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Surface Water Hydrology Within the Great Salt Lake Basin

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SURFACE WATER HYDROLOGY WITHIN THE GREAT SALT LAKE BASIN

by

Madeline F. Merck

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

of

DOCTOR OF PHILOSOPHY

in

Civil Engineering

Approved:

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UTAH STATE UNIVERSITY
Logan, Utah

2023

This work is dedicated to Emrys. You are my sunshine.

ABSTRACT

Surface Water Hydrology within the
Great Salt Lake Basin

by

Madeline F. Merck, Doctor of Philosophy

Utah State University, 2023

Major Professor: Dr. David G. Tarboton
Department: Civil Engineering

The Great Salt Lake (GSL) and its tributaries are ecologically and economically important resources for Utah. Lake uses are heavily influenced by salinity and lake level and, similarly, river uses by streamflow quantity. Currently, the GSL Basin is experiencing changes that affect tributary inflows, lake level, and salinity. While these changes are broadly understood from prior studies, there remain uncertainties related to trends in tributary inflows, which affect lake level, and the distribution of salinity, including changes in the deep brine layer as flows through the causeway fluctuate. This work addresses important gaps in our understanding of the lake and the changes it is undergoing to further the comprehension of hydrology within the GSL Basin in support of better management.

First, I examined the distribution of salinity and salt mass within GSL. Existing measurements from multiple agencies were aggregated to quantify the variability in salinity and the intermittent presence of the deep brine layer, which occurs only when causeway exchange supports flow from the north to the south arms. I found that the overall mass of salt in the lake is declining and quantified this in terms of mineral extraction records and historical density measurements.

Second, I estimated the historical magnitude of human consumptive water use within the GSL Basin based on the GSL water surface elevation. Lake volume changes and estimates of evaporation and precipitation were used to quantify the inflows corresponding to lake level fluctuations. The trends in these inflow estimates were used to quantify basin wide human consumptive water use to be upwards of 2.3 km^3/yr and the current lake level decline associated with this estimate to be as much as 4.5 meters.

I also developed a learning module targeting undergraduate hydrology students to advance innovative approaches in hydrologic education. While this project does not directly relate to the GSL, it enhances student learning of hydrologic processes within the GSL Basin. I developed content centered on case-based, data- and simulation-driven learning of the fundamentals of hydrology, rainfall-runoff processes, and engineering design for an online module focused on a detention basin at the mouth of a canyon in the GSL Basin.

Overall, this dissertation has contributed knowledge on the salinity, deep brine layer and declining salt mass in GSL due to mineral extraction. It has also provided a lake volume based water balance estimate of consumptive water use extending back prior to the period when streamflow was measured. These contributions provide important scientific information about the lake that can inform decision making on water management and efforts to restore the lake to healthy levels.

(162 pages)

PUBLIC ABSTRACT

Surface Water Hydrology within the Great Salt Lake Basin

Madeline F. Merck

The Great Salt Lake (GSL) and its tributaries are ecologically and economically important resources for Utah. It is a highly saline lake, with salinity that is several times saltier than the ocean. Lake uses are heavily influenced by its salinity and lake level and, similarly, river uses by its streamflow quantity. Currently, the GSL Basin is experiencing changes that affect tributary inflows, lake level, and salinity. For my dissertation and in support of better lake management, I addressed important gaps in our understanding of the lake and the changes it is undergoing.

Chapter 2 is an examination of the distribution of salinity and salt mass within the lake. Existing measurements from multiple agencies were aggregated to quantify the variability in salinity and the intermittent presence of a deep brine layer, which occurs only with causeway flow from the north to the south arms. I found that the overall mass of salt in the lake is declining and quantified this in terms of mineral extraction records and historical density measurements.

Chapter 3 estimates the historical magnitude of human consumptive water use within the basin. Lake volume changes and evaporation estimates were used to quantify inflows to the lake corresponding to changes in lake level. The trends in these inflow estimates were used to quantify basin wide human consumptive water use to be upwards

of 2.3 km^3/yr and the current lake level decline associated with this estimate to be as much as 4.5 meters.

Chapter 4 presents a learning module targeting undergraduate hydrology students that was developed to advance innovative approaches in hydrologic education. While this project does not directly relate to the GSL, it enhances student learning of hydrologic processes within the GSL Basin. The newly developed content is centered on case-based, data- and simulation-driven learning of the fundamentals of hydrology, rainfall-runoff processes, and engineering design for an online module focused on a detention basin at the mouth of a canyon in the GSL Basin.

Overall, this dissertation has contributed knowledge on the salinity, deep brine layer and declining salt mass in GSL due to mineral extraction. It has also provided a lake volume based water balance estimate of consumptive water use extending back prior to the period when streamflow was measured. These contributions provide important scientific information about the lake that can inform decision making on water management and efforts to restore the lake to healthy levels.

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Thank you as well to my committee members, coauthors, research group colleagues, and the many others I have learned from along the way. I am lucky to have been surrounded by such hard-working people. You all are inspiring and kept me on my toes.

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Madeline F. Merck

CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

The Great Salt Lake (GSL) and its tributaries are important resources for Utah, both ecologically and economically. The hypersaline lake supports migratory birds and the commercial brine shrimp and mineral extraction industries; drinking water and agricultural irrigation supplies are enormously dependent on its rivers; and both the GSL and its tributaries are used for recreation. Lake uses are heavily influenced by salinity and lake level and, similarly, river uses by streamflow quantity. Currently, the GSL Basin is experiencing changes that affect tributary inflows, lake level, and salinity. While these changes are broadly understood from prior studies, there remain uncertainties related to trends in tributary inflows, which affect lake level, and the distribution of salinity, including changes in the deep brine layer (DBL) as flows through the causeway fluctuate.

In the first two studies for my dissertation, I addressed important gaps in our understanding of the lake and the changes it is undergoing. First, I examined the distribution of salinity and salt mass within GSL. In this study, I aggregated existing measurements from multiple agencies to quantify the variability in salinity and the intermittent presence of the DBL, which is often cited in concerns related to GSL salinity and water quality. Second, I estimated the historical magnitude of depletions for GSL level using lake volume changes and evaporation estimates to quantify the inflows corresponding to lake level fluctuations. The trends from these inflow estimates were then compared with available information on development and depletions.

I also addressed advancements in hydrology education through development of learning material targeting undergraduate hydrology students. For this project, I developed content centered on case-based, data- and simulation-driven learning of hydrology for an online module focused on the detention basin at the mouth of Dry Canyon near Logan, Utah. The module enables students to develop mathematical modeling skills while also developing knowledge of the fundamentals of hydrology, rainfall-runoff processes, and engineering design. While this third project does not directly relate to the GSL, it enhances student learning of hydrologic processes within the GSL Basin. All three projects fit into my goal of furthering the understanding of hydrology within the GSL Basin, in terms of research and education, in support of better management.

Objectives and hypotheses

Three objectives were addressed in this dissertation. Each is described below.

Objective 1: Improve the understanding of the salinity distribution within GSL across space and time and the influence of flow through the causeway on the salinity distribution.

I hypothesized that (a) the DBL is caused by flow of dense brine from the north arm into the south arm and thus its presence and strength will be aligned with conditions where north to south flow occurs; (b) exchange through the causeway is needed to strengthen the DBL and that weakening of the DBL occurs when north to south flow is non-existent for long periods; and (c) when flow through the causeway does not exist, north to south seepage through causeway fill is not enough flow to create a DBL in the south arm if one is not already present.

Objective 2: Establish the magnitude of human water use depletions over the historical lake level record.

I hypothesized that (a) there has been a downward trend in tributary inflow to GSL since settlers arrived in 1847; (b) the downward trend is due to anthropogenic influence and has resulted in significantly lower lake levels; and (c) the uncertainty in the tributary inflow estimates (based on mass balance) due to the assumptions of constant evaporation and precipitation depths is relatively insignificant over the historical record of lake levels.

Objective 3: Advance education in hydrology as a multi-faceted discipline by creating a visual, case-based, data- and simulation-driven learning experience.

I expected to find that (a) students are able to effectively learn system processes, tools, and software included in an online module and the connection between these individual processes within the context of a real-world problem; (b) this new hydrologic learning module is adaptable to traditional classroom settings; (c) student feedback will appropriately and effectively guide the evolution of the module and aid in its ability to be more effective.

The research that stemmed from these objectives led to three accomplishments: 1) new insights regarding the decline of overall salt mass in GSL, 2) a novel approach to estimating the historical human consumptive water use within the GSL Basin and its effect on the lake, and 3) perceptions and considerations for instructors when designing hydrology course content. These outcomes will provide new understanding on hydrologic processes in the GSL Basin and advance innovative approaches in hydrologic education.

Background on the Great Salt Lake

The high concentrations of minerals and salts in Great Salt Lake (GSL) are not only characteristic features of its water but also one of the lake's greatest economic assets. The annual regional economic value of the mineral extraction industry is estimated to be $1.13 billion and supports 5,368 jobs; commercial brine shrimp production is estimated to be $56.7 million and supports 574 jobs (Bioeconomics, 2012). The brine shrimp are also a great ecological asset to the lake as a major food source for migratory birds. As part of the Western Hemisphere Shorebird Reserve Network, the lake and surrounding wetlands support upward of 5 million birds during the yearly migration (WHSRN, 2016). For some species, the GSL is the only stop in North America during their journey (Aldrich & Paul, 2002).

GSL water has an extremely high salt concentration, several times saltier than the ocean. The hypersaline water is prone to stratification, resulting in lesser concentrations of salt and other constituents at the lake's surface and much higher concentrations at the lake's bottom, which is often referred to as the DBL. To further complicate matters, the GSL is divided into two distinct arms by an earthen railroad causeway. The south arm, or Gilbert Bay, receives approximately 95% of the lake's freshwater surface inflow from three major rivers entering along the southeastern shores (Loving et al., 2000). In the north arm, or Gunnison Bay, freshwater input is limited to direct precipitation and intermittent runoff. Evaporation is the lake's only form of outflow from either arm, resulting in the high mineral and salt content of the water. These imbalances lead to an average salinity of the north arm that is currently twice that of the south arm (based on UGS data, 2023).

With its extremely high salinities and record low lake levels, the north arm can no longer support brine shrimp or brine fly populations (Barnes & Wurtsbaugh, 2015). Although the high salinities in the north arm aid in mineral extraction, the low lake levels make it more difficult to pump lake water to the mineral evaporation ponds for extraction. In fact, in 2014 Morton Salt dug a five-mile long canal in order to deliver brine from the now distant lake water to the salt ponds and processing plants (Wurtsbaugh et al., 2016).

Although the less saline south arm does not support fish, brine shrimp and brine flies flourish in most years (WHSRN, 2016), and the south arm is also home to MagCorp, a major producer of magnesium in North America. Furthermore, brine shrimp are considered a keystone species because they not only control phytoplankton but they are also a major food source for bird populations (Stephens, 1990; Aldrich and Paul, 2002). Laboratory studies suggest brine shrimp prefer salinities around 100 g/L. Although predation becomes a problem when salinities approach 50 g/L, maximum survival and growth for both brine shrimp and brine flies is thought to decrease at salinities above 125 g/L and below 25 g/L (Barnes & Wurtsbaugh, 2015). Therefore, changes in salinity, dissolved oxygen, and nutrients, especially at the surface of the water, can be harmful to the brine shrimp, brine fly, and algal blooms the shrimp feed on. Disruptions in the brine shrimp and brine fly populations propagate and result in disturbances further up the food chain, affecting migratory bird populations.

The south arm also includes the freshwater estuaries of Bear River and Farmington Bays. Both bays receive freshwater inflows and, therefore, have much lower salinity than the rest of the lake. When lake levels are at or above normal elevations (average ~4200 feet), these bays are commonly used for recreation and shorebird habitat. However, due to being relatively shallow areas of the lake, both bays are currently nearly dry, and the possibility of complete desiccation is a real threat. In addition, the freshwater ecosystems in these bays are especially fragile and struggle under low lake level conditions (Wurtsbaugh et al., 2016).

Another problem created by low lake levels is increased lakebed exposure, which increases the potential for dust pollution and related human health impacts. Dust storms have been known to be problematic in the eastern Great Basin due to sources like the Great Salt Lake Desert Dugway Proving Ground and Sevier Dry Lake (Hahnenberger and Nicoll, 2014). However, dust storms are increasingly coming from the exposed shores of the GSL as well (Hahnenberger and Nicoll, 2012). Recent work has also attributed significant dust from exposed GSL bed area with earlier snowmelt due to dust on snow albedo reductions (Lang et al., 2023). These issues are particularly worrisome and costly to mitigate due to the proximity of the GSL to Salt Lake City and the surrounding area, which is a growing metropolitan area.

The hypersaline lake and associated marshes within the GSL Basin are important for breeding and migrating shorebirds (IWJV, 2016). Within the Western Hemisphere Shorebird Reserve Network, the GSL ranks first in importance to shorebirds; ranked second is Oregon’s Lake Abert (IWJV, 2016). However, due to poor monitoring and management, Lake Abert’s low lake levels and high salinities have collapsed the lake’s ecosystem, destroying the brine shrimp and alkali fly populations and reducing shorebird use (Moore, 2016). Although the lakes share similar ecosystems, the GSL's ecology is now more complex due to the causeway dividing the lake into two waterbodies with distinct characteristics and ecologies. Recognizing the ecological and economic assets of the lake, Wurtsbaugh et al. (2016) noted that it would behoove Utah to protect its GSL and to learn from the undoing of lakes like Lake Abert, Owens Lake, and Lake Urmia, all of which have desiccated due to increased water withdrawals and consumptive use in their basins (Wurtsbaugh et al., 2016).

Lake volume, and therefore lake level, influences the concentration and distribution of salts, minerals, and other constituents of interest within the GSL which, in turn, impact lake ecology. Low lake levels are the result of reduced tributary inflows, which may be attributed to reduction in streamflow due to human consumptive water use or depletion. For this dissertation, depletion is defined as the net reduction in streamflow due to water use withdrawals but allowing for return flows. Low lake levels are of concern because they cause greater areas of exposed lakebed, difficulty accessing mineral extraction ponds, reduced water access for bird populations, reduced recreational use of the lake, and increased salinity. Increased salinity does aid in the evaporation process for mineral extraction; however, it reduces brine shrimp production. Therefore, tracking the quantity of GSL tributary inflows and the concentration and distribution of constituents of interest within the lake is important to management decisions.

Hydrology Education Overview

There have been increasing calls in recent years to make changes at the undergraduate level to better prepare students to apply mathematical modeling and critical thinking skills in general (Bordogna 1998; Radzi et al. 2009), and specifically in the field of hydrology and water resources engineering (e.g., Bourget 2006; CUAHSI 2010; Habib and Deshotel 2018; Howe 2008; Ledley et al. 2008; Merwade and Ruddell 2012; Wagener et al. 2010). Much of this is motivated by the perception that traditional approaches to teaching, focused on separate learning of distinct processes, do not provide a sufficiently holistic environmental and societal context for learning.

Hydrology is a multidisciplinary science that includes interconnected processes at varying scales within natural systems. Hydrology is also a rather new discipline. In fact, the first United States university department and degree program was only established in 1966 with the University of Arizona's Department of Hydrology and Water Resources (Ruddell and Wagener, 2015). Over the next few decades, several other universities around the world would offer hydrology degrees through varying departments (e.g., geography, physics, and engineering). Still, throughout the twentieth century, most hydrologists received early training through field practice and applied apprenticeship rather than formal education (Nash et al., 1990; Eagleson, 1991; NRC, 1991). However, by the 1990s, it was felt that development of core hydrology curriculum was stagnating due to the disparities of academia versus field training and the education paradigm of science versus engineering (Nash et al., 1990; Ruddell and Wagener, 2015). Up to that point, the development of hydrologic science had followed applications in engineering hydrology rather than led them. This resulted in advancements in hydrologic science being driven by engineering tasks that were narrow in scope rather than the underlying science (Eagleson, 1991; NRC, 1991). Recognizing this conflict, the community of hydrology educators began the search for a more holistic approach to hydrology education, which would incorporate science, engineering, and field experience (NRC, 1991).

As part of their review of the history of hydrology education, Ruddell and Wagener (2015) describe a recent shift in pedagogies to include internet-based data resources, modeling based activities, virtual trips, and gaming, among others. They write that one of the grand challenges of hydrology education in the twenty-first century is to "augment theoretical instruction with data and modeling driven cybereducation" (p. 5). Ruddell and Wagener argue that data and modeling driven cybereducation may be one of the best ways to teach complex systems and advocate for this type of instruction at the undergraduate as well as graduate levels. Integrating data and modeling driven cybereducation in hydrology courses requires the effective integration of technology, including cyberlearning resources, as well as mathematical modeling tasks. Traditional hydrology education looked at unit processes, prescriptive knowledge, idealized examples, and used textbook approaches. Opposed to this instructor-centered pedagogy of information conveyance, new approaches focused on constructivist or student-centered pedagogy of active exploration are being developed (Ruddell and Wagener, 2015). Changing the role of the instructor are the various new technologies that are being incorporated into learning, like the Internet, modeling, visualization, GIS, and Hydroinformatics, all easily accessible in today's classrooms. In addition, emerging phenomena like climate change began forcing the hand of approaches to solving applied problems.

The holistic, student-centered approach to education the community of hydrology educators was in search of also included the need for science-based instruction, real-world context, and problem-based learning. Active learning strategies that incorporate new technologies are instructional methods that suit this need. In 1991, Bonwell and Eison loosely defined active learning as learning strategies that include the element of “involving students in doing things and thinking about the things they are doing”. It is any instructional method that engages students in the learning process and leads to “better student attitudes and improvements in students’ thinking and writing” (Bonwell and Eison, 1991).

Significance

This dissertation addresses important gaps in our understanding of GSL and the changes it is undergoing. While these changes are broadly understood from prior studies, questions and uncertainties remain. Further understanding of these hydrologic processes within the GSL Basin is necessary to support the best possible management of the basin and its terminal lake. For example, with the knowledge gained from this work, lake management can better quantify the impact of salt mass transfer and changing salinities in each arm of the GSL as the causeway berm is used to adaptively manage the lake, policymakers can more accurately and confidently assess quantity and attribution of lake level decline when making difficult decisions about water use within the GSL Basin, and educators can inspire the modern engineering and science student to learn basic hydrologic theory and concepts through the use of new online publicly available free learning material.

This dissertation is presented as three papers, each submitted for publication separately to peer reviewed journals. Chapter 2, Merck and Tarboton (2023), contributed to the understanding of the distribution of salt and the occurrence and extent of the DBL by establishing a time series of salt concentration within GSL with respect to depth, delineating the DBL in time and space, comparing salinity at the lake's surface and at depth, and improving the understanding of salinity responses to causeway flow changes The paper in chapter 3 established the magnitude of depletions over the historical record and contributed to the understanding of how the depletions affect GSL. Chapter 4, Merck et al. (2021), applied a student-centered approach by including hands-on and active learning techniques through the use of the online educational module.

References

Aldrich, T.W., D.S. Paul. 2002. Avian ecology of Great Salt Lake. Great Salt Lake: An overview of change (J.W. Gwynn, ed). Special publication of the Utah Dept. of Natural Resources.

Barnes, B.D., & Wurtsbaugh, W.A. (2015), The effects of salinity on plankton and benthic communities in the Great Salt Lake, Utah, USA: a microcosm experiment. Canadian Journal of fisheries and Aquatic Sciences, 72(6):807–17.

Bioeconomics, Inc. Economic significance of the Great Salt Lake to the State of Utah. Prepared for State of Utah Great Salt Lake Advisory Council. 2012. Available online: https://documents.deq.utah.gov/water-quality/standards-technical-services/great-salt-lake-advisory-council/Activities/DWQ-2012-006863.pdf (accessed on 1 March 2023).

Bonwell, C.C., J.A. Eison. 1991. Active Learning: Creating Excitement in the Classroom. 1991 ASHE-ERIC Higher Education Report No. 1, George Washington University, Washington, DC.

Bourget, P. G. (2006). Integrated water resources management curriculum in the United States: Results of a recent survey. Journal of Contemporary Water Research & Education, 135(1), 107–114.

Consortium of Universities for the Advancement of Hydrologic Science, Inc. (CUAHSI). (2010). Water in a dynamic planet: A five-year strategic plan for water science. Cambridge: CUAHSI.

Eagleson, P.S. 1991. Hydrologic Science: A Distinct Geoscience. Reviews of Geophysics, 29(2): 237-248.

Habib, E., & Deshotel, M. (2018). Towards broader adoption of educational innovations in undergraduate water resources engineering: Views from academia and industry. Journal of Contemporary Water

Hahnenberger, M. & Nicoll, K. (2012), Meteorological characteristics of dust storm events in the eastern Great Basin of Utah, U.S.A. Atmospheric Environment, 60:601-612. doi:10.1016/j.atmosenv.2012.06.029

Hahnenberger, M. & Nicoll, K. (2014), Geomorphic and land cover identification of dust sources in the eastern Great Basin of Utah, U.S.A. Geomorphology, 204:657-672. doi:10.1016/j.geomorph.2013.09.013

Howe, C. W. (2008). A creative critique of U.S. water education. Journal of Contemporary Water Research & Education, 139(1), 1–2.

IWJV, Intermountain West Joint Venture. 2016. Retrieved from www.iwjv.org

Lang, O. I., Mallia, D., & McKenzie Skiles, S. (2023). The shrinking Great Salt Lake contributes to record high dust-on-snow deposition in the Wasatch Mountains during the 2022 snowmelt season. Environmental Research Letters, 18(6): 064045, http://doi.org/10.1088/1748-9326/acd409.

Ledley, T. S., Prakash, A., Manduca, C. A., & Fox, S. (2008). Recommendations for making geoscience data accessible and usable in education. Earth & Space Science News, 89(32), 291.

Loving, B.L.; Waddell, K.M.; Miller, C.W. Water and Salt Balance of Great Salt Lake, Utah, and Simulation of Water and Salt Movement through the Causeway, 1987–98; U.S. Geological Survey: Salt Lake City, UT, USA, 2000. Available online: https://pubs.usgs.gov/wri/2000/4221/report.pdf (accessed on 12 August 2022).

Merck, M.F., Gallagher, M.A., Habib, E., and Tarboton, D.G. 2021. Engineering students' perceptions of mathematical modeling in a learning module centered on a hydrologic design case study. International Journal of Research in Undergraduate Mathematics Education 7: 351-377. https://doi.org/10.1007/s40753-020-00131-8.

Merck, M.F., and Tarboton, D.G., 2023. The Salinity of the Great Salt Lake and Its Deep Brine Layer. Water 15:1488 DOI: 10.3390/w15081488.

Merwade, V., & Ruddell, B. L. (2012). Moving university hydrology education forward with community-based geoinformatics, data and modeling resources. Hydrology and Earth System Sciences, 16(8).

Moore, M. J. (1993). Three types of interaction. In K. Harry, M. John, & D. Keegan (Eds.), Distance education: New perspectives (pp. 19–24). Routledge.

Nash, J.E., P.S. Eagleson, J.R. Phillip, W.H. van der Molen. 1990. The education of hydrologists. Report of the IAHS-UNESCO Panel, Hydrological Sciences Journal, 35(6):597-607.

National Research Council Committee on Opportunities in the Hydrologic Sciences (COHS), (1991), Opportunities in the Hydrologic Sciences, Editor, P. S. Eagleson, National Academy Press, Washington, D.C., http://www.nap.edu/catalog.php?record_id=1543.

Radzi, N. M., Abu, M. S., & Mohamad, S. (2009). Math-oriented critical thinking skills in engineering. 2009 International Conference on Engineering Education (ICEED). https://doi.org/10.1109/ICEED.2009. 5490579.

Ruddell, B. L., & Wagener, T. (2015). Grand challenges for hydrology education in the 21st century. Journal of Hydrologic Engineering, 20(1), [A4014001]. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000956.

Stephens, D.W. 1990. Changes in lake levels, salinity and the biological community of Great Salt Lake (Utah, USA), 1847-1987. Hydrobiologia, 197: 139-146.

Wagener, T., Sivapalan, M., Troch, P. A., McGlynn, B. L., Harman, C. J., Gupta, H. V., Kumar, P., Rao, P. S. C., Basu, N. B., & Wilson, J. S. (2010). The future of hydrology: An evolving science for a changing world. Water Resources Research, 46(W05301). https://doi.org/10.1029/2009WR008906.

Western Hemisphere Shorebird Reserve Network (WHSRN). Conserving Shorebirds and Their Habitat through a Network of Key Sites across the Americas. Available online: www.whsrn.org (accessed on 1 March 2023).

