekong River Basin (Null et al., 2023).
- Coauthored review of dam removal as a climate adaptation strategy with American Rivers and Resources Legacy Fund (Null et al., in prep).
- Disseminate findings to state and federal agencies through annual research meetings.
- Published findings in peer-reviewed journal for water managers.

Graduate Research Assistant (M.S.), Department of Watershed Sciences, Utah State University, UT
August 2018- August 2020
40+ hrs/week
Supervisor: Sarah Null, Professor (sarah.null@usu.edu)
Selected duties/responsibilities

- Developed a statewide habitat suitability model for threatened Bonneville Cutthroat Trout *Oncorhynchus clarkii utah* and Green Sucker *Pantosteus virescens* (formerly Bluehead Sucker *Catostomus discobolus*).
- Developed novel approach and code for sigmoidal model predicting stream temperature from land surface temperature.
- Collaborated with Utah Division of Wildlife Resources partners and conducted 4 in-person project updates and collaborative model-building sessions.
- Contributed to a final report for Utah Division of Wildlife Resources focused on habitat management implications and recommendations for Utah rivers.
- Mentored undergraduate research technicians collecting streamflow and sediment data at 30 sites throughout Utah.
- Published findings in peer-reviewed journal for water managers (Goodrum and Null, 2023).

Biological Science Technician, National Park Service Sonoran Desert Inventory and Monitoring Network, AZ

November 2015- July 2018
GS-07; 40 hrs/week
Supervisor: Sarah Studd, Vegetation Ecologist (Sarah_Studd@nps.gov)
Selected duties/responsibilities

- Supervise 4-5 member crews in vegetation community data collection to determine species composition of vegetation communities in 11 National Park Service units for biannual 5-month sampling periods.
- Supervise 2-3 member crews in stream and spring hydrological monitoring including streamflow, sediment composition, macroinvertebrate community, and hydroperiod data collection.
- Oversee database management and quality control for vegetation, spring, and stream monitoring databases.
- Coauthored reports including the National Park Service Springs Inventory and Monitoring Protocol (McIntyre et al., 2018) and status report for climate and water resources at Gila Cliff Dwellings National Monument (Goodrum et al., 2019).
- Safely supervised fieldwork for extended periods in backcountry wilderness areas

Biological Science Technician, National Park Service Sonoran Desert Inventory and Monitoring Network, AZ
November 2011 - May 2015
GS-05; 40 hrs/week
Supervisor: Sarah Studd, Vegetation Ecologist (Sarah_Studd@nps.gov)
Selected duties/responsibilities

- Supervise 4-5 member crews in vegetation community sampling to determine species composition of vegetation communities in 11 National Park Service units for extended 5-month sampling periods.
- Developed GIS spatial data delineating vegetation communities.
- Oversee database management and quality control for vegetation monitoring database.
- Safely supervised fieldwork for extended periods in backcountry wilderness areas.

Biological Science Technician, Grand Staircase-Escalante National Monument, UT
May 2011 - November 2011
GS-05; 40 hrs/week
Supervisor: Amber Hughes, Botanist (contact information unknown)
Selected duties/responsibilities

- Supervised 2-4 8-person field crews removing non-native Russian Olive *Elaeagnus angustifolia* from over 20 miles of the Escalante River and tributaries.

- Conducted riparian vegetation community data collection to monitor community composition and effects of prior restoration activities.
- Safely supervised fieldwork for extended periods in backcountry wilderness areas.

Vegetation Protocols Intern, National Park Service Sonoran Desert Inventory and Monitoring Network, AZ
August 2010 - May 2011
GS-05 Equivalent; 40 hrs/week
Supervisor: Sarah Studd, Vegetation Ecologist (Sarah_Studd@nps.gov)
Selected duties/responsibilities

- Conducted vegetation community data collection to determine species composition of vegetation communities in 11 National Park Service units.
- Developed GIS spatial data delineating vegetation communities.
- Safely performed fieldwork for extended periods in backcountry wilderness areas.

Plants Restoration Intern, C&O Canal National Historical Park, MD
May 2010 - August 2010
GS-05 Equivalent; 40 hrs/week
Selected duties/responsibilities

- Remove invasive non-native plant species using mechanical and chemical treatment as part of 4 member treatment crew.
- Chainsaw removal of large invasive and hazard tree species.
- Disseminate information about non-native species and treatment with park visitors.

Geographic Information Systems Intern, Carolina Sandhills National Wildlife Refuge, SC
January 2010 - May 2010
GS-05 Equivalent; 40 hrs/week
Supervisor: Allyne Askins, Refuge Manager (843.335.6023)
Selected duties/responsibilities

- Developed a geospatial land acquisition map to guide refuge expansion.
- Research platt and sale records to clarify parcel ownership history.
- Monitored Southern Longleaf Pine *Pinus palustris* populations for tree health and community composition.
- Participated in stand marking for timber harvests and selective thinning for wildland fire fuels reduction operations.

TEACHING

Fish Ecology (Teaching Assistant) - Watershed Sciences 6230/7230 - Spring 2025 - Utah State University, Logan, UT

Fundamentals of Watershed Science (Teaching Assistant) - Watershed Sciences 3700 - Spring 2025 - Utah State University, Logan, UT

Planning & Executing Successful Rotenone & Antimycin Projects XXVIV (Teaching Assistant) - American Fisheries Society - May 20-24, 2024 - Utah State University, Logan, UT

Planning & Executing Successful Rotenone & Antimycin Projects XXVIII (Teaching Assistant) - American Fisheries Society - May 22-26, 2023 - Utah State University, Logan, U

Planning & Executing Successful Rotenone & Antimycin Projects XXVII (Teaching Assistant) - American Fisheries Society - May 23-27, 2022 - Utah State University, Logan, UT

Fish Diversity (Teaching Assistant) - Watershed Sciences 3100 - Fall 2021 - Utah State University, Logan, UT

Physical Geography Lab (Teaching Assistant) – Geography 1005 – Fall 2019, Fall 2020 - Utah State University, Logan, UT

PUBLICATIONS

Goodrum, G. C., Hawkins, C. P., Walsworth, T. E., & Null, S. E. (2025). Predicting road-crossing passability for river connectivity analysis. River Research and Applications. https://doi.org/10.1002/rra.4434.

Turney, E. K., **Goodrum, G.** C., Saunders, W. C., Walsworth, T. E., & Null, S. E. (2025). Comparing commonly used aquatic habitat modeling methods for native fish. Ecological Modelling, 499, 110909. https://doi.org/10.1016/j.ecolmodel.2024.110909.

Goodrum, G, & Null, SE. (2023). Reduced complexity models for regional aquatic habitat suitability assessment. JAWRA Journal of the American Water Resources Association. 2023; 59(1):107-126. https://doi.org/10.1111/1752-1688.13077.

Null SE, Farshid A, **Goodrum G**, Gray CA, Lohani S, Morrisett CN, Prudencio L, Sor R. A Meta-Analysis of Environmental Tradeoffs of Hydropower Dams in the Sekong, Sesan, and Srepok (3S) Rivers of the Lower Mekong Basin. Water. 2021; 13(1):63. https://doi.org/10.3390/w13010063.

REPORTS AND TECHNICAL PUBLICATIONS

Goodrum, G, E Gwilliam, L Palacios, K Raymond. 2019. Status of climate and water resources at Gila Cliff Dwellings National Monument: Water year 2017. Natural Resource Report. NPS/SODN/NRR—2019/1890. National Park Service. Fort Collins, Colorado

McIntrye, C, K Gallo, E Gwilliam, JA Hubbard, J Christian, K Bonebrake, **G Goodrum**, M Podolinsky, L Palacios, B Cooper, M Isley. 2018. Springs, seeps, and tinajas monitoring protocol: Chihuahuan and Sonoran Desert Networks. Natural Resource Report. NPS/CHDN/NRR—2018/1796. National Park Service. Fort Collins, Colorado

PRESENTATIONS

SE Null, **G Goodrum***, W Bosen, M Quinn, A Willis, S McClain. December 2024. Dam Removal as a Strategy for Climate Resilience [Abstract ID: 1581288]. American Geophysical Union Fall Meeting. Washington, DC.

SE Null*, **G Goodrum**, S Pineda, E Turney, G Sancho-Juarez, C Morrisett, C Gray, A Farshid. December 2023. Reservoir storage variability and volatility in the Western USA [Abstract ID: 1448656]. American Geophysical Union Fall Meeting. San Francisco, CA.

Goodrum, G* and SE Null. July 2023. Optimizing Water Management for Water Supply and Fish Habitat in the Bear River Basin. American Water Resources Association (AWRA) Summer Conference. Denver, CO.

Goodrum, G* and SE Null. August 2022. Improving Fish Habitat Representation for Water Management Modeling [Abstract ID: 494]. American Fisheries Society Annual Meeting. Spokane, WA.

Goodrum, G*. June 2022. Modeling Aquatic Habitat Suitability and Connectivity in Utah Rivers Workshop. Principal Organizers and Presenter. Utah Division of Wildlife Resources. Salt Lake City, UT.