Wurtsbaugh, W. A., Miller, C., Null, S. E., Wilcock, P., & Hahnenberger, M. (2016), Impacts of Water Development on Great Salt Lake and the Wasatch Front. Logan, Utah: Utah State University.

CHAPTER 2

THE SALINITY OF THE GREAT SALT LAKE AND ITS DEEP BRINE LAYER[1]

Abstract

The Great Salt Lake is a highly saline terminal lake with considerable fluctuations in water surface elevation and salinity. The lake is divided into two arms by a railroad causeway. River inflows enter the larger south arm, while the north arm only receives minimal surface runoff. Evaporation from both arms and limited exchange of water and salt through causeway openings result in complex water and salinity processes in the lake. The north arm is typically homogeneous and close to saturation. The south arm is typically stratified with periodic occurrences of a deep brine layer. This paper analyzes the lake's long-term historical salinity and water surface elevation data record. Its purpose is to better document the movement of salt and changes to salinity in time and space within the lake and the occurrence and extent of its deep brine layer. This work is important because of the lake's salinity-dependent ecosystem and industries as well as the role played by the deep brine layer in the concentration of salt and contaminants. We documented that the deep brine layer in the south arm is intermittent, occurring only when causeway exchange supports flow from the north to the south arms. We found that the overall mass of salt in the lake is declining and quantified this in terms of mineral extraction records and historical density measurements.

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[1] Merck, M.F., and Tarboton, D.G., 2023. The Salinity of the Great Salt Lake and Its Deep Brine Layer. *Water 15*:1488 DOI: 10.3390/w15081488.

1. Introduction

The high concentrations of minerals and salts in the Great Salt Lake (GSL) are not only characteristic features of this terminal lake's water but also its greatest economic and ecologic assets. The distribution of constituents and contaminants within the GSL impact the lake's ecology and economy. Changes in salinity, dissolved oxygen, nutrients, and contaminants, especially when entrained into the upper layers of the water, can be harmful to brine shrimp, brine fly, and algae the shrimp feed on [1]. These disruptions propagate up the food chain, affecting migratory bird populations [2]. Changes in salinity can also affect mineral extraction, which is an important economic use of the lake. While high salinity makes mineral extraction easier, the lower lake water surface elevation (WSE) associated with higher salinity requires more extensive and expensive mineral extraction brine intakes [3,4]. The total mass of salt in the GSL has been decreasing [5–7]. The findings reported here show that the mineral extraction industry is removing much more salt than is added through river and other inputs.

The hypersaline water in the GSL is several times saltier than the ocean and is prone to stratification [8], resulting in lower concentrations of salt and other constituents at the lake's surface and much higher concentrations at the lake's bottom. These higher concentrations at the lake's bottom are often referred to as the deep brine layer (DBL) [1,5,9–12]. To further complicate matters, the GSL is divided into two distinct arms by an earthen railroad causeway, which was constructed in 1959 by the Union Pacific Railroad Company (Figure 1). Gilbert Bay, the lake's south arm, receives 95% of the freshwater input from three major rivers entering along the southern and eastern shores [5].

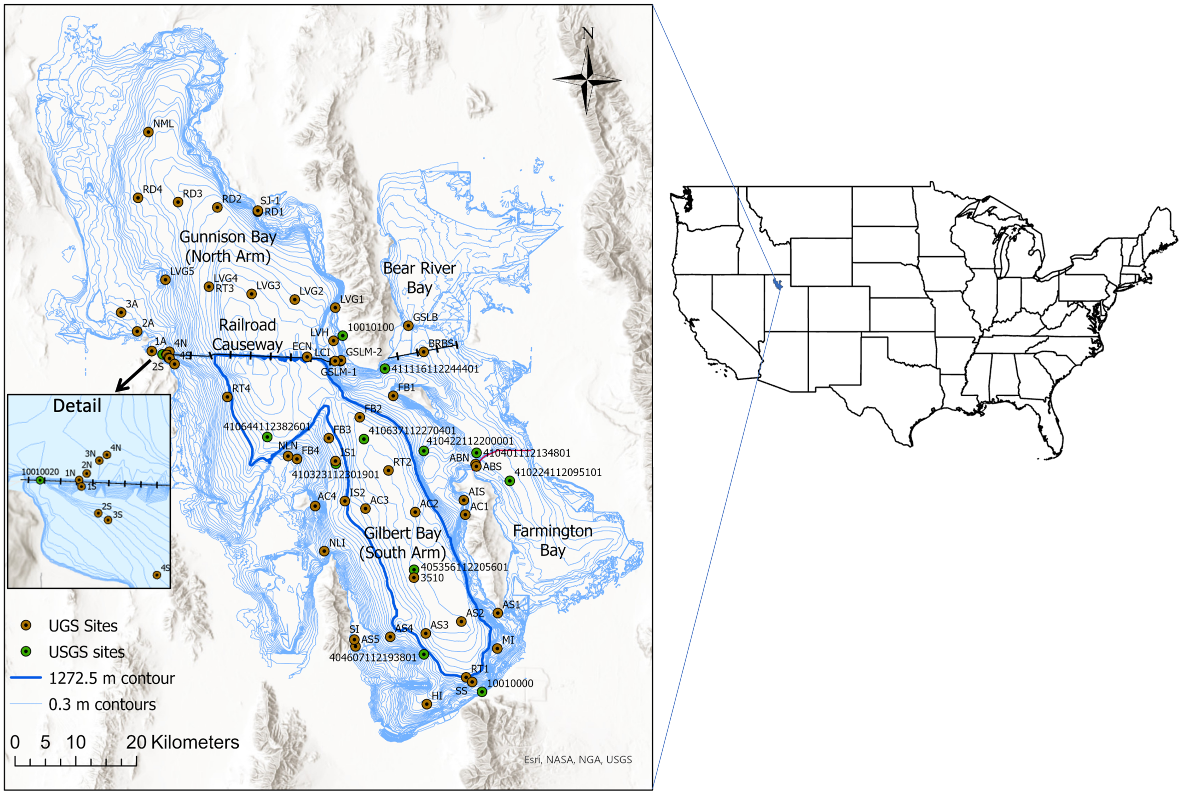

Figure 1. Locations of historical UGS (orange) and USGS (green) sampling sites within the GSL. Light blue lines are 0.3 m contours. Dark blue line is the 1272.5 m contour, within which the DBL can be found. Location of GSL in Northern Utah, USA, is shown.

In Gunnison Bay, the lake's north arm, water input is limited to direct precipitation and intermittent runoff. Evaporation removes water from the lake, but not salt, and is the only form of outflow from either arm, resulting in the high mineral and salt content of the lake water. The imbalances in inflow to each arm lead to an average salinity of the north arm that is as much as twice that of the south arm.

Over the last several decades, various state and federal agencies have collected data on salinity, temperature, density, and other GSL lake water constituents at multiple lo-cations in the lake (Figure 1). Most of the data collection started in 1966 shortly after construction of the causeway. Although the Utah Geological Survey (UGS), United Stated Geological Survey (USGS), and other organizations (both public and private) have monitored salinity in the GSL since the 1960s, the variability in the distribution of salinity and the occurrence and extent of the DBL within the lake over the period of record are not fully known. Yang et al. [11] noted that stratification in the south arm is associated with bi-directional exchange flow through the causeway, observing that destratification occurred within six months of causeway culvert closures in 2013. This has ramifications of displacing contaminants, such as selenium and methylmercury [10,13,14], which can negatively impact the GSL's ecology. In particular, the DBL stratification acts as a cap that prevents oxygen from the overlying mixed layer coming into contact with sediment organic matter on the lakebed, which drives the accumulation of methylmercury in deep waters. A more recent study [15] examined salt mass transfer and changing salinities in each arm of the GSL for the decade centered on 2016, when a new causeway breach and salinity control berm were opened. While their work informs immediate adaptive management, there is a need for a more holistic analysis of GSL salinity over the full record. Our paper addresses this need.

This paper presents an analysis and visualization of the full historical salinity data record for the GSL. Its purpose is to examine the distribution of salinity and the occurrence and extent of the DBL across space and time for use in future planning and management of the lake. Specifically, based on our analysis of all available data over an extended period, we are interested in more comprehensively understanding the following questions:

1. How does salinity change within the lake?
2. How does the DBL fluctuate in time, space, and concentration?
3. How does surface salinity relate to average salinity and the DBL?

4. How does salt move between the north and south arms?

5. How has the total salt mass changed over time?

While prior work has, to some extent, addressed some of these questions, the work presented here more fully documents the changes in salinity, stratification, and the intermittency of the DBL, and it sharpens our understanding of the answers to these questions.

2. Materials and Methods

Data used in our analysis include lake bathymetry, WSE, salinity and density, water withdrawals for mineral extraction, and west desert pumping and return flows. Salinity calculations were based on the Naftz et al. [16] equation of state (Equation (1), Section 2.3), and salt mass was determined using salinity and lake volume.

2.1. Bathymetry

A digital elevation model (DEM) was prepared by combining multiple elevation datasets into one contiguous DEM for the GSL and surrounding area. In general, elevations above 1280 m (4200 feet) were derived from the 10-meter National Elevation Dataset (NED) DEM, which was downloaded from the Utah Automated Geographic Reference Center in 2010. Elevations at and below 1280 m (4200 feet) came from a DEM representing the bathymetry of the entire lake, which was obtained from BIO-WEST, Inc. and was derived from the following data sources:

1. North and south arm contours from USGS [17,18];

2. Farmington Bay contours from Baskin [19] and modified by BIO-WEST in 2010, including minor contour manipulation and the introduction of a 1280 m (4200 foot) contour at the south end of the bay;

3. Bear River Bay survey by Hansen & Associates [20] under a contract with BIO-WEST.

For consistency with the DEM from BIO-WEST, the NED DEM heights were con-verted from their native North American Vertical Datum 1988 (NAVD88) elevations to National Geodetic Vertical Datum (NGVD29) by subtracting 0.97 m prior to merging the two.

DEMs for areas within the lake were created using tools in ArcGIS [21]. First, triangular irregular networks were created from the bathymetric contours utilizing vertices as mass points. Then, the ArcGIS Mosaic to New Raster tool was used to merge bathymetric DEMs with the upland DEM of the area surrounding the lake. This was completed such that bathymetric values would replace the upland values at and below 1280 m (4200 feet). Finally, another mosaicking process was performed to fix minor imperfections and fill "no data" values at the edges of adjoining DEMs. The resulting DEM was clipped approximately 5 km beyond the 1287.75 m (4225 foot) contour. The volume and area of each arm of the lake were then obtained in 0.15 m (0.5 foot) elevation increments using the completed DEM as input to the Surface Volume tool in ArcGIS. The resulting DEM is stored in HydroShare [22]. The volumes and areas used are also in HydroShare [23]. This paper used the total volume in each arm, including areas now separated into mineral extraction evaporation ponds because, at the times the lake was high, these pond areas were effectively part of the lake due to either being breached or not yet being constructed.

2.2. Water Surface Elevation Data

GSL lake WSE data are available through the USGS National Water Information System (NWIS) website (USGS Site Numbers 10010000 and 10010100, in https://maps.waterdata.usgs.gov/mapper (accessed on 1 March, 2013). The earliest WSE was recorded for the GSL on October 18, 1847. North arm WSE records start on 15 April 1966, nearly seven years after the causeway was constructed. Therefore, it is necessary to use the south arm WSE as a close proxy for the time between 1959, when the lake was divided, and 1966, when measurement of the north arm WSE began. The average monthly lake WSE for each arm was calculated on the first day the month as the average of the previous month.

2.3. Water Sample Data

Measured and recorded point sampling data from UGS and USGS include depth, density, temperature, and many other lake water constituents and characteristics. Lake water samples were collected with varying frequency at 70 sites (Figures 1–3) from 1966 to present. UGS sampling began in 1966 and is represented by 58 sites. These data are found in the Great Salt Lake Brine Chemistry Database and are available through the UGS website (https://geology.utah.gov/map-pub/data-databases/ (accessed on 1 March, 2013). USGS sampling began in 1995 and is represented by 12 sites. These data are available through the NWIS website (https://maps.waterdata.usgs.gov/mapper (accessed on 1 March 2013) using the site numbers from Figures 1 and 2.

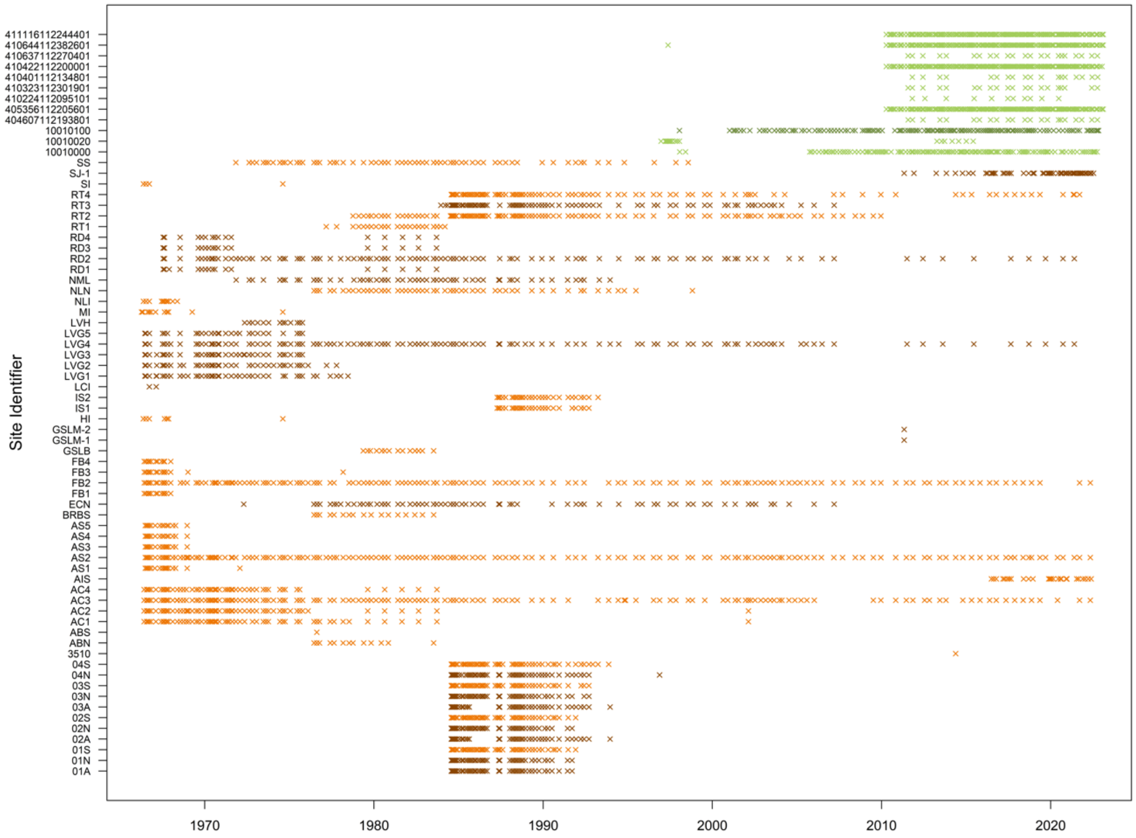

Figure 2. Timeline indicating when the GSL was sampled over the historical record, from 1966 to early 2023, using UGS north arm (dark orange), UGS south arm (light orange), USGS north arm (dark green), and USGS south arm (light green) sites. Each x represents one sampling event.

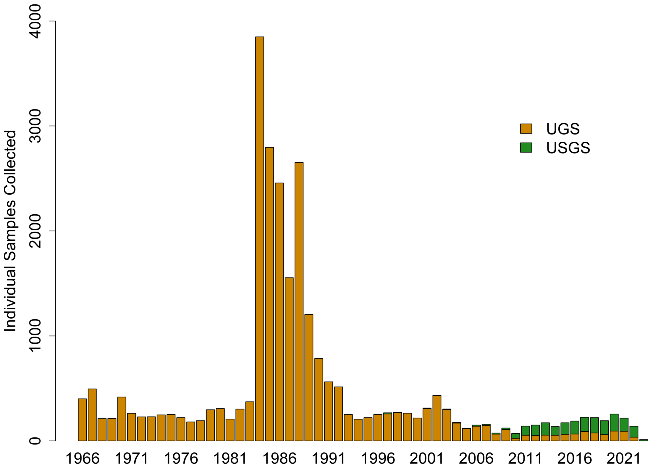

Figure 3. Annual count of individual UGS (orange) and USGS (green) samples over the historical record. Samples taken at different depths at a single site were counted separately.

Some of the UGS and USGS sample sites have been measured very sporadically, while others have been measured more frequently and therefore provide a more continuous record (Figure 2). Of the 70 sites, only one (AS2, Figure 2) has been sampled every year of the record up through 2022. UGS performed a great deal of sampling early on after the causeway was constructed and especially during the flooding in the mid-1980s, but it appears as though USGS has become the primary sampling agency in more recent years (Figures 2 and 3).

2.4. Salinity

Water density is temperature and salinity dependent, and it is common for salinity to be calculated from density and temperature measurements. The GSL Salinity Advisory Committee (SAC) was convened in 2018 by the Utah Division of Forestry, Fire and State Lands and the Utah Division of Water Quality. The committee comprised a group of scientists and stakeholders. One of its first tasks was to create a standard operating procedure (SOP) for measuring and reporting GSL water density and to establish a standard for calculating and reporting GSL salinity in weight per volume units. These SOPs were completed and adopted by UGS and USGS in 2020 [24]. The SOP includes the following definitions:

“Water Density: A measure of the mass (grams) per unit volume of water (cubic centimeter) including all solutes (g/cm3). Water density varies with temperature and total dissolved solids (TDS).”

“Salinity: A measure of the concentration of all solutes dissolved in water. Solutes in GSL water are unique and difficult to accurately measure; GSL salinity is typically defined as the mass of dissolved solids (or TDS) in grams per liter of water (g/L)." [24] (p. 1)

The GSL SAC SOP states that "measured densities of water samples collected from the GSL are used to compute the salinity of each sample" [24] (p. 1) using the following equation of state developed by Naftz et al. [16], which is specific to GSL waters.

$$\rho - \rho_o = 184.01062 + 1.04708S - 1.21061T + 0.000314721S^2 + 0.00199T^2 - 0.00112ST, \qquad (1)$$

where ρ = density of the water sample (kg/m3); ρ_o = density of pure water (kg/m3); S = conductivity salinity (g/L); and T = water temperature (K), which was taken as 20 °C (293.15 K) for all salinity calculations in this paper. Following Naftz et al. [16], density of pure water, o, was calculated using Spieweck and Bettin [25], resulting in ρ_o = 998.2031 kg/m3 (0.9982031 g/cm3) at 20 °C.

The bulk of the data in the historical record is from the time before the GSL SAC SOP was adopted and there is variability between UGS and USGS in how lake water samples were collected, which lake water constituents were measured, and how these measurements were performed and recorded. Therefore, the measurements used to determine salinity varied depending on measurement availability. We have included additional details on this in the supplementary material.

Additional preparation of both the UGS and USGS datasets included correcting obvious typos (e.g., 4110 foot versus 4210 foot elevations) and changing non-numeric measurements to numeric values (e.g., "near surface" to a depth of 0 m). Lake bottom elevation at each sample site was determined using the latitude and longitude of the measurement site together with lake bathymetry. The elevation of each sample was computed using lake WSE in the corresponding arm at the time of sampling minus the sample depth recorded with the observation.

2.5. Average Dissolved Salt Mass and Average Salinity

Average dissolved salt mass and average salinity were calculated using each sample at a single site on a given date for the corresponding arm of the lake assuming horizontal homogeneity (following [5,26]) but accounting for vertical variability (Figure 4). Calculations were only performed when 3 or more measurements were recorded at a particular sample site on the given date. To calculate the average dissolved salt mass of an arm of the GSL on a given date, each measurement at a fixed depth was taken to represent the layer of water closest in depth to that measurement. Bathymetry and lake WSE were used to estimate the volume for each layer. Specifically, for the lake at WSE h with measurements at n depths on a given date, the interfaces between the n layers are $h - (z_1 + z_2)/2, h - (z_2 + z_3)/2$ and so on for remaining layers (Figure 4). The volume of layer 1 was then calculated from the bathymetry-derived volume–WSE relationship as $V(h)-V(h-(z_1 + z_2)/2)$. The volume of layer 2 was calculated as $V(h-(z_1 + z_2)/2)-V(h-(z_2 + z_3)/2)$ and so on for remaining layers. The dissolved salt mass in each layer, L_n, is then the volume of the layer, V_n, times the salinity concentration based on the sample measurement, C_n, expressed as $L_n = C_nV_n$. The average dissolved salt mass for each arm, L, is then the sum of the dissolved salt masses for each layer, which was expressed as $L = L_1 + \ldots + L_n$. Average salinity of the arm of the lake, C, was then estimated using $C = L/V$, where V is the volume of the arm of the lake. These calculations, based on individual sites, are plotted in the results as sample event points for each date of observation. Note that while it is common for the DBL interface and sometimes a shallow freshwater lens interface to occur at consistent depths, we did not use this information in the salt mass calculations, as it would have introduced assumptions that may not always hold. Rather, we prefer the nearest depth layering approach, which is objective and repeatable albeit with accuracy dependent on n, which is the number of depths sampled.

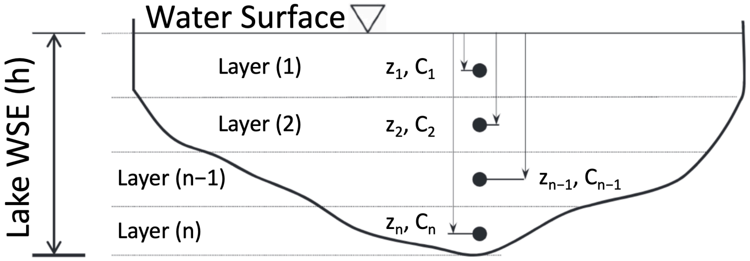

Figure 4. Hypothetical lake at WSE *h* with n number of measurements at depth on a given day. Cross-sections indicate layers used to calculate average dissolved salt mass and average salinity. Adapted with permission from Ref. [26], Copyright American Geophysical Union, 2012.

To estimate a regularly spaced monthly time series of average dissolved salt mass and average salinity for each arm of the lake, the sample event points were smoothed using the ksmooth function in R [27] with a “normal” or bell-shaped kernel and a bandwidth of 600 days. This bandwidth value was chosen to span the largest gaps between measurement times based on visual inspection.

2.6. Total Salt Mass Calculations

The total dissolved salt mass of the whole lake was obtained by summing the estimated monthly time series of average dissolved salt mass for each arm. This total dissolved salt mass represents only a portion of the total salt mass, as it does not include any salt that is precipitated on the lakebed and therefore not in solution. Following Loving et al. [10], the maximum total salt mass (i.e., dissolved + precipitated) was estimated based on the time of peak lake WSE after the flooding in the mid-1980s when salinity concentrations were lowest and precipitated salt mass accumulations are assumed to have been zero. Working forward in time from this maximum point, the total salt mass was calculated based on changes due to inflows, mineral pond withdrawal, mineral pond leakage and return, and west desert pumping and return. Total salt mass prior to the maximum point was back calculated in a similar manner. Contributions to the total salt mass calculations included:

1. Salt mass increases due to annual inflow from rivers, wastewater, stormwater runoff, and groundwater estimated by Hahl [28] to be 3,175,000 metric tons (3,500,000 US tons; a US ton, sometimes referred to as a short ton, is 2000 lb or 0.907 metric tons; a metric ton is 1000 kg).
2. Salt mass values for mineral pond withdrawal were estimated using volume from water rights data [29,30] and lake salinity during summer months when extraction occurred.
3. Salt mass values for mineral pond leakage and return were estimated using volume equal to 25% of water rights withdrawal values following Utah Division of Water Resources estimates that net withdrawals are 75% of the water right, and salinity of the returning brine, which was assumed to be at a saturation density of approximately 1220 kg/m3 (1.22 g/cm3) [31] and a salinity of 275 g/L based on the Naftz et al. [16] equation of state (Equation 1).

4. The West Desert Pumping Project circulated water through the west desert pond from 1987 to 1989 and then drained water back to the lake from 1990 to 1992, bringing salt with it [5]. Loving et al. [5] report a net loss of 0.478 billion metric tons (0.527 billion US tons) of salt that precipitated and remained in the west desert. To reconcile our total dissolved salt mass calculations and not have the total salt mass go below the observed dissolved salt mass over the 1987–1992 time period, west desert pumping salt loss values reported by Loving et al. [5] were reduced by a factor of 0.4.

We also computed an upper and lower bound for the total salt mass. While we know that mineral extraction does remove salt, the amount is uncertain, and setting this as zero provides an upper bound on total salt mass. The lower bound was set based on the condition that total salt mass stay above the value for the total dissolved salt mass, which is based on measurements. The precipitated salt mass, along with its upper and lower bounds, is calculated as the difference between the total salt mass, along with its upper and lower bounds, and dissolved salt mass, which also follows Loving et al. [5].

3. Results

3.1. Salinity

Salinity calculated using water sample data along with the Naftz et al. [16] equation of state, Equation (1), was plotted at depth for each site for the entire period of record from 1966 to present. For sites with frequent sampling information, such as UGS site AS2 (Figure 5a), location-specific stratification is visible, including freshening of upper water in the 1980s and late 1990s and the presence of higher salinities at depth (i.e., DBL) prior to that. However, other sites have scant data and provide very little

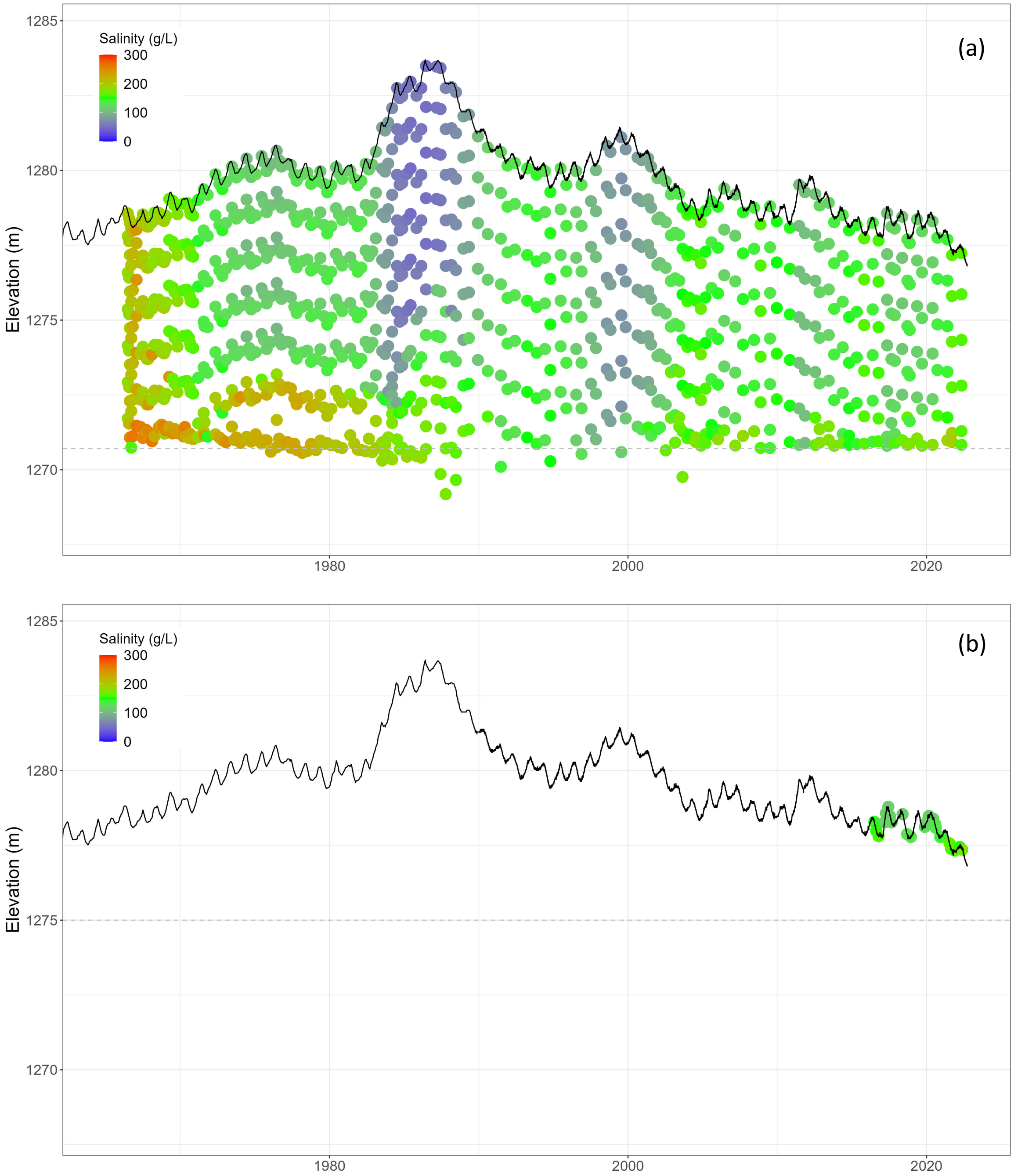

Figure 5. Example plots of salinity at depth over the period of record for individual sample sites (a) AS2 and (b) AIS, both of which are in the south arm (see Figure 1 for site locations). Each dot indicates a salinity calculation from a single sample site measurement. Salinity was calculated using the Naftz et al. [16] equation of state, Equation (1). Solid black line represents the WSE from USGS measurements. Dashed gray horizontal line represents the elevation of the bottom of the lake at the specific sample site. Due to drifting of the boat or instrument while being lowered into the water, some measurements have been recorded below the elevation of the lake bottom at the location of the measurement site.

insight on their own. For example, all that can initially be gathered from the plot of UGS site AIS (Figure 5b) is that surface water was consistently ~150 g/L for the last few years. All 70 of the site plots are included as supplementary material. Based on these site plots, we observe that GSL water samples were commonly collected every few months throughout the water column at 1.5 m (5 foot) increments.

To construct a better picture of salinity at depth over time for the entire lake, the salinity plots for all UGS and USGS sites were combined into two plots, one for each arm (Figures 6a,b). The points in these figures were written to the plot in ascending order of salinity, from lowest to highest, so that points representing high salinity plot in front and are not covered or obscured by overlapping points representing lower salinities. This ensures that high salinities are visualized and can indicate a brine layer if it is present.

Figure 6a,b include what is known about the infrastructure enabling or reducing flow through the causeway. A dashed line at 1272.5 m indicates the elevation that separates permeable and impermeable fill of the causeway structure as reported by Loving et al. [5]. Light dashed lines approximate the base and top elevations of culverts that were installed in the causeway at the time of its construction. However, both culverts were reported to subside and be blocked by the flooding in the mid-1980s and eventually decommissioned (i.e., filled in) in 2013. The upper dashed line starting at 1284.4 m represents the base elevation of causeway breach openings or the invert elevation of the breach. The first causeway breach, West Bridge, was installed in 1985 to alleviate south arm flooding. The West Bridge breach had a base elevation of 1280.2 m, which was then lowered to 1279.6 m in 1996 and 1278 m in 2000. A second causeway breach, West Crack, was installed in 2016, at a time when the first breach was high and dry. The West

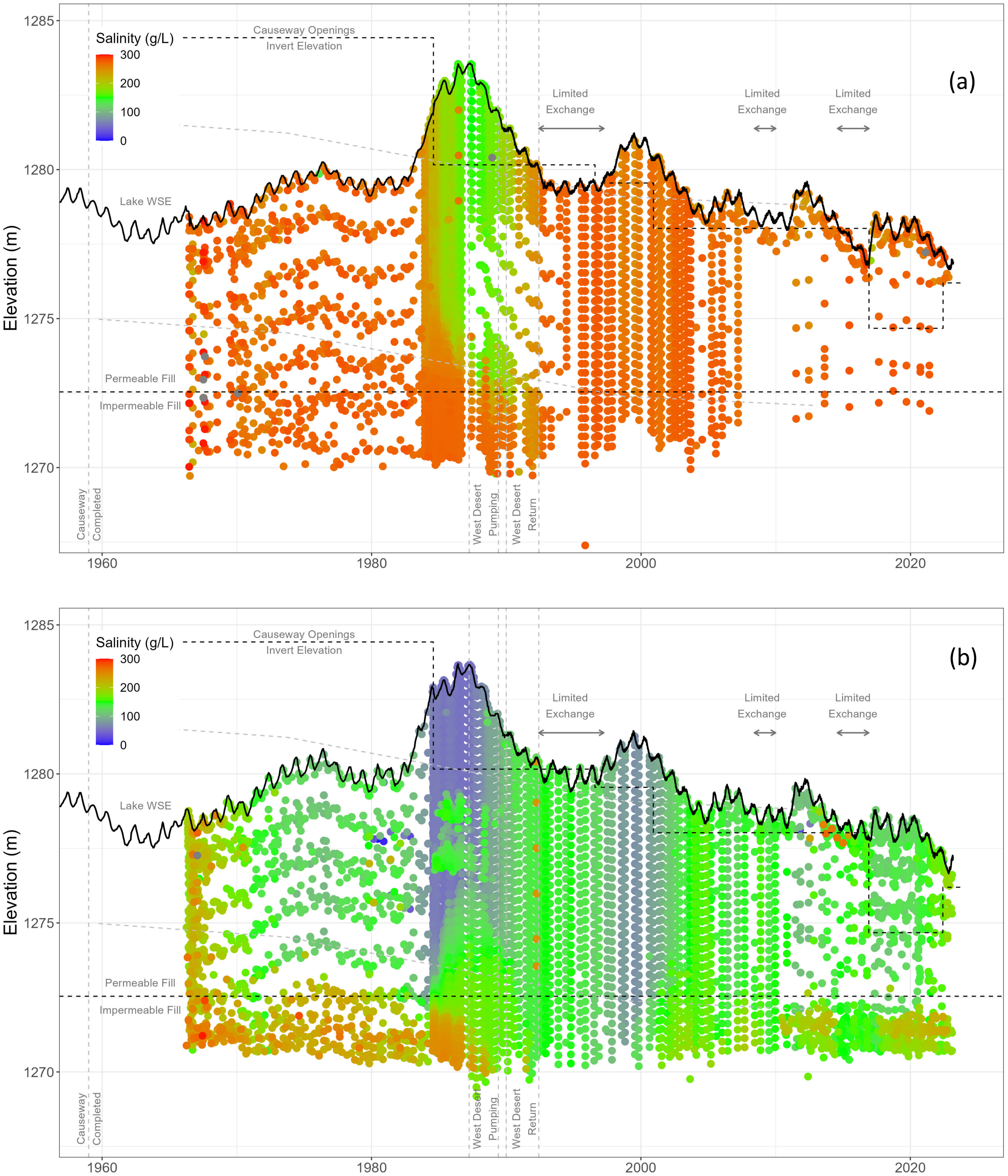

Figure 6. Salinity at depth over time in the (a) north arm and (b) south arm for all samples taken over the period of record at the UGS and USGS measurement sites shown in Figure 1. Each dot indicates a salinity calculation from a single sample site measurement. Salinity was calculated using the Naftz et al. [16] equation of state, Equation (1). Solid black line represents the WSE from USGS measurements. Horizontal dashed lines indicate causeway openings invert elevations, culvert base and top elevations, and the elevation separating permeable and impermeable fill in causeway base. Vertical dashed lines indicate date causeway was constructed and periods of west desert pumping and return.

Crack breach had a base elevation of 1274.7 m but was raised to 1276.2 m in 2022 to manage the flow of brine from north to south [32]. The years of west desert pumping and brine flow return are also indicated. Periods of limited exchange with lake WSE close to or below breach base elevations are labeled to aid in interpretation.

In Figures 6a and 6b, we see that the north arm is both more saline and more homogeneous than the south arm. Other than during the flooding in the mid-1980s and subsequent lake WSE decline, the north arm salinity remained at about 250–300 g/L throughout the water column for the entirety of the data record. In 1966, seven years after the installation of the causeway in 1959, the south arm salinity was approximately 200 g/L throughout the water column. However, the south arm progressively became more stratified with lower salinity at the surface, 100–150 g/L, and higher salinity at the bottom, 200–250 g/L. This bottom layer of high salinity is what would later become referred to as the DBL. The DBL persisted until the early 1990s and then disappeared during the time the lake WSE was declining after the floods. Hints of a return of the DBL start appearing in about 2000 but are not obvious in these plots until about 2010. The DBL faded once again in 2014 and returned in 2016. The timing of the presence of the DBL appears to align with the periods of limited exchange through the causeway.

3.2. Average Dissolved Salt Mass and Average Salinity

Of the 27,482 salinity calculations for the entire lake, 25,967 were produced using the UGS dataset and 1515 were produced using the USGS dataset. From these individual measurements, there were 1256 sample dates with 3 or more measurements in the south arm and 890 sample dates with 3 or more measurements in the north arm. Therefore, we were able to calculate 1256 sample event values for average dissolved salt mass and average salinity for the south arm and 890 sample event values of each for the north arm. These sample event calculations of average dissolved salt mass and average salinity are plotted as points in Figures 7 and 8 along with dashed lines representing the regularly spaced monthly time series obtained through smoothing of this data. Lake arm is indicated by the color of the point or dashed line.

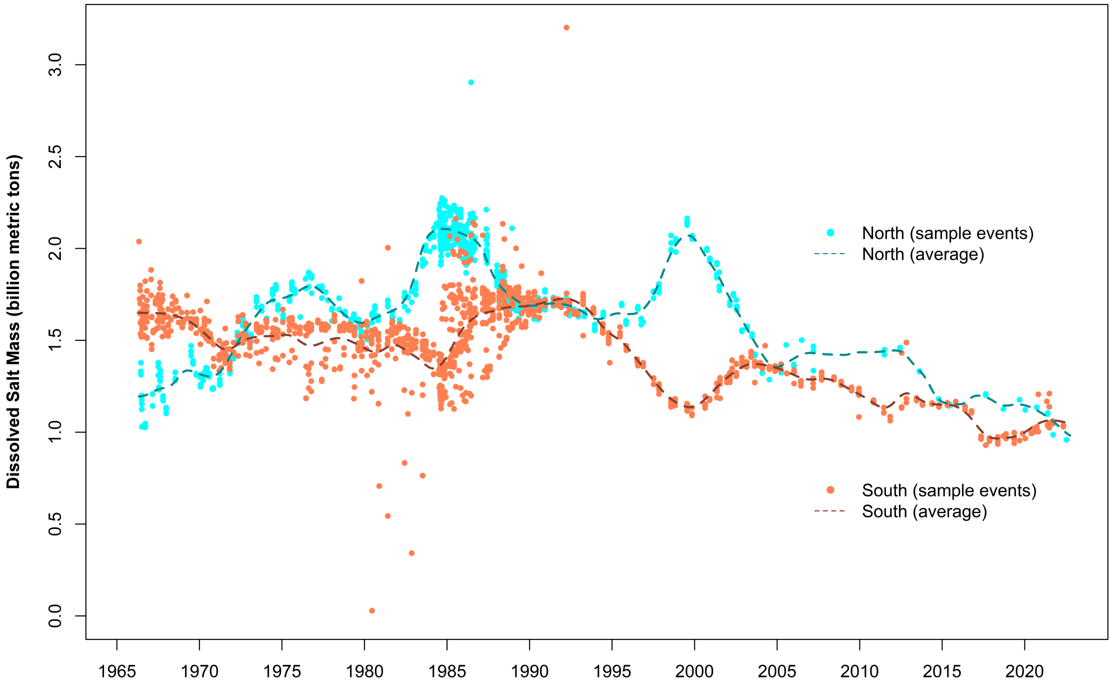

Figure 7. North and south arm average dissolved salt mass over the period of record at GSL measurement sites (Figure 1). Point values were calculated using all measurements at a single site on a given date. Dashed lines represent the estimated monthly time series.

Smoothing of the data quantifies visible trends and provides a way to interpolate in time between points to obtain estimates for each month. Figure 7 indicates that variability in the dissolved salt mass is coordinated between the two arms such that the north arm dissolved salt mass goes up when the south arm dissolved salt mass goes down. On the other hand, Figure 8 indicates the average salinity of each arm going up and down almost in unison. The average salinity in the north arm has remained close to saturation other than during the flooding in the 1980s [5,8,26,33], while the average salinity of the south arm decreased from the mid-1960s to the mid-1980s and then appears to be increasing thereafter.

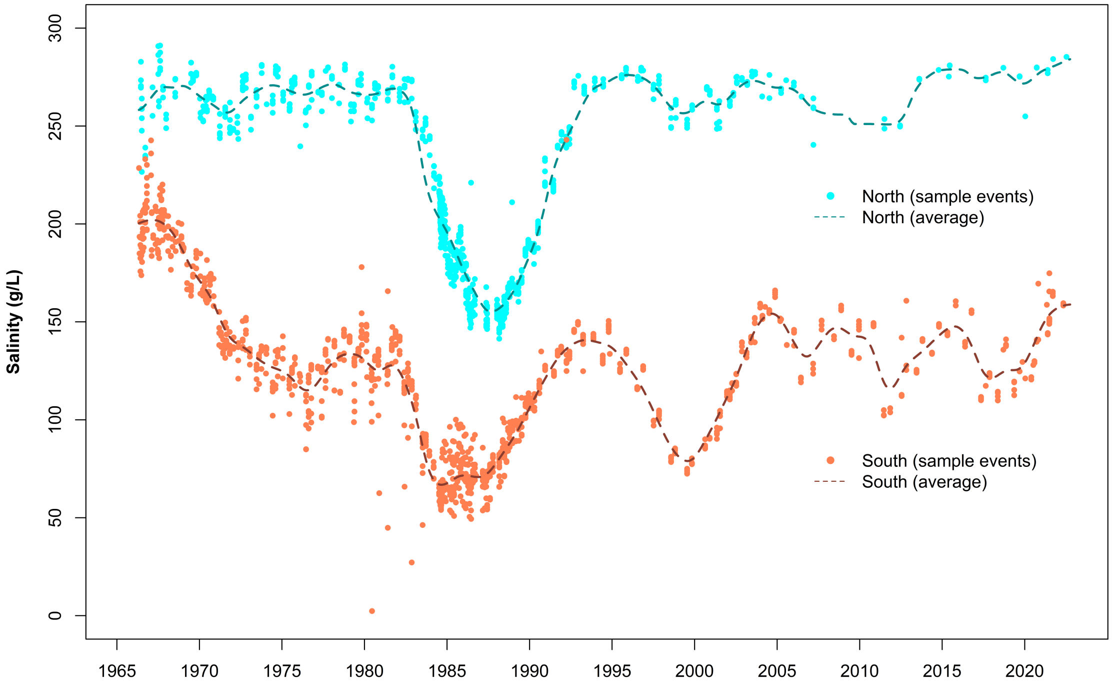

Figure 8. North and south arm salinities over the period of record at GSL measurement sites (Figure 1). Point values were calculated using all measurements at a single site on a given date. Dashed lines represent the estimated monthly time series.

Figure 9 is a plot of salinities in the south arm. Points in this figure represent salinities calculated using individual measurements from samples taken at the surface (less than 0.3 m depth) and bottom (below 1272.5 m elevation) of the south arm at sites within the 1272.5 m contour (Figure 1; including UGS sites RT4, RT2, RT1, NLN, FB2, AS2, AC3, and AC2, and USGS sites 405356112205601, 410637112270401, and 410644112382601). The dashed line represents the estimated monthly time series for average salinity, as shown in Figure 8. Figure 9 indicates that the surface salinity is typically slightly lower than the average salinity, whereas the salinity below 1272.5 m, where the DBL would appear, is typically considerably higher than the average salinity. However, from approximately 1992 to 1999, the surface, bottom, and average salinities were more or less the same, indicating there is no DBL during this time. A DBL reappeared following lowering of the causeway breach in 1996 and increased lake WSE in 1999. A similar merging of salinities also occurs during 2008–2010 and 2014–2016. All three occurrences of merging salinities coincide with limited exchange between the north and south arms and indicate the disappearance of a DBL (i.e., absence of higher salinities below 1272.5 m) when there is limited exchange through the causeway. This is consistent with Figure 6b, which shows no DBL during these times, and also the findings

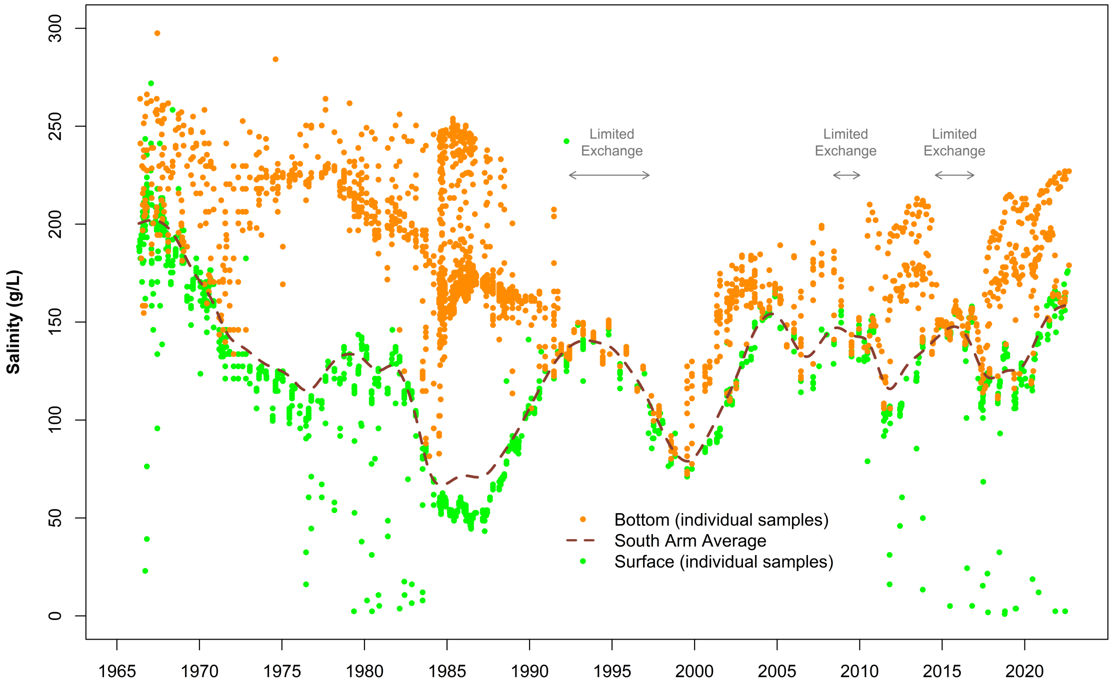

Figure 9. Salinities in the south arm. Surface (less than 0.3 m depth) and bottom (below 1272.5 m elevation) salinity points were calculated using individual measurements from sample sites within the 1272.5 m contour shown in Figure 1 (including UGS sites RT4, RT2, RT1, NLN, FB2, AS2, AC3, and AC2; and USGS sites 405356112205601, 410637,112270401, and 410644112382601). The dashed line is the estimated monthly time series of average salinity from Figure 8.

of Yang et al. [11]. The extended period from 1992 to 1999 without a DBL complements the findings of Yang et al.'s work, which is based on data subsequent to 2010.

3.3. Total Salt Mass

The calculated total salt mass, dissolved salt mass, and precipitated salt mass are shown in Figure 10. The dissolved salt mass (black line) is the sum of the estimated monthly time series for north and south arm average dissolved salt masses shown in Figure 7. The dissolved salt mass reaches a maximum of 3.672 billion metric tons (4.048 billion US tons) in September 1986 and is assumed to be the total salt mass at that time, following the assumption stated in Section 2.4 that all salt is in solution at peak lake WSE. Prior to and following this point, total salt mass was calculated forward and backward in time as described in Section 2.4. Precipitated salt mass is then calculated as total salt mass minus dissolved salt mass.

The time between the mid-1960s and peak WSE in 1986 shows a slight increase in total salt mass due to the small contribution from inflows. There is a notable increase in total dissolved salt mass and a corresponding decrease in total precipitated salt mass over this period. The time from the peak WSE in 1986 to present shows a decrease in total salt mass and dissolved salt mass and an increase in precipitated salt mass. Contributions to these masses accumulated over the respective periods are listed in Table 1.