Goodrum, G* and SE Null. December 2020. Fishing for the big picture: Aquatic habitat representation at large spatial scales [Abstract ID: 711941]. American Geophysical Union Fall Meeting. San Francisco, CA.

Goodrum, G*. November 2019. Improving aquatic habitat representation in Utah using large spatial scale environmental datasets. US Forest Service Region 4 Soil, Water, Air, Fisheries, Aquatics, and Wildlife Workshop. Ogden, UT.

Null, SE*, S Lohani, L Prudencio, **G Goodrum**, C Morrisett, CA Gray. October 2019. Environmental effects of dam construction in the Se Kong, Se San, and Sre Pok (3S) Rivers of the Lower Mekong Basin: A literature review. American Fisheries Society and The Wildlife Society Joint Annual Conference. Reno, NV.

* = Presenting author

TRAININGS AND CERTIFICATIONS

Current Wilderness First Responder + CPR + Wilderness Anaphylaxis Training

2022	Planning and Executing Successful Rotenone & Antimycin Projects, American Fisheries Society. Logan, UT.
2021	Enabling Interdisciplinary and Team Science Workshop, American Institute of Biological Science (AIBS). Logan, UT.
2019	Spatial statistical modeling on stream networks workshop, US Forest Service Rocky Mountain Research Station. Boise, ID.
2016	Field water quality methods for surface water, US Geological Survey. Devner, CO.

AWARDS AND HONORS

Student Travel Award, American Fisheries Society Annual Meeting, 2022
Melvin E. Hecht Award for Overall Excellence, University of Arizona, 2009

SERVICE AND OTHER PROFESSIONAL ACTIVITIES

2022-Present	Reviewer, Journal of the American Water Resources Association (JAWRA)
2021-2022	USU Ecology Center, Graduate Student Committee Member
2020-2021	QCNR Graduate Student Council, WATS Department Representative
2019-2020	QCNR Graduate Student Council, Ecolunch Coordinator

PROFESSIONAL SKILLS

- **Science communication:** Experience communicating scientific findings and project status through peer-reviewed publications, reports to agency and funding partners, and public presentations to scientific, practitioner, and public audiences.
- **Collaboration:** Experience collaborating with academic partners, federal and state agencies (US National Park Service, Fish and Wildlife Service, Bureau of Land Management, Utah Divisions of Wildlife Resources and Water Resources), and non-governmental organizations (American Rivers, Resources Legacy Fund).
- **Leadership**: Extensive experience organizing 4- to 6-person teams to accomplish organizational objectives over annual time periods including field-based data collection, data analysis, and report generation.
- **Mentorship**: Successful mentorship of 15+ agency interns with US National Park Service and undergraduate research assistants at Utah State University. Extensive teaching experience including lecturing and course material development for both university courses and practitioner professional training (in partnership with the American Fisheries Society).

- **Spatial analysis and cartography**: ArcGIS, R spatial, spatial statistical network modeling (SSN), cartographic design and map publication
- **Hydrological modeling**: WEAP, HEC-RAS
- **Optimization modeling**: General Algebraic Modeling Software (GAMS), Python
- **Computer and statistical programming**: R, Python, GitHub
- **Data management**: SQL Server, MS Access, data model design
- **Medical**: Wilderness First Responder
- **Wildland Fire**: Firefighter Type II (2012), READ Fireline Resource Advisor (2016)
- **Dam/Instream Barrier Assessment**: Fish passage assessment, remote/GIS barrier detection, hydroeconomic valuation, removal cost estimation, dam/barrier removal optimization, stream network connectivity modeling
- **Stream Field Techniques**: Water quality sampling, water temperature monitoring, flow monitoring, longitudinal and cross-sectional profiling, sediment sampling, macroinvertebrate sampling (kick net, drift net)
- **Fish Field Techniques**: Electrofishing (backpack, raft), fish netting (seine, trammel, gill, hoop), fish population monitoring (passive integrative transponder, visible implant elastomer), fish diets
- **Vegetation Field Techniques**: belt transect, nested plot, community mapping, dichotomous keying, fuel monitoring, burn severity, biological soil crust cover and identification

REFERENCES

Sarah Null, Professor
Utah State University
5210 Old Main Hill, Logan, UT 84322
sarah.null@usu.edu
435.881.9985 (Sarah is on sabbatical in Argentina until August 2025 and unavailable via phone)

Tim Walsworth, Assistant Professor
Utah State University
5210 Old Main Hill, Logan, UT 84322
timothy.walsworth@usu.edu
435.881.9985

Don Wiley, Aquatic Habitat/Migration Initiative Coordinator
Utah Division of Wildlife Resources
1594 W North Temple, Salt Lake City, UT 84116
donwiley@utah.gov
801.368.8664