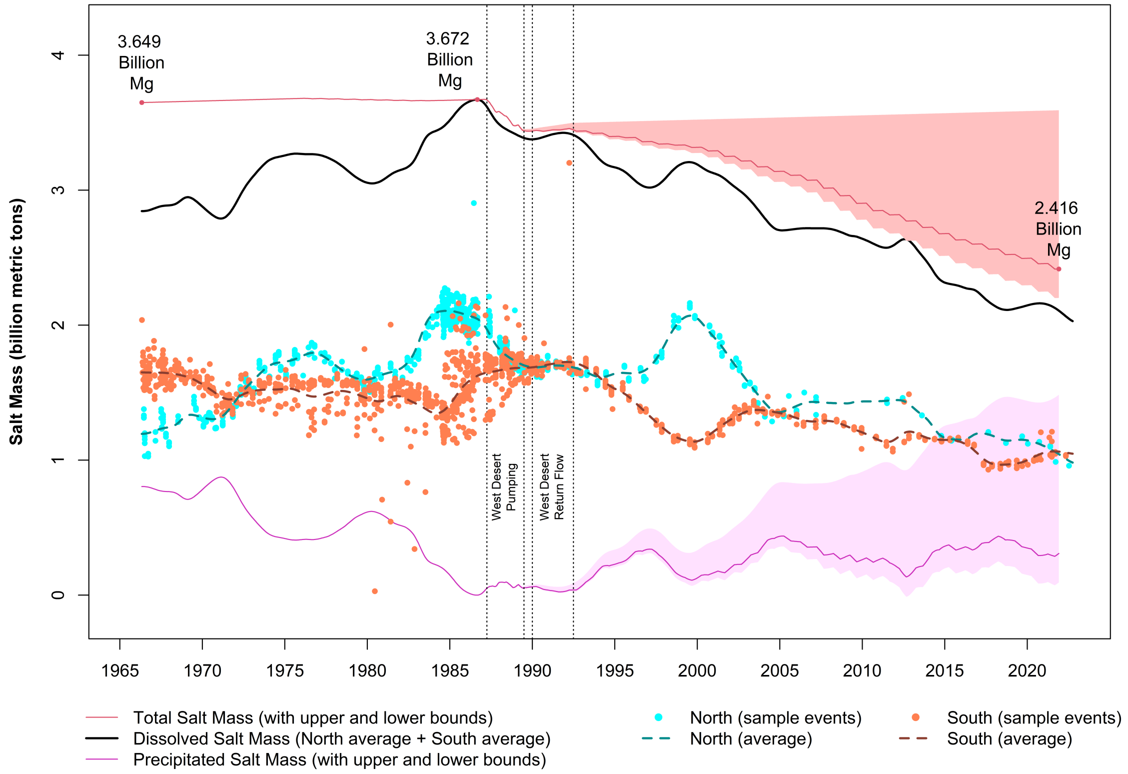

Figure 10. North and south arm salt mass calculations over the period of record at the UGS and USGS measurement sites shown in Figure 1. Calculations were only performed for sample events with 3 or more samples at depth. 1 Mg = 1 metric ton.

Table 1. Estimated cumulative contributions to the total salt mass calculations before (May 1966–September 1986) and after (October 1986–December 2021) the maximum mass in 1986. Values are in billion metric tons.

Mass Contribution	1966–1986 (20 years)	1986–2021 (35 years)
River, Groundwater, and Other Inputs	0.065	0.112
West Desert Project	-	−0.191
Mineral Extraction North Arm Withdrawal	-	−1.277
Mineral Extraction North Arm Return	-	0.346
Mineral Extraction South Arm Withdrawal	−0.099	−0.511
Mineral Extraction South Arm Return	0.057	0.265

4. Discussion

Prior to the construction of the railroad causeway and the separation of the GSL's north and south arms, the DBL had not been mentioned and likely did not exist [34]. The lake's salinity was essentially considered vertically and horizontally homogeneous other than in the bays near freshwater river input [34]. As tributary inflows to the GSL changed and causeway breaches and culverts opened and closed, salinity within each arm and the presence and strength of the DBL in the south arm fluctuated.

Plotting the salinities at depth over the period of record, which includes each water sample at every sample site throughout the GSL, presents the most complete picture of salinity in each arm of the lake. The consistent patterns that emerge from sample sites at different locations in each arm of the lake support and validate the assumption of horizontal homogeneity. From Figure 6a, we see that the tendency of the north arm is toward vertical homogeneity, with salinities consistently at or near saturation (275 g/L) throughout the water column except when the lake was high in the 1980s and there was an influx of fresh water from the south. In contrast, the tendency of the south arm is toward vertical stratification (Figure 6b). High salinity water periodically found at the bottom of the lake in the south arm, below approximately 1272.5 m (4175 feet), is what is referred to as the DBL. However, the remainder of the water column above the DBL in the south arm is nearly vertically homogeneous, with salinities of 100–150 g/L. Salinity at the sampling sites within the 1272.5 m (4175 foot) contour in the south arm shows that the concentration of the DBL is typically 150–250 g/L when present (Figure 9). It also shows that the surface water of the south arm is of similar salinity to the rest of its water column, other than the DBL (Figures 6b and 9). These respective phenomena appear throughout the historical period of record for both arms other than during the flooding in the mid-1980s to mid-1990s. This period of high river inflows and flooding affected the salinity of upper layers of both arms of the lake for over a decade.

The upper portion of the GSL experienced significant freshening in both the north and south arms due to higher-than-average river inputs to the south arm in the 1980s and 1990s and exchange of that freshwater through the causeway and into the north arm (Figures 6a,b). This resulted in reduced salinities of both arms by approximately 100 g/L. However, the salinity of the bottom lake water in the north arm experienced nearly no effects during this time, and the entire water column in the north arm returned to pre-flood conditions by 1992, when the lake WSE dropped below the elevation of the causeway opening and south-to-north flow became limited or non-existent (Figure 6a). This north arm homogeneity persisted through a second round of high inflow and high lake WSE around 2000. However, unlike the north arm, the salinity of the bottom water in the south arm was affected by both high-flow events (Figure 6b). By 1992, after the peak lake WSE in 1986, the DBL disappeared from the south arm (Figures 6b and 9), indicating destratification. The DBL did not begin to form again until about 1999 (Figures 6b and 9), which was coincident with exchange flow being re-established by deepening of the breach, giving rise to stratification. However, it was only in 2010 that the DBL made a strong reappearance (Figure 6b).

As shown in Figures 6a,b, the invert elevation of the causeway openings has changed over the course of the causeway's existence. The two original culverts are reported to have subsided and become filled with enough debris by the mid-1990s that they had little impact on exchange between the two arms [5]. Breach openings were added and then subsequently excavated to a lower elevation to facilitate causeway exchange as the WSE became lower (Figure 6a,b). However, lake WSE was still too low in the north arm to allow for anything but limited exchange or no flow through the causeway in 1992–1997, 2009–2011, and 2014–2016. It was approximately during these times that the DBL was either not present or weak in the south arm. Yang et al. [11] noted that the 2014–2016 destratification occurred six months following closure of the last culvert, putting a time scale on the period needed for mixing without input of high-salinity brine from the north arm.

Even with the lake being divided and times of limited exchange or no flow through the causeway, the average salinity is positively correlated between the two arms such that the salinity of each arm rises and falls in unison (Figure 8). The north arm average salinity has been consistently higher than the south arm throughout the historical record. The north arm salinity has also been more resilient to disturbances than the south arm, tending to equilibrate at a salinity of ~275 g/L, even after disruptions such as flooding and limited causeway exchange. In the 1960s, shortly after the causeway was completed and UGS sampling began, the south arm average salinity was ~200 g/L. Presumably, the south arm salinity was nearer to that of the north arm salinity when the lake was first divided, but the salinity of the two arms began diverging after the causeway was constructed. The south arm appears to have been settling into an average salinity of 100–150 g/L (Figure 8), which was lower than it was in the 1960s shortly after the causeway was completed, although with current low lake WSE, the south arm average salinity appears to be trending a bit higher. Note that the beneficial salinity range for brine shrimp is reported to be 90–130 g/L [4], and salinities higher than this are cause for concern for collapse of the brine shrimp ecosystem.

In contrast to the average salinities of each arm, the dissolved salt mass in each arm is negatively correlated such that the dissolved salt mass in the north arm increases as the dissolved salt mass in the south arm decreases and vice versa (Figure 7). This is easily seen during the flooding in the mid-1980s and around 2000. River inflows into the south arm raised the lake WSE and lowered the south arm salinities. High lake WSE then pushed south arm lake water through the causeway and into the north arm. In effect, this process pushed salt from the south arm into the north arm.

The north arm dissolved salt mass has been higher than that of the south arm throughout the historical record other than very recently, in the early 1990s, and most notably in the late 1960s, which is shortly after the causeway was completed and sampling began. All three episodes are associated with lower lake WSE. The earliest episode is likely due to the lake being much more homogeneous prior to the causeway construction and the smaller volume of the north arm, while the latter episodes appear to be due simply to reduction in north arm volume associated with low lake WSE. Within the range of historical lake WSE, 1276.5–1284 m (~4188–4212 feet), the south arm is nearly twice the volume of the north arm. The north arm dissolved salt mass is equal to or less than that of the south arm when the average salinities of each arm are within 100–110 g/L of one another at low lake WSE.

Between 1986 and 2022, the total salt mass in the GSL decreased by 1.256 billion metric tons, which is more than a 30% reduction (from 3.672 billion metric tons to 2.416 billion metric tons). This equates to a loss of over 35 million metric tons of salt per year.

Other than the west desert pumping in the 1980s and precipitated salt left on exposed shores due to low lake WSE, mineral extraction is the only process known to remove salt from the GSL during the period of record. The reduction in total salt mass is consistent with estimates of salt loss due to mineral extraction (Table 1, Figure 10). Based on the assumption that the mineral extraction industry uses 100% of their water rights and returns 25% of their water rights to the lake as saturated brine (i.e., salinity of 275 g/L), ap-proximately 1.3 billion metric tons of salt have been removed from the lake by the mineral extraction industry over the period of record. We noted earlier that Hahl [28] estimated the total inflow from rivers, wastewater, stormwater runoff, and groundwater adds 3.2 million metric tons of salt per year. This means that the amount of salt removed from the GSL by the mineral extraction industry every year is approximately ten times the amount added. Most recently, since 2017, there have been increases in south arm salt mass and decreases in north arm salt mass (Figure 10). Not only is this increase in south arm salt mass larger than would be possible from estimated inflows, it is also accompanied by reductions in north arm salt mass and therefore seems to be attributable to north-to-south exchange through the causeway.

The intensity of GSL data collection has varied over the years in both time and space. For example, water sampling and data collection was more frequent during the heavy precipitation and inflows in the 1980s and less frequent in the 1990s and thereafter. However, after the late 2000s, very little sampling occurred in the north arm with most being surface samples, and sampling in the south arm became concentrated at both the surface and bottom with sporadic sampling at depths in between. It is notable, in examining the plots of dissolved salt mass and average salinity, that points determined from single sampling events at individual sites line up and, other than a few anomalous points, the data cluster such that general trends can be seen in each arm of the lake. Lake water samples from spatially different locations yield similar average salt mass and average salinity information. This validates the use of a single site on a given date to estimate average dissolved salt mass and average salinity on the given date for the arm of the lake where that single site resides. This suggests that sampling that is less frequent in space but more frequent in time and depth would improve the tracking of salinity trends.

Our findings related to the decline in total salt mass and the sampling needed to quantify salt mass and salinity changes have ramifications for the GSL's economy and ecology. From a practical and lake management perspective, the annual regional economic value of the mineral extraction industry has been reported to be $1.13 billion and to support 5368 jobs [35]. Commercial brine shrimp production has been reported to produce $56.7 million economically and to support 574 jobs [35]. The brine shrimp are also a great ecological asset to the lake as a major food source for migratory birds. The GSL and surrounding wetlands support upward of 5 million birds during the yearly migration [36] and, for some species, is the only stop in North America during their journey [37]. In-creased salinity in the south arm and low lake WSE threatens the brine shrimp. At the present lake WSE, south arm salinity is above the optimal brine shrimp salinity range (90–130 g/L, Figure 8). In response to this, the state of Utah recently authorized the raising of a temporary berm in the West Crack breach to reduce flow through the causeway in an attempt to maintain lower salinity levels in the south arm and avoid collapse of the brine shrimp ecosystem. It will be important to monitor salinity in both the south and north arms to quantify the impact of these changes as the causeway berm is used to adaptively manage salinity.

5. Conclusions

We analyzed the historical record of salinity and WSE data for the GSL to better understand the movement and changes of salt in time and space within the lake and to evaluate the occurrence and extent of the DBL. Our analysis of the UGS and USGS datasets produced plots of salinity at depth over time and average salinity for both arms of the lake. The data show positive correlation between the average salinity in each arm such that their salinities rise and falls in unison. Our presentation of the salinities at depth over time show that, apart from flooding events, the north arm is homogeneous throughout the water column and consistently at or near a saturation salinity of approximately 275 g/L. In the south arm, we see fluctuating salinities and a lower portion of the water column that is prone to stratification. The upper portion of the water column in the south arm, above approximately 1272.5 m (4175 feet), is nearly homogeneous with surface salinities at or slightly below the average salinity of the south arm, which tends to remain around 125 g/L, although it was closer to 200 g/L shortly after the railroad causeway was constructed and may once again be increasing. High salinities in the bottom layer of the south arm are what is referred to as the DBL and appear in data from sample sites within the 1272.5 m contour. Consistent with prior studies [11], we found that the DBL is intermittent, occurring only when causeway exchange supports flow from the north to south arms, and that it has a salinity of approximately 150–250 g/L. Our analysis also produced time series of average dissolved salt mass and total salt mass for each arm of the lake. Based on our salinity and salt mass results, similar information from separate sites suggests that salinity trends can be tracked using fewer sampling sites and higher sampling frequencies in time and depth. We also found that the average dissolved salt mass is negatively correlated between the two arms, such that the north arm mass increases as the south arm mass decreases and vice versa. These changes in salt mass reflect net movements of salt through the causeway, from south to north when lake WSE is going up and from north to south when lake WSE is going down. In addition, we show that the GSL has experienced a drop in total salt mass by more than 30% since the peak lake WSE in 1986. This salt loss is driven by mineral extraction processes that have removed approximately 1.177 billion metric tons (1.297 billion US tons) since 1986, which is approximately ten times the estimated contribution from inflows over the same time period.

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References

1. Jones, E.F.; Wurtsbaugh, W.A. The Great Salt Lake's monimolimnion and its importance for mercury bioaccumulation in brine shrimp (Artemia franciscana). Limnol. Oceanogr. 2014, 59, 141–155. https://doi.org/10.4319/lo.2014.59.1.0141.

2. Wurtsbaugh, W.A.; Berry, T.S. Cascading effects of decreased salinity on the plankton, chemistry, and physics of the Great Salt Lake (Utah). Can. J. Fish. Aquat. Sci. 1990, 47, 100–109. https://doi.org/10.1139/f90-010.
3. Hassan, D.; Burian, S.J.; Johnson, R.C.; Shin, S.; Barber, M.E. The Great Salt Lake Water Level is Becoming Less Resilient to Climate Change. Water Resour. Manag. 2022, 1–24. https://doi.org/10.1007/s11269-022-03376-x.
4. Utah Division of Forestry, Fire and State Lands (UDFFSL). Final Great Salt Lake Comprehensive Management Plan and Record of Decision; Utah Division of Forestry, Fire and State Lands: Salt Lake City, UT, USA, 2013; 391p. Available online: https://geodata.geology.utah.gov/pages/view.php?ref=8267 (accessed on 6 January 2023).
5. Loving, B.L.; Waddell, K.M.; Miller, C.W. Water and Salt Balance of Great Salt Lake, Utah, and Simulation of Water and Salt Movement through the Causeway, 1987–98; U.S. Geological Survey: Salt Lake City, UT, USA, 2000. Available online: https://pubs.usgs.gov/wri/2000/4221/report.pdf (accessed on 12 August 2022).
6. Tripp, T.G. Production of Magnesium from Great Salt Lake, Utah USA; Natural Resources and Environmental Issues: Vol. 15, Article 10; Utah State University: Logan, UT, USA, 2009. Available online: https://digitalcommons.usu.edu/nrei/vol15/iss1/10 (accessed on 22 May 2012).
7. White, J.S.; Null, S.E.; Tarboton, D.G. How do changes to the railroad causeway in Utah’s Great Salt Lake affect water and salt flow? PLoS ONE 2015, 10, e0144111. https://doi.org/10.1371/journal.pone.0144111.

8. Madison, R.J. Effects of a Causeway on the Chemistry of the Brine in Great Salt Lake, Utah; Water-Resources Bulletin; Utah Geo-logical and Mineralogical Survey: Salt Lake City, UT, USA, 1970; Volume 14, 50 p. https://ugspub.nr.utah.gov/publications/water_resources_bulletins/WRB-14.pdf (accessed on 1 March 2023).
9. Naftz, D.; Angeroth, C.; Kenney, T.; Waddell, B.; Darnall, N.; Silva, S.; Perschon, C.; Whitehead, J. 2008. Anthropogenic influ-ences on the input and biogeochemical cycling of nutrients and mercury in Great Salt Lake, Utah, USA. Appl. Geochem. 2008, 23, 1731–1744. https://doi.org/10.1016/j.apgeochem.2008.03.002.
10. Valdes, C.; Black, F.J.; Stringham, B.; Collins, J.N.; Goodman, J.R.; Saxton, H.J.; Mansfield, C.R.; Schmidt, J.N.; Johnson, W.P. Total Mercury and Methylmercury Response in Water Sediment, and Biota to Destratification of the Great Salt Lake, Utah, USA. Environ. Sci. Technol. 2017, 51, 4887–4896. https://doi.org/10.1021/acs.est.6b05790.
11. Yang, S.; Johnson, W.P.; Black, F.J.; Rowland, R.; Rumsey, C.; Piskadlo, A. Response of density stratification, aquatic chemistry, and methylmercury to engineered and hydrologic forcings in an endorheic lake (Great Salt Lake, U.S.A.). Limnol. Oceanogr. 2019, 65, 915–926.
12. Wurtsbaugh, W.A.; Sima, S. Contrasting Management and Fates of Two Sister Lakes: Great Salt Lake (USA) and Lake Urmia (Iran). Water 2022, 14, 3005. https://doi.org/10.3390/w14193005.
13. Diaz, X.; Naftz, D.L.; Johnson, W.P. Selenium Mass Balance in the Great Salt Lake, Utah. Sci. Total Environ. 2009, 407, 2333–2341.

14. Diaz, X.; Johnson, W.P.; Fernandez, D.; Naftz, D.L. Johnson; Size and Elemental Distributions of Nano- to Micro-Particulates in the Geochemically-stratified Great Salt Lake. Appl. Geochem. 2009, 24, 1653–1665. https://doi.org/10.1016/j.apgeochem.2009.04.031.
15. Brown, P.D.; Bosteels, T.; Marden, B.T. Salt load transfer and changing salinities across a new causeway breach in Great Salt Lake: Implications for adaptive management. Lakes Reserv. Sci. Policy Manag. Sustain. Use 2023, 28, e12421. https://doi.org/10.1111/lre.12421.
16. Naftz, D.L.; Millero, F.J.; Jones, B.F.; Green, W.R. An Equation of State for Hypersaline Water in Great Salt Lake, Utah, USA. Aquat. Geochem. 2011, 17, 809–820. https://doi.org/10.1007/s10498-011-9138-z.
17. Baskin, R.L.; Allen, D.V. Bathymetric Map of the South Part of Great Salt Lake, Utah: U.S. Geological Survey Scientific Investiga-tions Map 2894; USGS: Reston, VA, USA, 2005. Available online: https://pubs.usgs.gov/sim/2005/2894/ (accessed on 1 March 2023).
18. Baskin, R.L.; Turner, J. Bathymetric Map of the North Part of Great Salt Lake, Utah: U.S. Geological Survey Scientific Investiga-tions Map 2006–2954; USGS: Reston, VA, USA, 2006. Available online: https://doi.org/10.3133/sim2954 (accessed on 1 March 2023).
19. Baskin, R.L. Farmington Bay Contours in 2009 and Modified by BIO-WEST in 2010, Including Minor Contour Manipulation and the Introduction of a 1280 Meter (4200 Foot) Contour at the South End of the Bay. Personal communication, 2010.

20. Hansen & Associates. Bear River Bay Survey in 2009 under a Contract with BIO-WEST. Personal communication, 2010.
21. ESRI. ArcGIS Desktop: Release 10; Environmental Systems Research Institute: Redlands, CA, USA, 2015.
22. Tarboton, D. Great Salt Lake Bathymetry. HydroShare. 2017. Available online: http://www.hydroshare.org/resource/582060f00f6b443bb26e896426d9f62a (accessed on 1 March 2023).
23. Tarboton, D. Great Salt Lake Area Volume Data. HydroShare. 2017. Available online: http://www.hydroshare.org/resource/89125e9a3af544eab2479b7a974100ba (accessed on 1 March 2023).
24. Great Salt Lake Salinity Advisory Committee. Standard Operating Procedure—Great Salt Lake Water Density Measurement and Salinity Calculation; Utah Geological Survey Open-File Report 728; Great Salt Lake Salinity Advisory Committee: Salt Lake City, UT, USA, 2020; 6p. https://doi.org/10.34191/OFR-728.
25. Spieweck, F.; Bettin, H. Review: Solid and liquid density determination. Tech. Mess. 1992, 59, 285–292.
26. Mohammed, I.N.; Tarboton, D.G. An examination of the sensitivity of the Great Salt Lake to changes in inputs. Water Res. Res. 2012, 48, W11511. https://doi.org/10.1029/2012WR011908.
27. R Core Team. R: A Language and Environment for Statistical Computing; R Foundation for Statistical Computing: Vienna, Aus-tria, 2012. Available online: http://www.R-project.org/ (accessed on 1 March 2023).

28. Hahl, D.C. Dissolved-Mineral Inflow to Great Salt Lake and Chemical Characteristics of the Salt Lake Brine: Summary for Water Years 1960, 1961, and 1964; Water-Resources Bulletin 10; Utah Geological Survey: Salt Lake City, UT, USA, 1968, 35p.
29. Utah Division of Water Rights. WUSEVIEW Water Records/Use Information Viewer. Available online: https://waterrights.utah.gov/cgi-bin/wuseview.exe (accessed on 28 February 2023).
30. Merck, M.; Tarboton, D. Great Salt Lake Mineral Extraction Water Withdrawals. HydroShare. 2023. Available online: http://www.hydroshare.org/resource/46b98820b7214850aadf6fa60c9bc1d1 (accessed on 8 March 2023).
31. Rupke, A.; Jagnieki, E. The Significance of Great Salt Lake's North Arm on Lake Salinity; Survey Notes; Utah Geological Survey: Salt Lake City, UT, USA, 2021. Available online: https://ugspub.nr.utah.gov/publications/survey_notes/snt53-1.pdf (accessed on 1 March 2023).
32. Rasmussen, M.; Dutta, S.; Neilson, B.T.; Crookston, B.M. CFD Model of the Density-Driven Bidirectional Flows through the West Crack Breach in the Great Salt Lake Causeway. Water 2021, 13, 2423. https://doi.org/10.3390/w13172423.
33. Waddell, K.M.; Bolke, E.L. The Effects of Restricted Circulation on the Salt Balance of Great Salt Lake, Utah; Water-Resources Bulletin; Utah Geological Survey: Salt Lake City, UT, USA, 1973; Volume 18, p. 54, https://ugspub.nr.utah.gov/publications/water_resources_bulletins/WRB-18.pdf (accessed on 1 March 2023).

34. Wold, S.R.; Thomas, B.E.; Waddell, K.M. Water and Salt Balance of Great Salt Lake, Utah, and Simulation of Water and Salt Movement through the Causeway; Water Supply Paper 2450: 1–64; US Geological Survey: Salt Lake City, UT, USA, 1997. Available online: https://doi.org/10.3133/wsp2450 (accessed on 1 March 2023).
35. Bioeconomics, Inc. Economic significance of the Great Salt Lake to the State of Utah. Prepared for State of Utah Great Salt Lake Advisory Council. 2012. Available online: https://documents.deq.utah.gov/water-quality/standards-technical-services/great-salt-lake-advisory-council/Activities/DWQ-2012-006863.pdf (accessed on 1 March 2023).
36. Western Hemisphere Shorebird Reserve Network (WHSRN). Conserving Shorebirds and Their Habitat through a Network of Key Sites across the Americas. Available online: www.whsrn.org (accessed on 1 March 2023).
37. Aldrich, T.W.; Paul, D.S. Avian ecology of Great Salt Lake. In Great Salt Lake: An Overview of Change; Gwynn, J.W., Ed.; Utah Department of Natural Resources: Salt Lake City, UT, USA, 2002; pp. 343–374.
38. Rupke, A. (Utah Geological Survey, Salt Lake City, Utah, USA). Personal communication, 2022.

CHAPTER 3

EVALUATING VARIATIONS IN GREAT SALT LAKE INFLOW TO INFER HUMAN CONSUMPTIVE USE, A VOLUME RECONSTRUCTION APPROACH [2]

Abstract

The declining water level in Great Salt Lake (GSL) has been attributed to human consumptive water use that depletes natural streamflow into the lake. Understanding depletions due to historical consumptive water use within the GSL Basin is important to managing present and future lake conditions. Direct calculations of consumptive water use in the basin are made by summing detailed uses and return flows. However, this method is limited by insufficient data and resulting estimates thus far have been disparate. In this study, we reconstructed total GSL water inputs and stream inflows using lake levels recorded from 1847-present to estimate the magnitude of reductions due to consumptive use and the associated lake level decline. To do so, we developed a method that uses lake volume changes derived from bathymetry and water surface elevation measurements along with estimates of annual evaporation and precipitation over the lake to hindcast inflow volume to the lake. The declining trend in lake inflow, without associated precipitation or natural streamflow trends, was used to quantify basin wide water depletions to be upwards of 2.5 km^3/yr and the current lake level decline associated with this estimate to be as much as 4.5 meters. This basin wide depletion estimate depends only on lake level, precipitation, and evaporation estimates and is not limited by the challenges of aggregating individual diversions and return flows.

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[2] Coauthored by Madeline F. Merck and David G. Tarboton.

1 Introduction

The Great Salt Lake (GSL) is a terminal lake located in northern Utah within the Great Basin (Figure 11). It is the largest terminal lake in North America. The lake is divided into two arms by a railroad causeway that was built in 1959. The south arm, Gilbert Bay, receives approximately 95% of the surface inflow to the lake entering along the southeastern shores from three major rivers, Bear, Weber, and Jordan (Loving et al., 2000). In the north arm, Gunnison Bay, input is limited to direct precipitation and intermittent runoff. Gilbert Bay is roughly twice the area and volume of Gunnison Bay. Evaporation is the only outflow from either arm, resulting in the lake's high salinity (e.g., Loving et al., 2000). Level, area, and volume of GSL adjust to balance differences in these inflows and outflows and, with its large size and relatively shallow depth (13 meters at its deepest), area and volume can vary greatly with fluctuating levels.

In recent years, the GSL water surface elevation (WSE) has declined to critically low levels, with much of the decline being attributed to depletion of streamflow through human consumptive water use (Wurtsbaugh et al., 2017). This is superimposed on natural climate driven low frequency cycles and periodic extremes (Lall and Mann, 1995). There is thus a need to quantify historical reductions in inflow to the GSL due to the depletion of streamflow and associated declines of GSL WSE. However, while GSL WSE has been measured since 1847, streamflow measurements from all the main lake inflows are complete only following 1949. Much development of agricultural water use within the GSL Basin started immediately upon settlement of the GSL valley by European (Mormon) settlers in 1847. The impacts of the resultant reductions in streamflow are therefore already part of streamflow measurements making it difficult to determine reductions in streamflow due to water use depletions from current trends in streamflow measurements alone.

Mohammed and Tarboton (2012) defined a GSL volume sensitivity measure, denoted as ϕ, as the ratio of the standard deviation of input variables to the standard deviation of the lake volume change at an annual time scale. They found that lake volume is eight times more sensitive to streamflow ($\phi = 0.83$) than evaporation ($\phi = 0.10$) and nearly three times more sensitive than precipitation ($\phi = 0.30$). The strong relationship between lake volume changes and streamflow suggests that volume changes derived from changes in WSE may be useful to infer inflow to GSL back to the time when levels were first measured and thus extract information not available in post 1949 streamflow measurements on how streamflow may have been reduced by water use development.

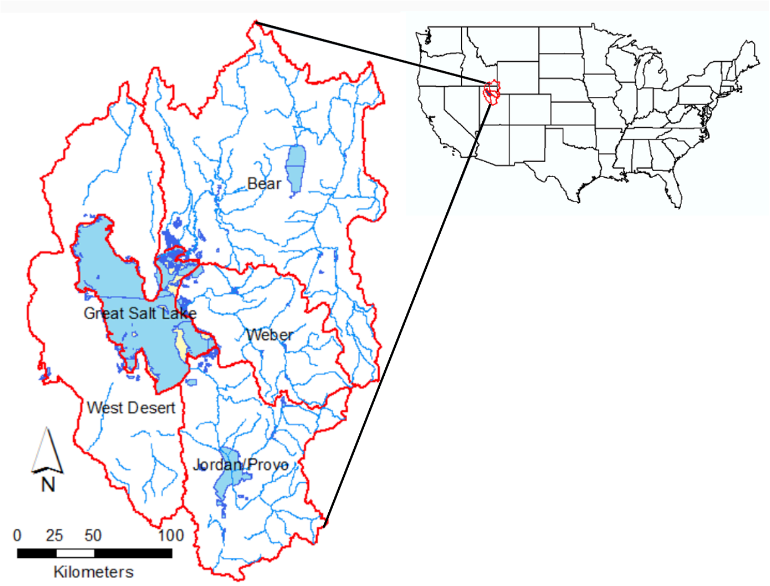

Figure 11. Location of the Great Salt Lake and its contributing basins.

Tree-ring reconstructions of streamflow extend several centuries into the past and provide information on streamflow prior to the availability of measurements. Based on climate and soil moisture driven growth of trees, tree ring reconstructions are not impacted by diversions and thus represent estimates of natural flow. Streamflow reconstructions from tree-ring estimates dating back approximately 1200 years for the Bear River (DeRose et al., 2015), 600 years for the Weber River (Bekker et al., 2014), and 800 years for the Jordan River (Tikalsky, 2007) show no significant long-term trends. Therefore, any trend in streamflow into the lake inferred from lake volume changes over the period of human development prior to the availability of complete lake inflow streamflow measurements can be attributed to human influence reflecting streamflow depletion due to consumptive use (CU).

The goal of this paper was to investigate and reconstruct streamflow into GSL from volume change measurements and, from trends in these reconstructions, infer how human consumptive water use has impacted streamflow as an alternative to, and check or validation of, uncertain and unknown early direct consumptive use depletion estimates. We developed a volume reconstruction approach to reconstruct the historical record of inflow to the GSL from 1847-2023 by using lake volume changes along with evaporation and precipitation hindcasts as inputs to a water mass balance for the lake. Our hindcast and mass balance process, along with supporting assumptions, are described in the methods section. The objective was to establish the magnitude of streamflow reductions due to CU based on mass balance evidence in the historical record for GSL WSE as an alternative to and check on direct CU streamflow depletions that are only available during recent periods with streamflow measurement and are uncertain. Trends from the reconstructed inflow were used to estimate CU in the GSL Basin and how, over the period that WSE has been measured, CU as led to changes in WSE.

1.1 Background

Both arms of GSL have a salt concentration several times higher than the ocean. The hypersaline lake and associated marshes are vital for breeding and migrating shorebirds (IWJV, 2016). The Western Hemisphere Shorebird Reserve Network has designated the GSL as a site of Hemispheric Importance, the highest rank of importance (WHSRN, 2016). A major food source for the birds is the lake's brine shrimp, which are also considered a keystone species because they control the lake's phytoplankton (Stephens, 1990; Aldrich and Paul, 2002). The north arm of GSL can no longer support brine shrimp or brine fly populations due to extremely high salinities (Barnes & Wurtsbaugh, 2015). Although the less saline south arm does not support fish, brine shrimp and brine flies flourish in most years (WHSRN, 2016). However, salinity nearing or reaching biotic thresholds can be harmful to the brine shrimp and brine flies. Disruptions in the brine shrimp and brine fly population propagate and result in disturbances further up the food chain, affecting migratory bird populations.

The south arm is also home to the freshwater estuaries of Bear River Bay and Farmington Bay. Both bays receive freshwater inflows and, therefore, have much lower salinity than the rest of the lake. When GSL WSE is at or above what is regarded as normal elevations (average ~4200 feet or 1280 meters), these bays are commonly used for recreation and shorebird habitat. However, being shallower areas of the lake, both bays are currently nearly dry due to drought and the possibility of complete desiccation is a real threat. In addition, the freshwater ecosystems in these bays are especially fragile and struggle under low WSE conditions (Wurtsbaugh et al., 2016).

Low WSE and high salinities throughout the lake also make it more difficult to pump lake water to the evaporation ponds for mineral extraction, which are located on the periphery of the lake. In 2014, Morton Salt, the leading producer of table salt in the US, dug a five-mile-long canal in the south arm to deliver brine from the now distant lake water to their salt ponds and processing plants (Wurtsbaugh et al., 2016). US Magnesium (MagCorp), a major producer of magnesium in North America located in the south arm, is in the process of extending two of their canals by several miles (UDEQ, 2022). In the north arm, accumulating salt precipitate as thick as 8 feet requires repeated dredging from the Behrens Trench, an underwater canal used in the mineral extraction process by Compass Minerals (Standard Examiner, 2016; FGSL, 2018).

Another problem created by low WSE is increased lakebed exposure, which increases the potential for dust pollution and related human health impacts due to dust from the exposed shores of the GSL (Hahnenberger and Nicoll, 2012; 2014). This is particularly worrisome and costly to mitigate due to the proximity of GSL to Salt Lake City and its growing metropolitan area. Recent work has also attributed significant dust from exposed GSL bed area with earlier snowmelt due to dust on snow albedo reductions (Lang et al., 2023). All of the concerns mentioned here that threaten the lake’s uses are exacerbated by low WSE. Therefore, water use in the GSL Basin and its effect on the lake are important to understand and manage.

Following the settlement of Salt Lake City in 1847, the population of Utah has grown steadily (Figure 12a). Much of this growth is centered around Salt Lake City within the basins draining into GSL. With increased population comes increased demands on the land and its resources, including water. Agricultural irrigation is the largest water consumer in Utah, accounting for over 70% of the state's water use (UGS, 2021), with other uses making up the balance (Figure 12b). Increases in water use within the GSL Basin impact WSE, volume, and salinity and, therefore, the many uses of the lake.

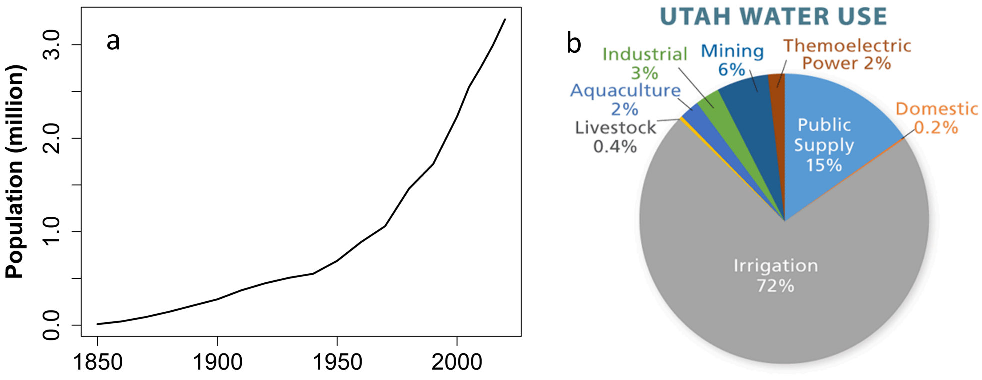

Figure 12. a) Population of Utah, 1850-2020. b) Water use in Utah (UGS, 2021).

In recent years, there have been efforts to estimate CU for the GSL Basin. However, existing estimates of CU in the literature are disparate. For example, Wurtsbaugh et al. (2017) estimate present day total annual CU to be ~1.7 km^3 while the GSL Strike Team (GSLST, 2023) estimate is ~2.6 km^3 (Figure 13), more than a 50% difference. The GSL Strike Team reported individual year CU for the contemporary period, 1989-2020, and found CU within that period to be fairly consistent with no overall trend (black line, Figure 13). Wurtsbaugh et al. infers CU back to ~1850 and their estimate (red line, Figure 13) suggests that the majority of CU growth occurred shortly after the GSL Basin was settled, prior to the turn of the century and prior to complete stream gaging. Wurtsbaugh et al. (2017) also estimated that the total CU in the GSL Basin between ~1850 and present day has decreased the WSE of GSL by over 3 meters.

These direct approaches to quantifying CU are challenging as they involve the aggregation of uncertain inputs, including summaries of land use and estimates of evapotranspiration, ungauged inflows, and irrigation return flows (Wurtsbaugh et al., 2017).

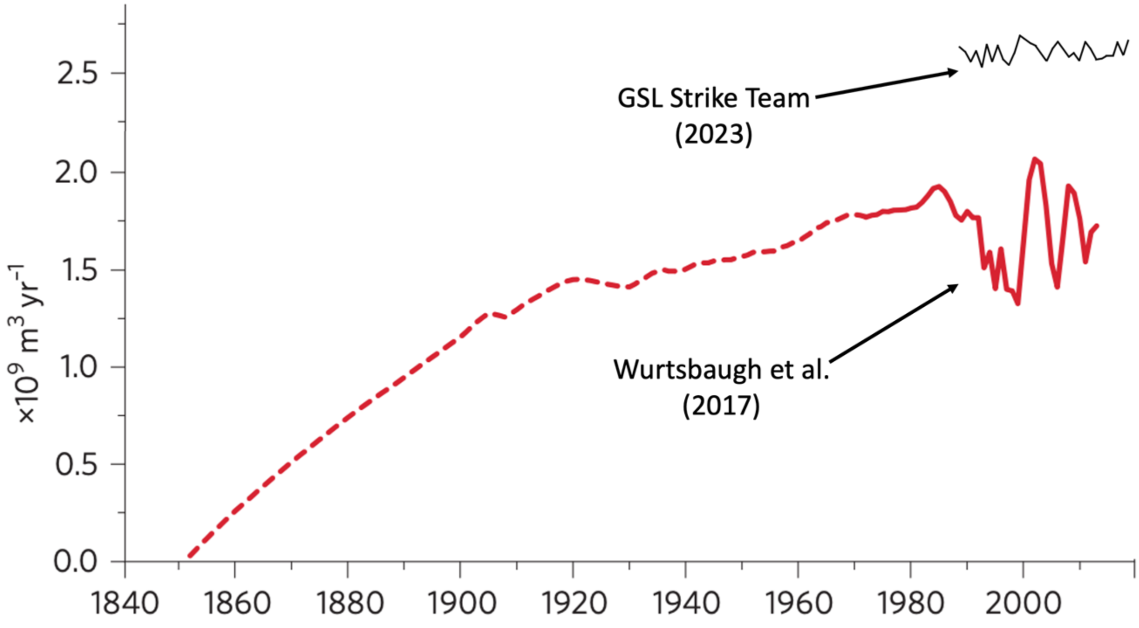

Figure 13. Contrasting estimates of consumptive use for the GSL Basin, including historical consumptive water use from Wurtsbaugh et al (2017, red line), and contemporary consumptive use reported by GSL Strike Team (2023, black line). Consumptive uses prior to 1989 (dashed line) are estimated and based on unpublished data from Utah Division of Water Resources (Wurtsbaugh et al., 2017).

2 Methods

The water mass balance equation for a closed basin lake such as GSL may be stated as:

$$\text{Change in Volume} = \text{Inflow} + \text{Precipitation} - \text{Evaporation} \tag{1}$$

Given our interest in estimating streamflow prior to its measurement, Equation 1 may be rearranged as:

$$\text{Inflow} = \text{Change in Volume} - \text{Precipitation} + \text{Evaporation} \tag{2}$$

This arrangement offers opportunities for estimating hindcast Inflow through measurements of the change in volume and estimates of lake precipitation and evaporation. As part of Inflow, streamflow into the lake from all three major rivers is available since only 1949. Change in Volume can be calculated from WSE data, which are available starting in 1847 through the USGS National Water Information System website (USGS Site Numbers 10010000 and 10010100, in https://maps.waterdata.usgs.gov/mapper, accessed on 1 March 2023). Precipitation over the GSL Basin is available to a varying degree of quality from sources such as PRISM since approximately 1900 (Daly et al., 2008, https://prism.nacse.org). Evaporation has not been directly measured and is generally calculated from mass balance closure, which limits its availability to 1949 to present. Therefore, to extend estimates of Inflow back over times prior to its measurement, suitable assumptions or approximations must be made for Precipitation and Evaporation.

Here we evaluated a total of four approaches to hindcasting. For all four we assumed that the depth of the freshwater equivalent lake evaporation each year was constant at its average value. For precipitation we considered three options. First, because precipitation data is not available for the full duration of our study, we assumed precipitation depth was constant at its long-term average value. Second, recognizing that precipitation and streamflow are correlated, we assumed a constant runoff ratio and constant proportion between basin and lake precipitation. Third, we hindcast streamflow using the actual PRISM data for the period it was available. Fourth, we included precipitation volume in the inflow quantity being hindcast, effectively estimating streamflow plus precipitation from volume changes as the hindcast quantity, avoiding introducing uncertainty due to not knowing precipitation, and instead transferring the uncertainty to the interpretation of the combined input quantity hindcast. These four approaches all exploit the fact, reported by Mohammed and Tarboton (2012), that GSL Change in Volume is significantly more sensitive to Streamflow variability than Precipitation or Evaporation variability and, therefore, that the sensitivity of hindcast Inflow to errors introduced through approximating Precipitation and Evaporation is likely to be relatively small. The uncertainty in these inflow hindcasts was quantified through comparison of their estimates to actual streamflow and, in the case of the runoff ratio based precipitation hindcast, to PRISM precipitation over the periods when there is streamflow and precipitation data. Common hydrologic performance metrics (Nash-Sutcliffe Efficiency, Kling-Gupta Efficiency, Root Mean Square Error) were used to quantify this uncertainty. These hindcasts were then used to infer how lake inputs (either streamflow or streamflow plus precipitation) have reduced since lake levels were first measured, presumably due to the development of water resources and CU. In each of the subsections below, we give details of the calculations and equations involved.

2.1 GSL Specific Water Mass Balance

To fully describe the process of developing a hindcast estimate of the Inflow specific to streamflow into GSL, a more detailed expression of Equation 1 is shown in Equation 3.

$$\begin{aligned}\mathit{\Delta} V &= V_i(WSE_i) - V_{i-1}(WSE_{i-1}) \\ &= Q_S + Q_G + Q_{ME} + Q_{WD} + P_L * A_L - E_L * A_L\end{aligned} \tag{3}$$

As expressed here, ΔV = Change in Volume; Inflow has been separated into Q_S = surface inflow (streamflow) volume, Q_G = groundwater flow volume, Q_{ME} = mineral extraction pumping (negative) and return flow volume (positive), and Q_{WD} = west desert pumping (negative) and return flow volume (positive); Precipitation has been expressed as P_L = precipitation depth over the lake times A_L = area of the lake; and Evaporation as E_L = evaporation depth over the lake times A_L. Lake volume and lake area are both functions of WSE through the bathymetry of the lake. WSE is the quantity that has been measured over time. Equation 3 can be rearranged to solve for surface inflow volume, Q_S, and used to estimate the hindcast of historical inflow to GSL once data, assumptions, and approximations for variables on the right-hand side of Equation 4 are established.

$$Q_S = \Delta V - Q_G - Q_{ME} - Q_{WD} - P_L * A_L + E_L * A_L \tag{4}$$

In this equation, ΔV and A_L are calculated directly from WSE measurements back to 1847. Constant Groundwater Inflow, Q_G, is estimated based on prior work (Waddell and Fields, 1977). Mineral extraction, Q_{ME}, and west desert pumping, Q_{WD}, are known quantities. They are 0 prior to when they began in 1960 and 1987 respectively. This leaves the variables P_L and E_L to be estimated in order to use Equation 4 for hindcasting. Flow quantities and lake areas were evaluated using annual or 12-month average data for the U.S. Water year starting October 1. Lake volumes were taken as end of water year values so that ΔV was a water year difference associated with the period flows were averaged.

2.2 Inflow

In Equation 4, inflow to GSL is separated into streamflow volume (Q_S), groundwater flow volume (Q_G), mineral extraction pumping and return flow volume

(Q_{ME}), and west desert pumping and return flow volume (Q_{WD}). We used streamflow data from the United States Geological Survey (USGS), https://maps.waterdata.usgs.gov/mapper/ (accessed 1 June 2023). Missing data was filled in using regression with nearby stations to create a complete $Q_{S,measured}$ dataset for 1949-2023 using methods documented by Tarboton (2023) that were adapted from Loving et al. (2000) and Mohammed and Tarboton (2012). Waddell and Fields (1977) estimated annual GSL groundwater inflow to be $Q_G = 0.0925$ km^3/year. We took this quantity as a constant for the entire 1847-2022 period due to the lack of information on temporal variability of groundwater inflows. There is uncertainty in this assumption, but errors due to this assumption are expected to be small due to the small overall contribution from groundwater. The West Desert Pumping Project circulated water out of GSL from 1987-1989 and then back to GSL from 1990-1992. Flow estimates for Q_{WD} were obtained from Loving et al. (2000). Mineral extraction in GSL started in the 1960s. Flow rates for Q_{ME} were estimated based on withdrawals reported by mineral industries to the Utah Division of Water Rights. More detailed information can be found on the Q_{WD} and Q_{ME} time series in Merck and Tarboton (2023).

2.3 Area and Volume

Lake area and lake volume are functions of WSE. They were tabulated in 0.15 m (0.5 foot) increments, for elevations from 1269.5 m to 1286.45 m, from the bathymetry using methods detailed in Merck and Tarboton (2023). These areas and volumes are available in HydroShare (Tarboton, 2017a), as is the lakebed bathymetry digital elevation model (Tarboton, 2017b) used to derive them and more detailed descriptions of methodology. The historical time series of WSE was used to interpolate time series of A_L, volume, and hence *ΔV* needed for our analysis from the lake area and volume bathymetry tables. This paper used the total volume in each arm of the lake, including areas now separated into mineral extraction evaporation ponds because, at the times the lake was high, these pond areas were effectively part of the lake due to either being breached or not yet being constructed and our focus is on inferring what inflows were prior to pond construction.

2.4 Evaporation

Measured evaporation data is not available for GSL. However, all other terms in Equation 3 are available from 1949 to present. Thus, Equation 3 can be rearranged to calculate evaporation for the years 1949-2022 using mass balance closure.

$$E_{L,MB} = \frac{Q_S + Q_G + Q_{ME} + Q_{WD} + P_L * A_L - \Delta V}{A_L} \tag{5}$$

Recognizing that evaporation is sensitive to salinity, which changes from year to year, the evaporation term is further expressed as

$$E_{L,MB} = E_{f,MB} * SCF \tag{6}$$

where $E_{f,MB}$ = mass balance freshwater evaporation and SCF = salinity correction factor, which reduces freshwater evaporation based on salinity. The freshwater evaporation depth over the lake, $E_{f,MB}$, can be calculated for 1949-2022 using Equation 6 once the *SCF* has been calculated. Mohammed and Tarboton (2012) developed a modification to the Penman method for calculating lake evaporation based on salinity using an activity coefficient to reduce saturation vapor pressure. This was used to calculate GSL evaporation over the period of their study. Comparing their salinity dependent evaporation and freshwater evaporation, we developed the following empirical equation for SCF as a function of salinity, *S*.

$$SCF = -1 \times 10^{-11} * S^4 + 3 \times 10^{-9} * S^3 - 2 \times 10^{-4} * S + 1 \tag{7}$$

Salinity is required to use Equation 7 and was calculated based on salt mass divided by lake volume, $S = M_{salt}/V_{Lake}$, where V_{Lake} is a function of bathymetry and WSE. Merck and Tarboton (2023) estimated GSL salt mass based on salinity and volume measurements for the period 1966 to present. Salt mass prior to these dates (1847-1966) was inferred based on the salinity of river inputs (Hahl, 1968). The mean $E_{f,MB}$ for 1949-2022, $E_{f,mean}$, was used along with estimated SCF to calculate the times series of evaporation depth over the lake, E_L, for 1847-2022.

$$E_L = E_{f,mean} * SCF \tag{8}$$

2.5 Precipitation

Gridded data for precipitation depth are available with a 4 km resolution for the years 1895 to present from the PRISM Climate Group based at Oregon State University (https://prism.nacse.org, accessed 1 June 2023). PRISM uses interpolation based on physiographic similarity to estimate precipitation from discontinuous and intermittent point observations (Daly et al., 2008). PRISM estimates do suffer from uncertainty, especially during the early years, when the underlying point observations are sparse. There are also other gridded precipitation data sources (e.g., NLDAS, DAYMET, gridMET) available in easy-to-use format from sites such as climateengine.org (Huntington et al., 2017), but these start no earlier than 1950. We performed spot check comparisons of PRISM precipitation versus some of these other sources, and versus point observations for some long running precipitation stations in the GSL basin, and found differences to be generally small, though there were some sites with notable biases. However, we decided that relying on the knowledge built into PRISM methods for interpolation and addressing shortcomings due to missing data was preferable to us attempting our own interpolation from point precipitation observations. Thus, our analysis has used PRISM data.

PRISM precipitation data were extracted for the area of the three river basins (Bear, Weber and Jordan) that contribute to streamflow into GSL, $P_{B,PRISM}$, and the area over the lake, $P_{L,PRISM}$, for the full duration of the PRISM dataset. A hindcast of precipitation was still needed for 1847-1895, the years for which PRISM is not available, and, as noted above, we evaluated two options: (1) constant precipitation at its long-term average value; and (2) lake precipitation estimated from runoff ratio and the ratio with basin precipitation ratio being assumed constant.

Detailing the second approach, streamflow volume in a basin is related to the precipitation volume over that basin through the runoff ratio, r, expressed as

$$r = \frac{Q_S}{P_B * A_B} \tag{9}$$

where Q_S = streamflow volume in the basin, P_B = precipitation depth over the basin, and A_B = 35,637 km^2, the area of the combined Bear, Weber, and Jordan River basins. While r varies year to year, an average value for r was estimated based on data from 1949-2022, the years data is available for all three variables in Equation 9. Another assumption is that the precipitation depth over the basin and the precipitation depth over the lake are linearly related for the GSL Basin such that

$$P_B = a * P_L \tag{10}$$

where a = basin to lake precipitation ratio and P_L = precipitation depth over the lake. A value for a was estimated based on PRISM data, $P_{B,PRISM}$ and $P_{L,PRISM}$, for the years 1895-

2022. Average values for *r* and *a* were substituted into Equation 3 and then solved for precipitation depth over the lake.

$$P_{L,ra} = \frac{\Delta V - Q_G - Q_{ME} - Q_{WD} + E_{f,mean} * SCF * A_L}{(r * a * A_B + A_L)} \tag{11}$$

All variables on the right side of Equation 11 now have either measured data or have been estimated for the years 1847-2022 and can be used to estimate a time series of precipitation depth over the lake, $P_{L,ra}$.

2.6 GSL Inflow Hindcasts

The first hindcast inflow to GSL, $Q_{S,Pmean}$ or just the *Pmean* hindcast, was calculated for 1847-2022 using Equation 4 based on the assumption of constant depths over the lake for precipitation and freshwater evaporation. The mean of the PRISM time series data for the years 1895-2022, $P_{L,mean}$, was used for precipitation depth, P_L. The mean of the mass balance freshwater evaporation depth for the years 1949-2022, $E_{f,mean}$, was used for freshwater evaporation depth, E_f, along with estimated SCF for the years 1847-2022. Substituting these variables into Equation 4 we get

$$Q_{S,Pmean} = \Delta V - Q_G - Q_{ME} - Q_{WD} - P_{L,mean} * A_L + E_{f,mean} * SCF * A_L \tag{12}$$

The second hindcast inflow to GSL, $Q_{S,ra}$ or just the *ra* hindcast, was also calculated for 1847-2022 using constant freshwater evaporation depth over the lake in Equation 4. However, this hindcast used the assumption that the runoff coefficient, *r*, and precipitation ratio, *a*, are both constant over the years 1847-2022, and therefore the hindcast precipitation, $P_{L,ra}$, was used for precipitation, P_L. Substituting into Equation 4 we get

$$Q_{S,ra} = \Delta V - Q_G - Q_{ME} - Q_{WD} - P_{L,ra} * A_L + E_{f,mean} * SCF * A_L \tag{13}$$

A third hindcast inflow to GSL, $Q_{S,PRISM}$ or just the *PRISM* hindcast, was calculated using PRISM data, $P_{L,PRISM}$, and constant freshwater evaporation depth over the lake in Equation 4 for the dates PRISM data is available, 1895-2022. Substituting into Equation 4 we get

$$Q_{S,PRISM} = \mathit{\Delta}V - Q_G - Q_{ME} - Q_{WD} - P_{L,PRISM} * A_L + E_{f,mean} * SCF * A_L \tag{14}$$

The *PRISM* hindcast was used in both reconstructions of inflow to GSL for the years 1895-1948, the years PRISM data is available but streamflow data is not.

2.7 Primary Inputs Hindcast: $Q + P$ Using $\mathit{\Delta}V$ and Constant E_L

Equation 3 can be rearranged to calculate the primary inputs to GSL, inflow and precipitation, using mass balance closure as follows

$$Q_S + P_L * A_L = \mathit{\Delta}V + E_L * A_L - Q_G - Q_{ME} - Q_{WD} \tag{15}$$

All variables on the right-hand side of Equation 15 are known or have reasonable approximations for the years 1847-2022. This fourth hindcast provides information on the total input to the lake without the uncertainties introduced by precipitation assumptions and serves as another line of evidence quantifying reduced inputs.

2.8 GSL Inflow Reconstructions

Inflows to GSL were reconstructed using inflow hindcasts and measured streamflow. The *Pmean* and *ra* hindcasts were used for 1847-1894, the years there is no precipitation, evaporation, or streamflow data available. The *PRISM* hindcast was used for 1895-1948, the years there is PRISM precipitation data available but no evaporation or streamflow available. And measured streamflow was used for 1949-2022.

$$\begin{gathered} Q_{R,Pmean} = concatinate(Q_{S,Pmean}(1847 - 1894), \\ Q_{S,PRISM}(1895 - 1948), Q_{measured}(1949 - 2022)) \end{gathered} \tag{16}$$

$$Q_{R,ra} = concatinate(Q_{S,ra}(1847 - 1894), \quad Q_{S,PRISM}(1895 - 1948), Q_{measured}(1949 - 2022)) \tag{17}$$

These inflow reconstructions were used to determine the associated input reductions, natural flow, and WSE for GSL.

2.9 Consumptive Use and Natural Flow

The natural flow of a stream, Q_N, is equal to the measured streamflow, Q_S, plus the reductions due to water depletions for its basin, Q_D.

$$Q_N = Q_S + Q_D \tag{18}$$

Historical streamflow in the GSL Basin measured at points above diversions, or tree-ring reconstructed flows not subject to diversions that quantify the natural flow of the basin, does not show long-term trends. Therefore, any long-term, ongoing trend in the historical time series of inflow to GSL can be attributed to human water use depletions within the GSL Basin. Mean inflows to GSL were determined for the first and last 30 years of the historical time series in order to establish starting and ending points for determining input reductions. There is some arbitrariness in this selection of 30 years, but it is a common averaging period used for climate averages as it spans a period a longer period than the typical annual and decadal frequencies present in many hydrologic and climate series. The 30-year moving average was used to determine the general trend of input reductions in the GSL Basin, $Q_{D,Pmean}$, $Q_{D,ra}$, $Q_{D,Q+P}$, for their respective inflow reconstructions. Note that the input reductions associated with the primary inputs hindcast were determined using the same methods as the reductions associated with the reconstructed inflows, with early and late means for start and end points and trends for decreasing flows.

2.10 Natural Water Surface Elevation

The water mass balance in Equation 3 was solved using implicit finite differences to calculate what the lake volume and corresponding WSE would have been given reconstructed natural flows, $Q_{N,Pmean}$ and $Q_{N,ra}$. With an initial WSE of $WSE_{i=0}$ = 1280.267 meters on 1847-10-01 (the beginning of water year 1848), the inflow, precipitation, and evaporation for each water year, i, were used to step ahead to a new lake volume, V_i, and corresponding WSE_i at the end of the water year. Evaluation of the fluctuations in the annual WSE indicate that end of water year WSE_i + 0.15 meters better represents the mean annual WSE over a water year, and therefore this value was used to determine $A_{L,i}$ in the calculation of area dependent precipitation and evaporation volumes. SCF was calculated based on the lake volume of the previous water year. The natural flow and associated WSE were not calculated for the primary inputs hindcast because it has built into it the historical area of the lake (A_L is on the left-hand side of equation 15) and adding estimated depletion to this would not account for the effect of larger lake area associated with the resulting higher lake levels.

2.11 Hindcast Performance, Validation and Error

The metrics used to evaluate and validate hindcast performance and estimate error include the coefficient of variation (*CV*), Root Mean Square Error (*RMSE*), normalized RMSE (*nRMSE*), Nash-Sutcliffe Efficiency (*NSE*), and Kling-Gupta Efficiency (*KGE*). The formulas for each are as follows:

$$CV = \frac{\sigma}{\mu} \tag{19}$$

$$RMSE = \sqrt{\frac{1}{n}\sum\nolimits_{i=1}^{n}(S_i - O_i)^2} \tag{20}$$

$$nRMSE = \frac{RMSE}{\mu_{obs}} \tag{21}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \tag{22}$$

$$KGE = 1 - \sqrt{(r-1)^2 + \left(\frac{\sigma_{sim}}{\sigma_{obs}} - 1\right)^2 + \left(\frac{\mu_{sim}}{\mu_{obs}} - 1\right)^2} \tag{23}$$

where σ = standard deviation; μ = mean; S = the simulated value; O = the observed value; and r = Pearson correlation coefficient. The *CV* was used to evaluate the performance of the evaporation hindcasts while the *RMSE*, *nRMSE*, *NSE*, and *KGE* were used to evaluate the precipitation and validate inflow hindcasts. In order to determine which hindcast to use in the final inflow reconstruction during certain time periods, all three inflow hindcasts were compared with measured inflow for a validation period, 1949-2022, while the *Pmean* and *ra* hindcasts were comparted with the *PRISM* hindcast for a test period, 1895-1948.

3 Results

3.1 Evaporation

Evaporation depths and volumes over GSL are shown in Figure 14. The mass balance time series of evaporation depth, $E_{L,MB}$, for the years all measured data were available, 1949-2022 (Figure 14a, black solid line), was found to have a mean annual depth of 1.09 m. The mass balance freshwater evaporation depth, $E_{f,MB}$ (Figure 14a, gray solid line), has mean, $E_{f,mean}$, of 1.16 m (Figure 14a, gray dashed line) and

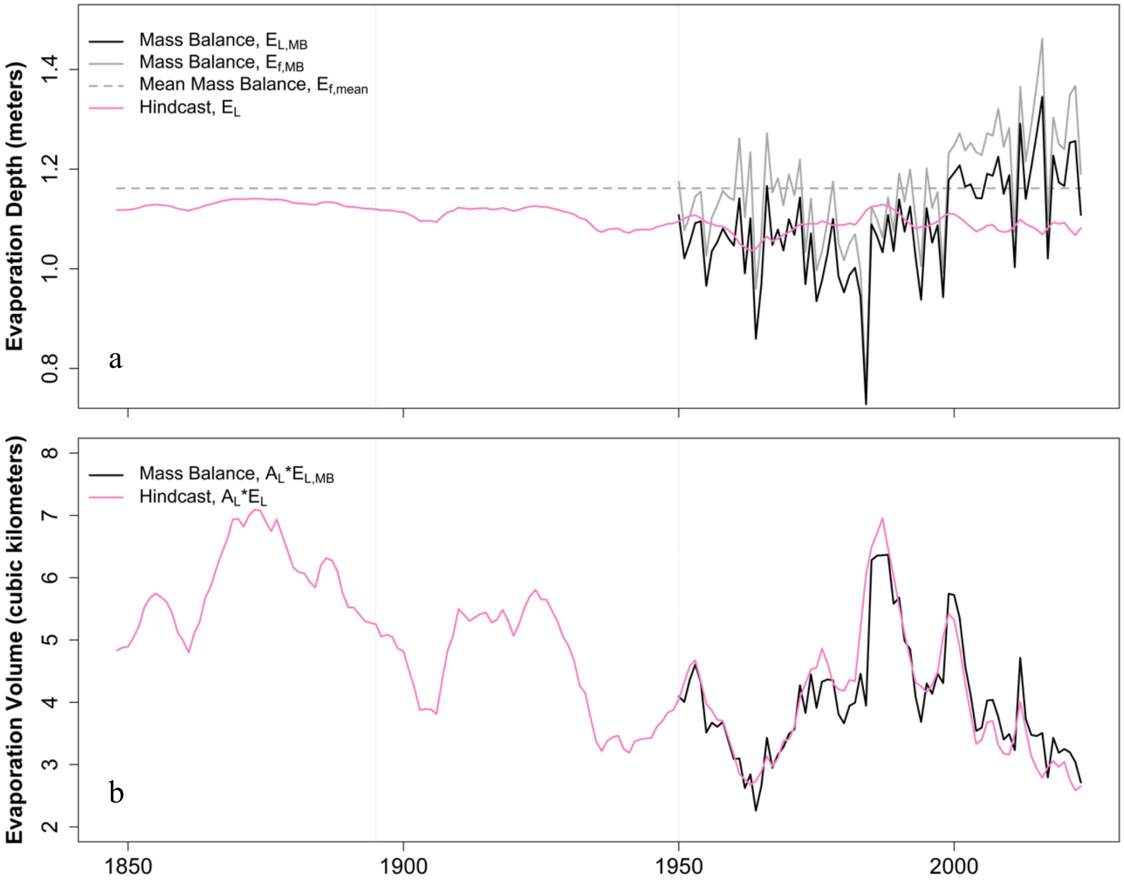

Figure 14. Evaporation (a) depths and (b) volumes over GSL. Results using measured data for mass balance closure over the years 1949-2022 include mass balance freshwater evaporation depth ($E_{f,MB}$, gray solid line), its mean of 1.16 m ($E_{f,mean}$, gray dashed line), and mass balance evaporation depth ($E_{L,MB}$, black solid line). Hindcast results for the years 1847-2022 include evaporation depth over the lake (E_L, pink solid line).

standard deviation 0.1 m, reflecting a CV of less than 0.1. This small CV supports the approximation of E_f as a constant (i.e., $E_f = E_{f,mean} = 1.16$ m) for use in Equation 8 when calculating the hindcast evaporation depth over the lake, E_L (Figure 14a, yellow solid line).

3.2 Precipitation

PRISM precipitation depths were used along with measured USGS streamflow in Equation 9 for years both datasets were available, 1949-2022, to estimate the average GSL Basin runoff ratio, $r = 0.13$ (Figure 15a), and in Equation 10 for years 1895-2022 to estimate the basin to lake precipitation ratio, $a = 1.55$ (Figure 15b). The mean annual PRISM precipitation depth over the lake, $P_{L,Pmean}$, is 0.340 m (Figure 16a, gray line). Based on the assumption of constant values for r, a, and $E_{f,mean}$, a hindcast times series was calculated for precipitation depth over the lake, $P_{L,ra}$ (Figure 16a, orange line), for the years from 1847-2022 using Equation 11, which is driven by WSE that inform lake volume change, lake area, and SCF. The mean depth of $P_{L,ra}$ for the years 1895-2023 is 0.364 m, which is 7% more than the mean $P_{L,PRISM}$ (Figure 16a, black line) for the same period. Comparing evaluation metrics for $P_{L,ra}$ and $P_{L,PRISM}$ on the overlapping years, the RMSE is 0.124 m, reflecting a normalized RMSE of 37%, which is rather high. Interestingly, the NSE is -0.37, indicating that $P_{L,Pmean}$ is a better predictor of precipitation depth over the lake than $P_{L,ra}$, while the KGE is 0.43, indicating $P_{L,ra}$ is a reasonable predictor of precipitation depth over the lake. Both $P_{L,ra}$ and $P_{L,Pmean}$ were used to estimate hindcasts of inflow to GSL and these metrics for the precipitation should be held in mind when interpreting each inflow hindcast.

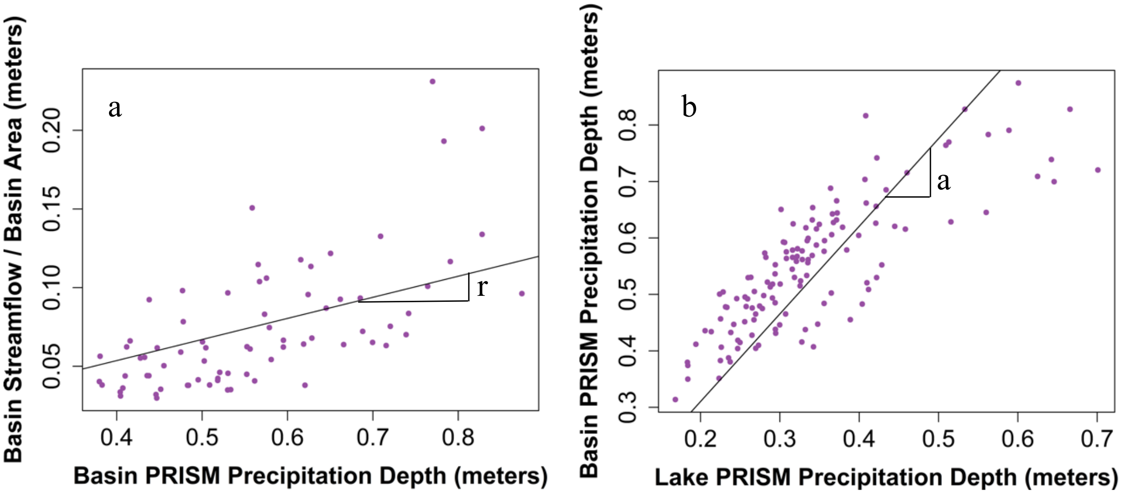

Figure 15. (a) Streamflow volume and precipitation volume in the GSL Basin and the correlation between the two (black line) representing the runoff ratio, $r = 0.13$ (Equation 9). (b) Precipitation depth over the GSL Basin and lake and the linear relationship between the two (black line) representing the basin to lake precipitation ratio, $a = 1.55$ (Equation 10).

3.3 Inflow Hindcasts

Inflow hindcast results are shown in Figure 17. All three inflow hindcasts were compared with measured inflow (blue line) in a validation period, 1949-2022, and with the *PRISM* hindcast (green line) in a test period, 1895-1948. All evaluation metrics establish the *ra* hindcast (blue line) as a more accurate hindcast than the *Pmean* hindcast (red line) for the validation period, 1949-2022 (Table 1, “Validation” columns), and the *Pmean* hindcast as a more accurate hindcast than the *ra* hindcast for the test period, 1895-1948 (Table 1, “Test” columns). These metrics for the inflow hindcasts should be held in mind when interpreting each inflow reconstruction.

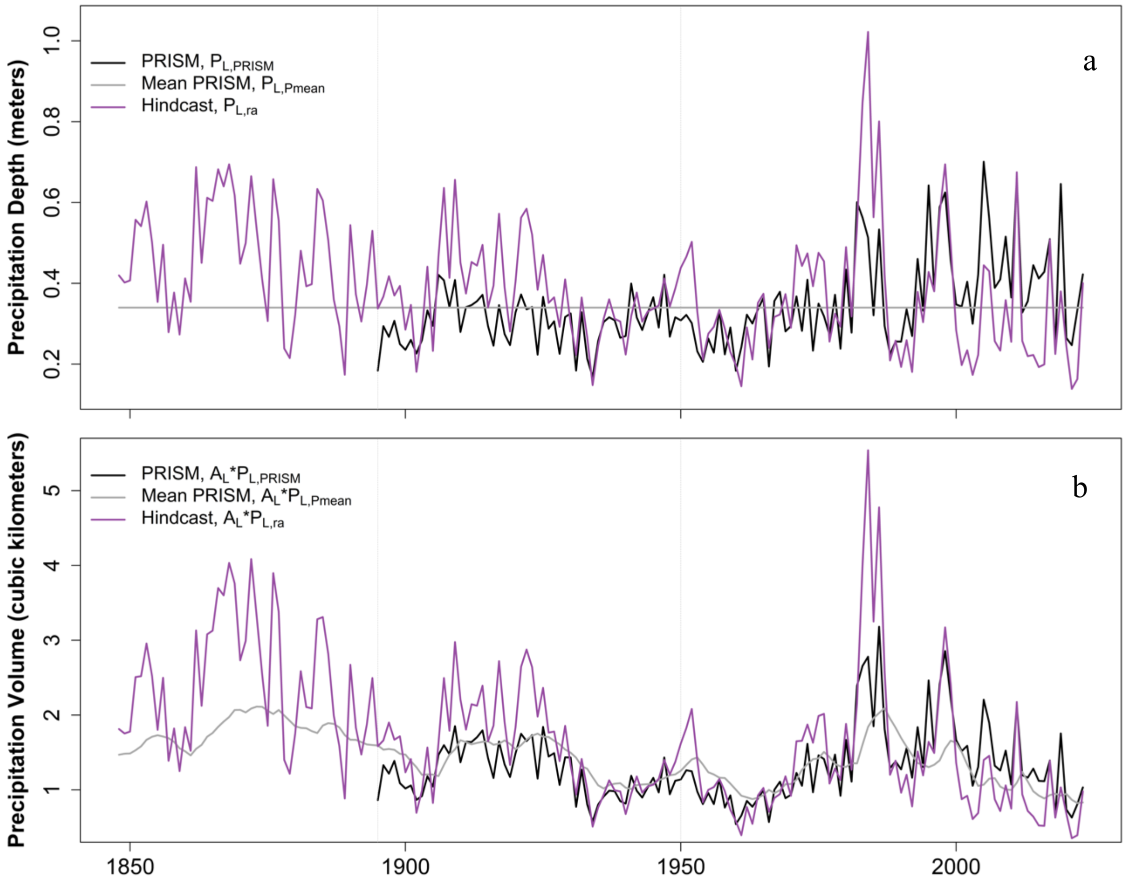

Figure 16. Precipitation depths (a) and volumes (b), including PRISM data over the lake (black solid line), mean PRISM data over the lake (gray solid line), and calculated depth over the lake using constant *r* and *a* (purple solid line).

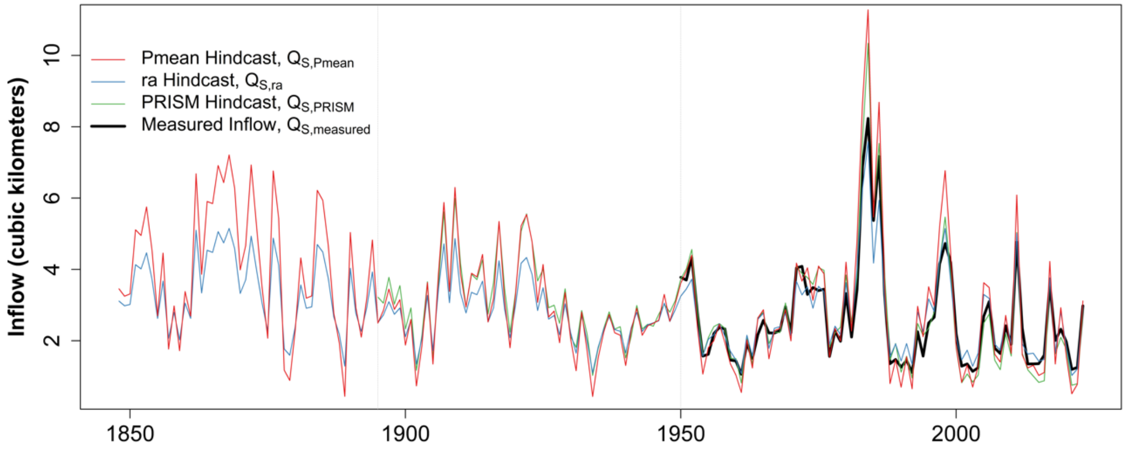

Figure 17. Inflow hindcast results for *Pmean* ($Q_{S,Pmean}$, red line), *ra* ($Q_{S,ra}$, blue line), and *PRISM* ($Q_{S,PRISM}$, green line). Measured inflow (black line) is included for comparison.

Table 2. Evaluation metrics for the inflow hindcasts in Figure 17 for the periods 1895-1948 and 1949-2022.

Evaluation Metric	Test (1895-1948)		Validation (1949-2022)		
	Pmean	*ra*	*Pmean*	*ra*	*PRISM*
NSE	0.93	0.80	0.76	0.92	0.91
KGE	0.86	0.70	0.60	0.86	0.80
RMSE	0.29 m	0.48 m	0.70 m	0.39 m	0.42 m
nRMSE	9%	16%	27%	15%	16%

3.4 Input Reductions Inferred from Reconstructions and Hindcasts

Two reconstructed times series were developed for inflow to GSL, $Q_{R,Pmean}$ and $Q_{R,ra}$ (Equations 16 and 17, respectively) using the respective *Pmean* and *ra* inflow hindcasts for 1847-1894, the *PRISM* inflow hindcast, $Q_{S,PRISM}$, for 1895-1948, and the measured streamflow, $Q_{S,measured}$, for 1949-2022. The *Pmean* and *ra* reconstructed inflows are shown in Figure 18a, specifying the individual components, *Pmean* hindcast (red solid line), *ra* hindcast (blue solid line), *PRISM* hindcast (green solid line), and measured streamflow (black solid line). Also included are the 30-year moving averages (black solid lines). Note the moving averages are separate for *Pmean* and *ra* for 1847-1894 and then overlap for the remainder of the reconstruction where both use the *PRISM* inflow hindcast and measured streamflow. Also indicated are the starting and ending points of the moving average represented by 30-year spans (horizontal dashed lines).

Similarly, a hindcast of primary inputs to GSL, $Q_S+P_L*A_L$, was calculated for 1847-2022 using Equation 15. As with the inflow hindcasts, change in lake volume and inflows due to groundwater, mineral extraction, and west desert pumping are known volumes for the entire period and therefore predetermined, and the mean freshwater mass

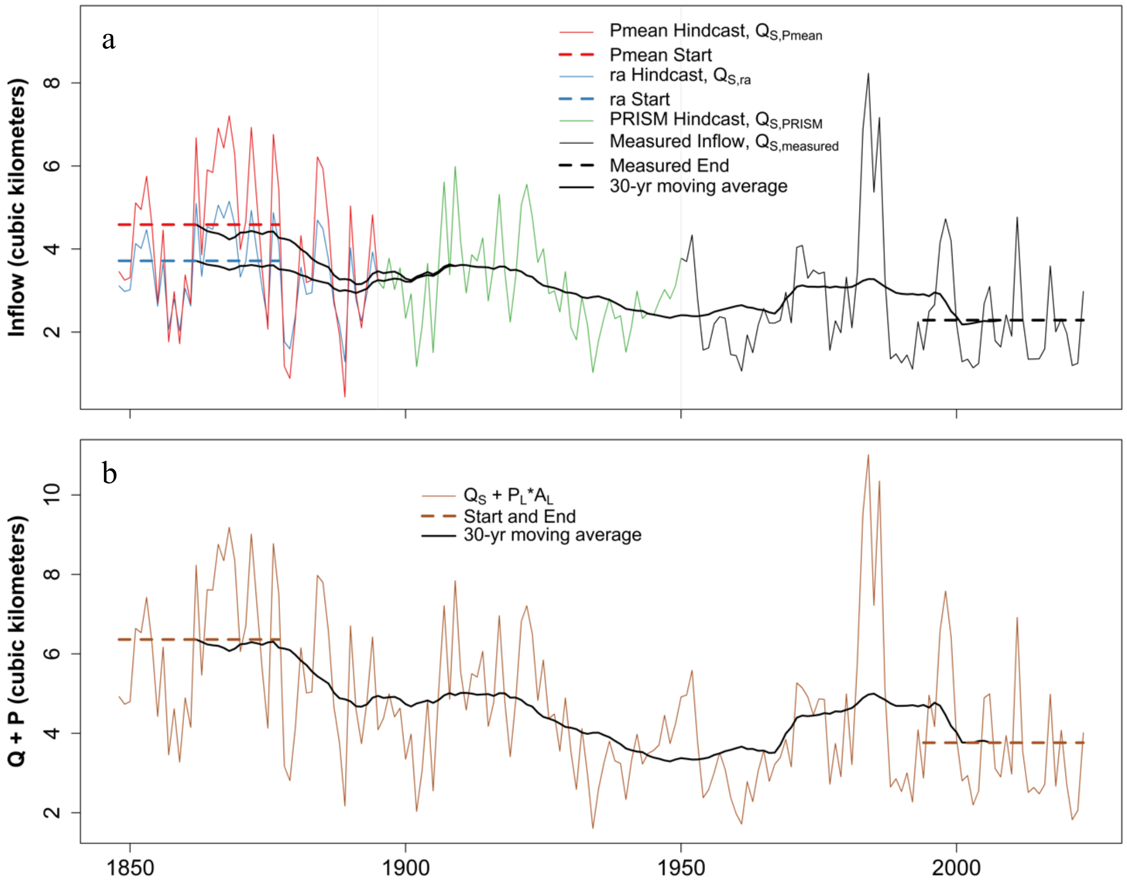

Figure 18. (a) Inflow reconstructions using $Q_{S,\ Pmean}$ (red line) and $Q_{S,ra}$ (blue line) for 1847-1894, $Q_{S,PRISM}$ (green line) for 1895-1948, and $Q_{S,measured}$ (black line) for 1949-2022. Also included are the 30-year moving averages (black lines) and the 30-year spans representing the start and end of the moving average (dashed lines). (b) Primary inputs hindcast (brown line) with 30-year moving average and 30-year spans representing start and end of the moving average (dashed lines).

balance evaporation, $E_{f,mean}$, was also used in Equation 15. The results for the primary inputs hindcast are shown in Figure 18b along with the 30-year moving average (black solid line) as well as the 30-year spans representing the starting and ending points of the moving average (horizontal dashed lines).

The reduced input, representing changes to inflow into GSL between 1847 and 2022, was inferred by taking the difference between the starting and ending points, defined by the 30-year spans (dashed horizontal lines) for each reconstruction method.

The decline in the 30-year moving averages seen in *Pmean* and *ra* in Figure 18a and the primary inputs in Figure 18b approximate the input reductions due to water depletions over the historical record. These input reductions were used to determine time series for the *Pmean* and *ra* reconstructions, $Q_{D,Pmean}$ *and* $Q_{D,ra}$, and the primary inputs hindcast, $Q_{D,Q+P}$. Starting points of $Q_D = 0$ in 1847 were used based on the respective starting point mean flows for *Pmean* (red dashed line, Figure 18a), *ra* (blue dashed line, Figure 18a), and primary inputs flows (brown dashed line, Figure 18b). Ending points in 2022 were used based on the recent mean measured inflow (black dashed lines, Figures 18a and b). The Q_D in all three time series were increased from $Q_D = 0$ in 1847 to their respective recent magnitudes by 1960, $Q_D = Q_{start} - Q_{end}$, based on the rate inferred by the general trend and shape of the 30-year moving averages. The resulting current depletion magnitudes, Q_D, are 2.30 km^3/yr, 1.43 km^3/yr, and 2.60 km^3/yr for *Pmean*, *ra*, and the primary inputs, respectively (Figure 19). Note that the selection of 1960 as the year to switch from increasing consumptive use to flat consumptive use is based on the 30 years means in Figure 18 essentially flattening out by then. While recognizing the uncertainty

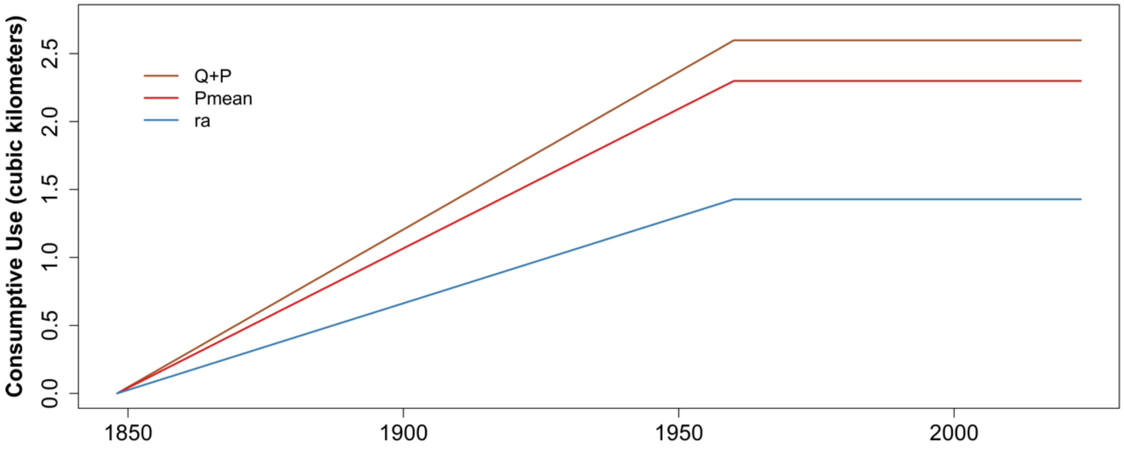

Figure 19. Input reductions inferred from reconstructions and hindcasts are 2.30 km^3/yr, 1.43 km^3/yr, and 2.60 km^3/yr for *Pmean*, *ra*, and the primary inputs, respectively.

in selection of this point is about plus or minus 15 years, this uncertainty does not tangibly affect our results.

3.5 Natural Inflow Reconstructions and Associated Water Surface Elevation

The Q_D from Figure 19 were added to the respective *Pmean* and *ra* reconstructed flows in Figure 18a based on Equation 18 to develop two estimated time series of natural flow into GSL, $Q_{N,Pmean}$ and $Q_{N,ra}$ (Figure 20). By definition, neither the *Pmean* nor *ra* time series for natural flow have a trend. The time series of estimated WSE corresponding to the *Pmean* and *ra* natural flows are presented in Figure 21 and show the current decline in WSE due to reduced inflow to be 4.46 m and 2.67 m, respectively.

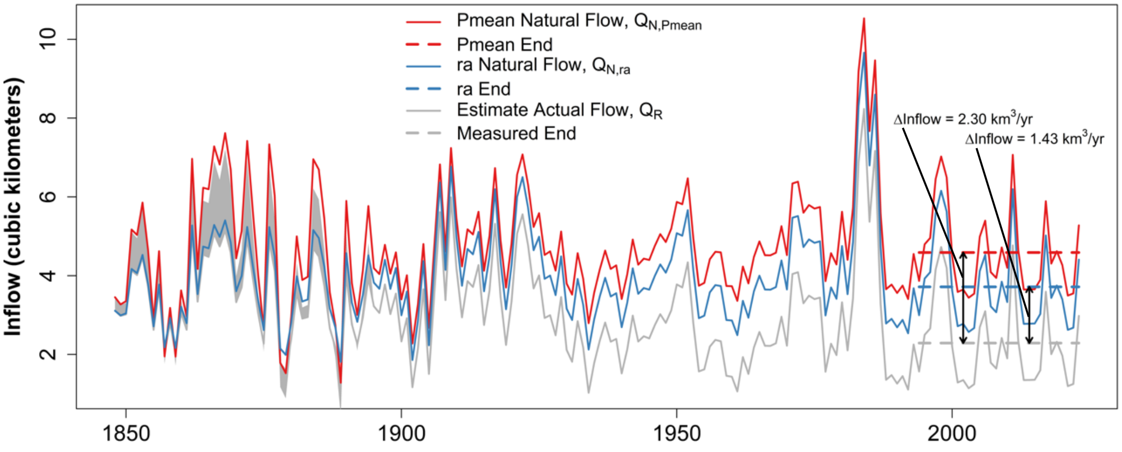

Figure 20. Reconstructed natural inflows to GSL $Q_{N,Pmean}$ (red line) and $Q_{N,ra}$ (blue line), not including depletions, shown in comparison to the respective reconstructed inflows (gray line).

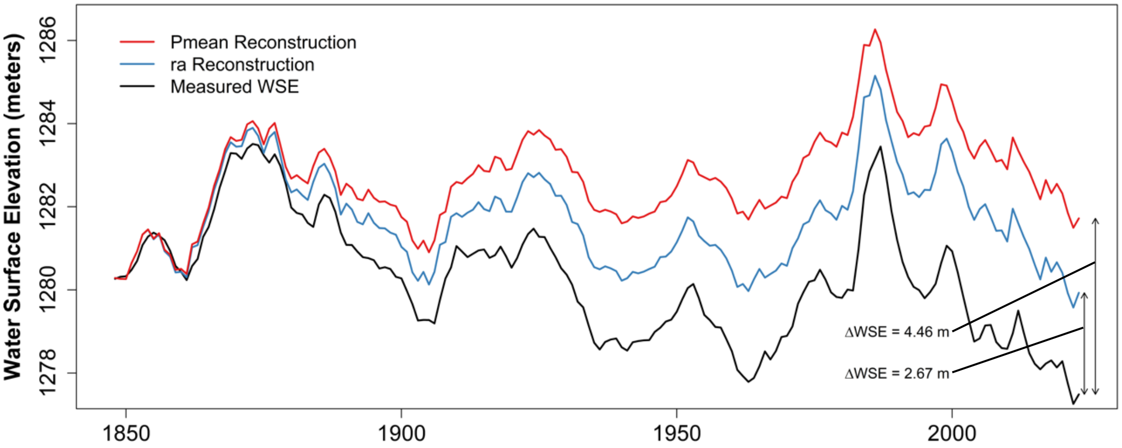

Figure 21. Great Salt Lake water surface elevation based on respective reconstructed natural inflows, $Q_{N,Pmean}$ (red line) and $Q_{N,ra}$ (blue line), shown in comparison to USGS measured water surface elevation (black line).

4 Discussion

The time series of mass balance evaporation depth over GSL, $E_{L,MB}$ (dotted black line, Figure 14a), is generally consistent with the mass balance results reported in Figure 10 of Mohammed and Tarboton (2012), and both time series produce a mean annual evaporation depth of approximately 1.1 m. The time series of mass balance freshwater evaporation depth, $E_{f,MB}$ (solid gray line, Figure 14), calculated using Equation 5 has mean depth, $E_{f,MBmean}$, of 1.16 m, which differs from the mean annual freshwater evaporation depth of 1.29 m that Mohammed and Tarboton calculated using climate data. They point out that GSL WSE modeled using a freshwater evaporation depth of 1.29 m is consistently lower than observed WSE (Figure 11 of their publication). The calculations in Mohammed and Tarboton are based on data through 2008, including estimated bathymetry and PRISM modeling methods that have both since been refined. In addition, since the publication of their work, there have been refinements to streamflow datasets and the state equation for estimating GSL salinity, which affect measured streamflow and the calculation of *SCF* and therefore the mass balance. It is for these reasons that we recalculated the value of $E_{f,MBmean}$ for use in our mass balance hindcasts rather than using their published values.

Overall, the metrics comparing the *Pmean*, *ra*, and *PRISM* inflow hindcasts indicate that all hindcast methods give a good prediction of inflow that enables interpretation of how inflows have been reduced over the historical record of WSE measurement and the associated uncertainty (Figure 17, Table 2). In evaluating these, we feel that the *Pmean* hindcast best captures long-term average lake inflow. The differences among the methods serve as an indicator of uncertainty which is small relative to the overall magnitude of the inflow reductions that are interpreted as being due to human consumptive use depletions. The *Pmean* hindcast using constant precipitation underestimates dry periods and overestimates wet periods ($Q_{S,Pmean}$, red solid line, Figure 17) with a relatively high RMSE (0.70 m), which is 27% of the mean (nRMSE). Because of this, we were motivated to develop a hindcast that better represents precipitation and its natural variation to use in the mass balance. Taking advantage of the correlations between basin precipitation, lake precipitation, and lake inflow, the *ra* hindcast precipitation we developed was estimated using a constant basin runoff ratio, *r*, and constant basin to lake precipitation relationship, *a*. The performance metrics are better for the *ra* inflow hindcast ($Q_{S,ra}$, blue line, Figure 17) than the *Pmean* hindcast for the validation period, 1949-2022. It is apparent in Figure 17 that the variability of the *Pmean* hindcast is amplified relative to the *ra* hindcast for the full period (1847-2022). However, the *ra* hindcast is generally below the *Pmean* hindcast prior to 1900. Although the two hindcasts overlap after 1900, crossing nearly every time there is a high-low or low-high transition, the low offset of the *ra* hindcast noticed before 1900 does not appear in later years and also does not appear in comparison to measured streamflow. This early period coincides with the period prior to significant water development and, therefore, significant depletions, when the GSL Basin was just being settled. Since *r* was calculated using present day precipitation and streamflow, it includes some CU effects. The *r* for the first 50 years or more (e.g., 1847-1900) may be expected to be more than our calculated *r* and we surmise that this may be the cause for the *ra* hindcast being less than the *Pmean* hindcast during that time. Another place this effect can be seen is when comparing the mean precipitation depth for *ra* for the years 1900-2022 and 1847-1900, which are 0.36 and 0.45 m. Using a larger runoff ratio prior to 1900 would result in higher flow than the *ra* hindcast flow, likely closer to the *Pmean* hindcast flows. In addition, when comparing these hindcasts (Figure 17a) with the primary inputs hindcast (Figure 17b) for the early period, 1847-1894, the *Pmean* and primary inputs hindcast are very similar and there is no bias or error included in the primary inputs hindcast due to precipitation. Thus, while the *ra* hindcast is better at capturing one to two year time scale variability, we feel that the *Pmean* hindcast, averaged over a longer period, better captures long-term average lake inflow.

When summing detailed CU to determine overall CU for a basin, like the method used for existing estimates for the GSL Basin, any diversions into or out of the basin would be included in the final result. The transbasin diversions that enter the GSL Basin fulfill CU within the basin but do not contribute to the decrease in flow into the lake or otherwise affect the lake volume. We estimated the decrease in GSL inflow based on changes in volume of the lake and therefore these types of diversions are not included in our result. However, we believe that they are effectively part of the CU reported by Wurtsbaugh et al. (2017) and the GSL Strike Team (GSLST, 2023). Therefore, for comparison to our results it is necessary to remove these diversions from the existing estimates of CU. The average annual transbasin diversion from the Colorado River Basin to the GSL Basin in Utah between 2001 and 2020 was 145,700 AF or 0.18 km^3 (Bureau of Reclamation, 2022). This is similar to the 0.16 km^3/yr transbasin diversion that Wurtsbaugh et al. (2017) reported and included in their water mass balance calculations. Subtracting these transbasin inputs from the reported CU values we are comparing to, we get an equivalent 2.42 km^3/yr for GSL Strike Team and 1.54 km^3/yr for Wurtsbaugh et al. (2017). This is similar to the range of our results, 1.43-2.30 km^3/yr, based on the range of *ra* and *Pmean*. However, as noted above, our *ra* hindcast appears to be biased low in early years due to *r* having been calculated with streamflow that includes CU and applying it to a time when there presumably were nearly no depletions. Therefore, the estimate of 2.30 km^3/yr from the *Pmean* hindcast is more defensible and is very close to the GSL Strike Team results, yet it is approximately 50% higher than the results from Wurtsbaugh et al. (2017). This leads us to believe that Wurtsbaugh et al. (2017) may not have had as complete information or data as was available for this study and that was used by the GSL Strike Team. On the other hand, the GSL Strike Team included CU from areas of the basin that are hydrologically disconnected from the lake, like the west desert, which does not affect the GSL WSE and makes an estimate based on summing CU higher. It is also worth noting that the characteristics of the early trend in both the

Pmean and *ra* flow hindcasts mimic what Wurstbaugh et al. (2017) asserted about the majority of CU occurring shortly after the GSL Basin was settled, and the characteristics of the recent trend mimic the constant CU shown in the estimate by the GSL Strike Team.

5 Conclusions

Reductions in streamflow into the GSL are responsible for declines in the terminal lake's WSE. Present estimates of consumptive water use within the GSL Basin based on summing detailed uses and return flows are disparate and range from 1.5 to 2.4 km^3/yr. This paper offers an additional line of evidence for quantifying consumptive use by estimating inflow depletions through volume reconstruction from records of WSE. We analyzed annual changes in lake volume for GSL to reconstruct inflow corresponding to the full historical record of WSE and estimated the magnitude of CU in the basin and associated lake level decline for the water years 1848-2023. Our analysis included developing hindcasts for annual evaporation and precipitation depths over the lake and inflow volume to the lake, from which we reconstructed annual streamflow using a water mass balance. Two methods were used to estimate precipitation, giving us a range for CU of 1.43-2.30 km^3/yr and the associated lake level decline of 2.67-4.46 m. Our hindcast of evaporation depth over the lake is consistent with previous mass balance estimates for the years 1950-2010 but was extended to include the entire 1848-2023 period. A bias may be present in the *ra* hindcast of precipitation using a constant runoff ratio due to its dependency on measured streamflow that includes CU. This bias would be more pronounced, and would therefore result in an underestimate of CU, during years immediately after the initiation of irrigated agriculture following Mormon Pioneer settlement in the GSL basin starting in 1847. Because of this bias in the *ra* based estimate, we believe that the *Pmean* estimate of CU in GSL Basin of 2.30 km^3/yr based on constant average precipitation is better and lake level decline due to this estimate is closer to 4.46 meters. These findings are important because they quantify the degree to which CU has impacted the lake and serve as a reference for efforts towards conservation and other water management actions aimed at restoring the lake to levels where it better supports its uses.

References

Aldrich, T.W., Paul, D.S. (2002), Avian ecology of Great Salt Lake. Great Salt Lake: An overview of change (J.W. Gwynn, ed). *Special publication of the Utah Dept. of Natural Resources.*

Barnes, B.D., & Wurtsbaugh, W.A. (2015), The effects of salinity on plankton and benthic communities in the Great Salt Lake, Utah, USA: a microcosm experiment. *Canadian Journal of fisheries and Aquatic Sciences, 72*(6):807–17.

Bekker, M. F., DeRose, R. J., Buckley, B. M., Kjelgren, R. K., & Gill, N. S.(2014), A 576-Year Weber River Streamflow Reconstruction from Tree Rings for Water Resource Risk Assessment in the Wasatch Front, Utah. *Journal of the American Water Resources Association, 50*(5),1338-1348. doi:10.1111/jawr.12191

Bureau of Reclamation, https://qcnr.usu.edu/coloradoriver/files/news/Tranbasin-Fact-Sheet.pdf

Daly, C., Halbleib, M., Smith, J. I., Gibson, W. P., Doggett, M. K., Taylor, G. H., Curtis, J. & Pasteris, P. P. (2008), Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. *International Journal of Climatology, 28*(15): 2031-2064, http://dx.doi.org/10.1002/joc.1688

DeRose, R. J., M. F. Bekker, S. Y. Wang, B. M. Buckley, R. K. Kjelgren, T. Bardsley, T. M. Rittenour and E. B. Allen, (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.

Friends of the Great Salt Lake. (2018). *Behrens Trench: The Underwater River of Great Salt Lake*. Volume 24, Number 4. Retrieve from https://www.fogsl.org/newsroom/newsletters/8-2018-autumn/file

GSL Strike Team. (2023). *Great Salt Lake Policy Assessment A synthesized resource document for the 2023 General Legislative Session.* Retrieve from https://gardner.utah.edu/wp-content/uploads/GSL-Assessment-Feb2023.pdf?x71849

Hahl, D.C. Dissolved-Mineral Inflow to Great Salt Lake and Chemical Characteristics of the Salt Lake Brine: Summary for Water Years 1960, 1961, and 1964; Water-Resources Bulletin 10; Utah Geological Survey: Salt Lake City, UT, USA, 1968; 35p.

Hahnenberger, M. & Nicoll, K. (2012), Meteorological characteristics of dust storm events in the eastern Great Basin of Utah, U.S.A. *Atmospheric Environment, 60*:601-612. doi:10.1016/j.atmosenv.2012.06.029

Hahnenberger, M. & Nicoll, K. (2014), Geomorphic and land cover identification of dust sources in the eastern Great Basin of Utah, U.S.A. *Geomorphology, 204*:657-672. doi:10.1016/j.geomorph.2013.09.013

Huntington, J., Hegewisch, K., Daudert, B., Morton, C., Abatzoglou, J., McEvoy, D., and T., Erickson. (2017). Climate Engine: Cloud Computing of Climate and Remote Sensing Data for Advanced Natural Resource Monitoring and Process Understanding. Bulletin of the American Meteorological Society, http://journals.ametsoc.org/doi/abs/10.1175/BAMS-D-15-00324.1

IWJV, Intermountain West Joint Venture. 2016. Retrieved from www.iwjv.org

Lall, U. & Mann, M. (1995), The Great Salt Lake: A barometer of low-frequency climatic variability. *Water Resources Research*, 31(10): 2503-2515, https://doi.org/10.1029/95WR01950.

Lang, O. I., Mallia, D., & McKenzie Skiles, S. (2023). The shrinking Great Salt Lake contributes to record high dust-on-snow deposition in the Wasatch Mountains during the 2022 snowmelt season. *Environmental Research Letters, 18*(6): 064045, http://doi.org/10.1088/1748-9326/acd409.

Loving, B.L., Waddell, K.M. & Miller, C.W. (2000), Water and Salt Balance of Great Salt Lake, Utah, and Simulation of Water and Salt Movement through the Causeway, 1987–98; U.S. Geological Survey: Salt Lake City, UT, USA, 2000. Retrieved from https://pubs.usgs.gov/wri/2000/4221/report.pdf

Merck, M. F. and D. G. Tarboton, (2023), The Salinity of the Great Salt Lake and Its Deep Brine Layer. *Water, 15*(8), doi:10.3390/w15081488

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, W11511. doi:10.1029/2012WR011908

Standard-Examiner. (2016). *Mineral extraction on Great Salt Lake has local, national and global impact.* Retrieve from https://www.standard.net/news/environment/2016/may/01/mineral-extraction-on-great-salt-lake-has-local-national-and-global-impact/

Stephens, D.W. (1990). Changes in lake levels, salinity and the biological community of Great Salt Lake (Utah, USA), 1847-1987. *Hydrobiologia*, 197: 139-146.

Tarboton, D. (2017a). Great Salt Lake Area Volume Data. HydroShare. Available online: http://www.hydroshare.org/resource/89125e9a3af544eab2479b7a974100ba (accessed on 1 March 2023).

Tarboton, D. (2017b). Great Salt Lake Bathymetry. HydroShare. Available online: http://www.hydroshare.org/resource/582060f00f6b443bb26e896426d9f62a (accessed on 1 March 2023).

Tarboton, D. (2023a). Streamflow entering the Great Salt Lake. HydroShare. Available online: http://www.hydroshare.org/resource/bb2bba84e1d5424db9211a991a7e5dd8

Tarboton, D. (2023b). Collection of Great Salt Lake Data. HydroShare. Available on: http://www.hydroshare.org/resource/b6c4fcad40c64c4cb4dd7d4a25d0db6e

Tikalsky, B. P. (2007). *An 828 year streamflow reconstruction for the jordan river drainage basin of northern Utah* (master's thesis). Retrieved from ScholarsArchive. (https://scholarsarchive.byu.edu/etd/1444/). Provo, Utah: Brigham Young University.

UGS Survey Notes. (2021). *Glad you asked: does Utah really use more water than any other state?* Retrieved from https://geology.utah.gov/map-pub/survey-notes/glad-you-asked/does-utah-use-more-water/

UDEQ. (2022). *US Magnesium Canal Continuation Project Section 401 Water Quality Certification Decision.* Retrieve from https://deq.utah.gov/water-quality/us-magnesium-canal-continuation-project-section-401-water-quality-certification-decision

USCB. (2023). *United States Census Bureau QuickFacts*. Retrieve from https://www.census.gov/quickfacts/geo/chart/UT,US/PST120222

WHSRN, Western Hemisphere Shorebird Reserve Network (2016). www.whsrn.org Accessed 3/2016

Wurtsbaugh, W. A., Miller, C., Null, S. E., Wilcock, P., & Hahnenberger, M. (2016), *Impacts of Water Development on Great Salt Lake and the Wasatch Front*. Logan, Utah: Utah State University.

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*. doi: 10.1038/ngeo3052.

CHAPTER 4

ENGINEERING STUDENTS’ PERCEPTIONS OF MATHEMATICAL MODELING IN A LEARNING MODULE CENTERED ON A HYDROLOGIC DESIGN CASE STUDY[3]

Abstract

Engineering students need to spend time engaging in mathematical modeling tasks to reinforce their learning of mathematics through its application to authentic problems and real world design situations. Technological tools and resources can support this kind of learning engagement. We produced an online module that develops students’ mathematical modeling skills while developing knowledge of the fundamentals of rainfall-runoff processes and engineering design. This study examined how 251 students at two United States universities perceived mathematical modeling as implemented through the online module over a 5-year period. We found, subject to the limitation that these are perceptions from not all students, that: (a) the module allowed students to be a part of the modeling process; (b) using technology, such as modeling software and online databases, in the module helped students to understand what they were doing in mathematical modeling; (c) using the technology in the module helped students to develop their skill set; and (d) difficulties with the technology and/or the modeling decisions they had to make in the module activities were in some cases barriers that interfered with students’ ability to learn. We advocate for instructors to create modules

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[3] Merck, M.F., Gallagher, M.A., Habib, E., and Tarboton, D.G. 2021. Engineering students’ perceptions of mathematical modeling in a learning module centered on a hydrologic design case study. *International Journal of Research in Undergraduate Mathematics Education* 7: 351-377. DOI:https://doi.org/10.1007/s40753-020-00131-8.

that: (a) are situated within a real-world context, requiring students to model mathematically to solve an authentic problem; (b) take advantage of digital tools used by engineers to support students' development of the mathematical and engineering skills needed in the workforce; and (c) use student feedback to guide module revisions.

Introduction

There have been increasing calls in recent years to make changes at the undergraduate level to better prepare students to apply mathematical modeling and critical thinking skills in general (Bordogna 1998; Radzi et al. 2009), and specifically in the field of hydrology and water resources engineering (e.g., Bourget 2006; CUAHSI 2010; Habib and Deshotel 2018; Howe 2008; Ledley et al. 2008; Merwade and Ruddell 2012; Wagener et al. 2010). Much of this is motivated by the perception that traditional approaches to teaching, focused on separate learning of distinct processes, do not provide a sufficiently holistic environmental and societal context for learning. To address these problems, we created an innovative online module, a unit of instruction organized around a central theme and hosted on the Internet. Our module develops mathematical modeling skills in addition to knowledge of the fundamentals of rainfall-runoff processes and engineering design. The HydroViz Dry Canyon module (HDC; https://hydroviz.org/Lessons/Index/UT/DryCanyonFFP), adopts the pedagogical strategy of a case-study in which an instructor uses "a written description of a problem or situation" to teach a concept situated in a real-world context (McDade 1995, p. 9). The problem of providing flood protection to the community living below the Dry Canyon watershed near Logan, Utah, United States, serves as a case study representative of many flooding problems throughout the world. The HDC module leads students through a series of data- and modeling-driven activities to design the dam and outlet structure for a flood detention basin used to hold flood water and reduce peak flow during times of flooding. In an effort to update the teaching approach for the required undergraduate hydrology course in the civil and environmental engineering degree programs at two United States universities, the HDC module was incorporated into the curriculum. HDC was designed with these courses in mind and developed for use in a blended learning setting, which includes face-to-face lectures, class time dedicated to a computer lab, and self-directed online learning. However, we also developed HDC with the intention that it could be a stand-alone learning tool.

The HDC module was designed for students to create a mathematical model based on the hydrological processes in Dry Canyon for the purposes of designing a detention basin to protect against flash flooding. The module assumes that students have completed prerequisite courses in mathematics typical in an engineering curriculum (e.g. calculus), but that context-based learning of these topics may have been limited (consistent with the findings of Faulkner et al. 2019, reviewed in the literature review). Additionally, in our experience, engineering students need support in applying the mathematics skills acquired through these prerequisite courses. Therefore, our first goal for the module is to elevate and reinforce basic mathematics knowledge through authentic problem based learning and mathematical modeling (consistent with recommendations of Crawley et al. 1994, reviewed in the literature review). The module also assumes that students have not yet been introduced to the hydrologic theory (e.g. precipitation, infiltration, runoff generation) needed to complete the module activities. Rather than following an approach of introducing the theory first, as is often done, the module introduces the content knowledge in the context of the authentic problem case study and then immediately requires students to problem solve. First it introduces how to delineate a watershed in the context of determining the watershed attributes needed for the case study and asks students to delineate the Dry Canyon watershed. This requires combining the geographic skill of watershed delineation with the mathematical skills of area calculation and area averaging. Next it examines precipitation measurements and the mathematical probability and statistics of precipitation data analysis, just before asking students to use historical data to design theoretical precipitation events based on established probabilities (e.g., a 100 year event with 1/100 probability of occurrence in any year). Then the module presents soil properties and the mathematics of infiltration and runoff generation just in time to model the runoff produced from the previously calculated precipitation. Then it introduces the mathematics of hydrograph theory to help students learn how watershed properties, as well as flood protection infrastructure (i.e. a detention basin and its outlet structure), modulate potentially damaging hydrograph peaks. Finally it introduces students to engineering software that encodes the mathematical and hydrologic process knowledge that they have learned, to enable them to experience the challenges of iterating on different protection design alternatives (detention basin and outlet flow control structure sizes) to learn about and evaluate the trade offs involved in engineering design.

The innovative module is premised on pedagogical studies indicating that student learning of mathematical and engineering concepts is enhanced through active interaction with the content (Prince 2004). Mathematical modeling facilitates these interactions.

Thus, our second goal was for the HDC module to incorporate digital learning tools to engage students in mathematical modeling in the context of an authentic hydrologic design case study, and to develop students' skills not just to compute or execute mathematical models, but to use them thoughtfully to make engineering decisions. It is our hope that this also serves as an example for other instructors to develop case studies in other areas where mathematical modeling is used in engineering.

The purpose of this study was to engage students in a teaching and learning innovation bridging mathematical modeling with hydrologic processes through the HDC module, and to examine their perceptions of their experience with the module. This paper examines student perceptions, the mental impressions they formed, expressed in their descriptions and opinions from doing this module, as reported in student surveys. Without a direct measure of student learning, these perceptions serve as descriptions of students' experiences with the module rather than the impact of the module on their learning. The findings, based on perceptions, clearly have limitations, but do offer insights into students' experiences with mathematical modeling embedded within the HDC learning module. Moreover, it is important to factor in student perceptions when considering curricular changes. The following research question guided this study: What are students' perceptions of the use of mathematical modeling in an online module (i.e., HDC)?

The next section is a literature review that provides background on the key knowledge on technology and mathematical modeling in engineering education that underpins this paper. This is followed by the theoretical framework that draws upon Greefrath's (2011) conception of mathematical modeling. The methods section then describes the iterative development of the HDC module and the data collected to understand student perceptions following their experience with the module. This is followed by sections giving findings, then discussion, limitations and implications.

Literature Review

As part of their review of the history of hydrology education, Ruddell and Wagener (2015) describe a recent shift in pedagogies to include internet-based data resources, modeling based activities, virtual trips, and gaming, among others. They write that one of the grand challenges of hydrology education in the twenty-first century is to "augment theoretical instruction with data and modeling driven cybereducation" (p. 5). Ruddell and Wagener argue that data and modeling driven cybereducation may be one of the best ways to teach complex systems and advocate for this type of instruction at the undergraduate as well as graduate levels. Integrating data and modeling driven cybereducation in hydrology courses requires the effective integration of technology, including cyberlearning resources, as well as mathematical modeling tasks. In the next sections we review research on each of these topics (i.e., technology and modeling) focusing on literature on innovative practices as well as on student perceptions, and then combine them in the theoretical framework.

Technology in Engineering Education

The United States' National Science Foundation's Task Force on Cyberlearning (2008) wrote that "widespread access to technology, increasingly sophisticated tools, and advances in understanding of how individuals learn combine to provide a stunning opportunity to transform education worldwide" (p. 7). In their report, they highlight how technological advances can bring new learning opportunities to students in science, technology, engineering, and mathematics (STEM) fields and call on researchers to leverage emerging technologies to enhance the learning opportunities of students in STEM. They note that cyberlearning could “allow interaction with scientific data, visualizations, remote and virtual laboratories, and human expertise” (p. 7). The Learning Enhanced Watershed Assessment System and the Online Watershed Learning System integrate these suggestions from the Task Force on Cyberlearning (Brogan et al. 2016). Specifically, these online learning platforms created a virtual laboratory for collecting and analyzing data while learning hydrologic content, and surveys of students using these platforms reported positive results. Other researchers have also found positive effects on student understanding of engineering concepts after working with virtual laboratories in their courses (Baher 1998; Habib et al. 2012; Kollöffel and de Jong 2013; Koretsky et al. 2011).

The National Science Foundation (2008) has called on STEM educators to integrate technology meaningfully to leverage student learning based on research indicating student learning gains for engineering students who participated in courses that integrated technology (Baher 1998; Brogan et al. 2016; Kollöffel and de Jong 2013; Koretsky et al. 2011). Researchers are still studying the best ways to do this. In 2012, Merwade and Ruddell surveyed hydrology instructors to better understand what the challenges and priorities should be for integrating data and modeling driven cyberlearning in university hydrology courses. One of the many suggestions by the faculty surveyed was to use publicly available datasets and generally accessible tools (e.g., spreadsheets software such as Excel or geographic information system software such as ArcGIS). They also cautioned against creating "black box" tools, meaning tools which allow the user to interact with the inputs and outputs but obscure the tool's internal workings, making the concepts and modeling less apparent to the user. Habib and Deshotel (2018) conducted a set of 78 informal interviews with faculty members and practicing engineers in the field of hydrology and water resources. Their results emphasized the value of using emerging technologies in undergraduate classrooms, but also highlighted critical barriers such as time limitations for integration of technologies, the need to keep up with continuous updates to the modeling tools and datasets, and the steep learning curve of the technological tools by students and instructors. These findings suggest that, as instructors integrate technology into their teaching, they should be mindful of pitfalls, including technology as a "black box" and the potentially steep learning curve.

Student Perceptions of Content

There are three types of interactions that happen in distance education: learner-instructor, learner-learner, and learner-content (Moore 1993). Given that HDC was used as an independent learning module for students to complete individually, the interaction that is most important to consider is the learner-content interaction. Moore wrote that "it is the process of intellectually interacting with content that results in changes in the learner's understanding, the learner's perspective, or the cognitive structures of the learner's mind" (p. 20). Gosmire et al. (2009) found that graduate students' perceptions of their interactions with the content were statistically significantly positively correlated to their overall interactions in an online course. The importance of the interaction between the learner and the content in changing the learner's perspectives highlights the need to examine learners' perspectives on the content they engage with through cybereducation. Moreover, exploring student perceptions may give insight into what they found engaging or disengaging about the content, which is especially important as student engagement in mathematics is tied to student achievement (Middleton et al. 2017).

Mathematical Modeling in Engineering

The traditional structure of engineering curricula at most United States colleges and universities originated in the early 1950's (Ruddell and Wagener 2015; Shea 1997). However, the modes and applications of the engineering concepts within industry are constantly changing and fundamental changes in engineering concepts will not occur nearly as quickly as their application (Moussavi 1998). Therefore, not only must new technology be brought into the classroom, but so must the modes and applications of the engineering concepts within industry. College level engineering students must graduate not only learning the fundamentals of engineering concepts, but prepared to apply current technology as an engineer in industry in today's society (Crawley et al. 1994).

Over two decades ago, the need for "a revision of the engineering education and a change of attitude toward mathematics and modeling" (p. 966) was highlighted by Moussavi (1998) as a necessary essential to keep engineering students competitive in the global market. Since then, researchers on mathematical modeling in engineering have found that engineers often work with existing models to interpret situations and to predict and design solutions (Alpers 2011; Bissell and Dillon 2000). In a recent effort, Faulkner et al. (2019) interviewed 27 engineering faculty members within 11 disciplines from a large United States research-intensive institution about their experience teaching core engineering courses and, specifically, the mathematical abilities of their students. Every single interview participant made at least one statement which the authors coded as “a mathematically mature student uses and interprets mathematical models” (p. 111) and at least one statement coded as “computational tools reshape ‘what needs to be known’ to be mathematically mature” (p. 111). The interviews from this study indicate that faculty believe that mathematical modeling skills are the most important skills for engineering students. However, the students hold dysfunctional, underdeveloped epistemic beliefs about mathematics that undermine their ability to develop these skills; in particular, the students believe that “mathematics is unrelated to the real world and has little practical value” (p. 128). The primary recommendation made by Faulkner and colleagues is twofold: not only is there a need for more modeling in the engineering curricula, but also a need to do this in the context of authentic or real world problems. Or, as Crawley et al. (1994) stated, mathematical modeling is “a natural requirement of almost any engineering course” (p. 55) and it is “more effective and meaningful when integrated into existing subjects” (p. 53). This sentiment has been echoed by others as well, suggesting that the engineering curricula should be considered dependent on modeling (e.g., Bissell and Dillon 2000; Moussavi 1998).

Although engineering faculty members expect their students to be adept at both mathematics and mathematical modeling, students are entering core engineering curricula lacking the necessary skills (Faulkner et al. 2019; Ferguson 2012; Gainsburg 2006). At least part of the problem may be attributed to the fact that, according to existing literature, mathematicians and engineers have different perspectives on what constitutes “mathematical modeling” (Alpers 2017; Bissell and Dillon 2000; COMAP and SIAM

2019; Faulkner et al. 2019;). Leaders in the mathematical community collaborated to produce the Guidelines for Assessment and Instruction in Mathematical Modeling Education (GAIMME) report (COMAP and SIAM 2019). The intention of the report was to help teachers incorporate the practice of mathematical modeling into primary and secondary classrooms and beyond. The definition of mathematical modeling used in the GAIMME report is used repeatedly throughout educational literature (e.g. English 2009; Maiorca and Stohlmann 2016; Suh and Seshaiyer 2017): “Mathematical modeling is a process that uses mathematics to represent, analyze, make predictions or otherwise provide insight into real-world phenomena” (p. 12). Mathematical modeling in education has two primary purposes: to solve a specific problem, and to learn the skills of mathematical modeling (Stillman et al. 2013). The GAIMME report specifies the following skills or components of the mathematical modeling process:

1. Identify the Problem: Identify something in the real world we want to know, do, or understand. The result is a question in the real world.

2. Make Assumptions and Identify Variables: Select ‘objects’ that seem important in the real world. Question and identify relations between them. Decide what will be kept and what will be ignored about the objects and their interrelations. The result is an idealized version of the original question.

3. Do the Mathematics: Translate the idealized version into mathematical terms and obtain a mathematical formulation of the idealized question. This formulation is the model. Do the mathematics to see what insights and results we get.

4. Analyze and Assess the Solution: Consider: Does it address the problem? Does it make sense when translated back into the real world? Are the results practical, the answers reasonable, the consequences acceptable?

5. Iterate: Iterate the process as needed to refine and extend our model.

6. Implement the Model: For real world, practical applications, report the results to others and implement the solution. (COMAP and SIAM 2019 p. 12)

However, the full definition of mathematical modeling in the GAIMME report differs from the aspects of modeling to which the engineering faculty members interviewed by Faulkner et al. (2019) referred. Bissell and Dillon (2000) point out that practicing engineers are much more likely to need to select (component 2), apply (component 4), and possibly adapt an existing model than to create a model (component 3).

There are many mathematical models and software tools used in engineering. In the context of this module, students used the United States Army Corps of Engineers Hydrologic Engineering Center Hydrologic Modeling System (HEC-HMS) (USACE n.d.). HEC-HMS is engineering software applied to the mathematical modeling of hydrologic processes throughout the world to solve hydrologic design problems. Engineers also extensively use Excel spreadsheets for calculations and mathematical modeling in their work.

Theoretical Framework

We used Greefrath's (2011) conception of mathematical modeling using digital tools to frame the creation of the HDC module as well as to examine students' perceptions of mathematical modeling using technology. Greefrath describes how modeling using digital tools requires two translations: one translation of the real world situation into the mathematical world (i.e., components 1 and 2: identify the problem, and make assumptions and identify variables) and a second translation from a mathematical model to a computer model (Figure 22). One benefit to using digital tools to solve mathematical models is that they enable students to solve models that they might not be able to solve by hand, or that are more efficient to solve using the tools (Greefrath 2011). In the case of engineering students, the integration of digital tools in coursework allows students to engage with tools used by engineers in the field. Additionally, digital tools can support students in understanding the real problem (i.e., component 1: identify the problem) as students can examine data sets, graphs, and even maps to better understand the context of the problem they are looking to model and solve. Given these benefits, Greefrath suggested integrating technology throughout the mathematical modeling process.

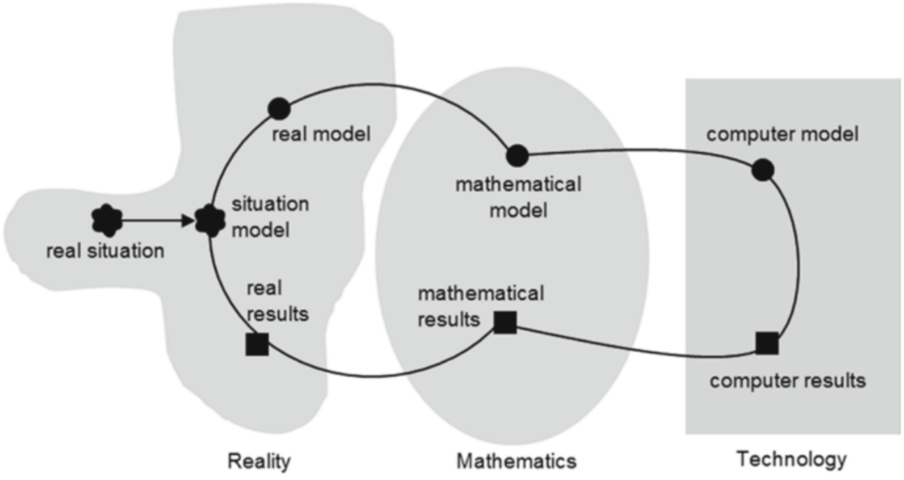
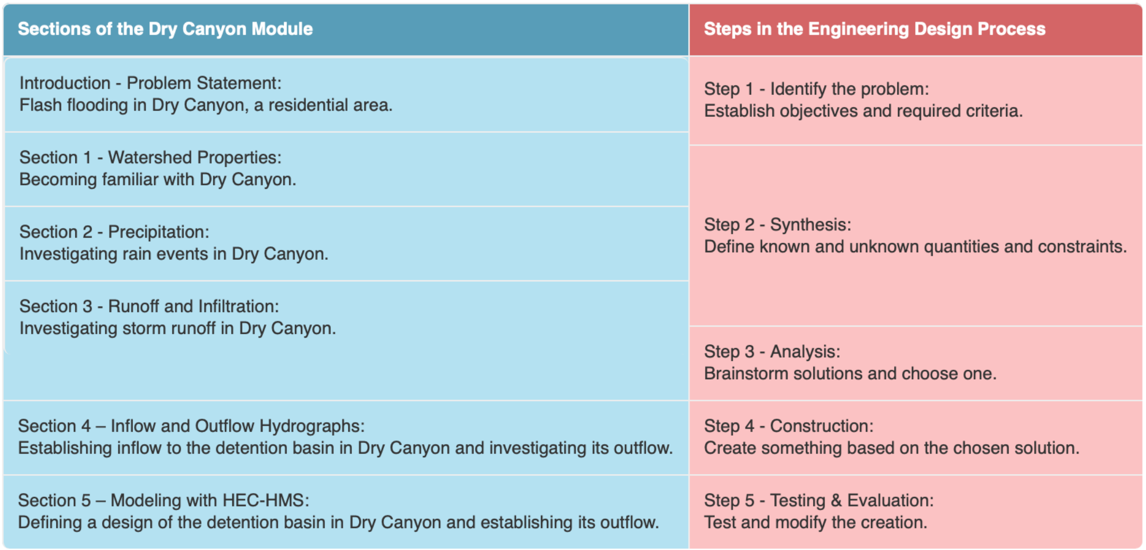


Figure 22. Modeling cycle (Blum and Leiß 2006) with added computer model (Greefrath 2011, p. 302).

The HDC module was designed for students to: (a) solve a specific problem (i.e., to use the fundamentals of rainfall-runoff processes and the engineering design process to design a detention basin to mitigate flash flooding); (b) develop the skills of modeling; and (c) model using publicly available datasets and free-to-use engineering modeling and analysis software. Specifically, they were asked to create a mathematical model for the hydrological processes in Dry Canyon in order to design a detention basin to protect against flash flooding. The model encodes hydrologic process knowledge that students learn by doing hand calculations and using spreadsheets (i.e., Excel), as well as through using engineering software (i.e., HEC-HMS). In the HDC module, students were given the problem, variables, and fundamental equations, but had to gather data and formulate the assumptions associated with alternative design choices in the context of and constrained by real world data in order to design a detention basin. Although students were given the necessary formulas (e.g., probability density function) and fundamental equations (e.g., Darcy's Law), they were asked to do the algebraic computations themselves. The module focused on having students analyze and assess the solution, iterate the model in both Excel and HEC-HMS using different variables and assumptions, and implement the model (i.e., report the results), including reconciling Excel results and HEC-HMS results (Figures 23 and 24).

Figure 23. Looking west out of the mouth of the Dry Canyon detention basin (main). Aerial view of the Dry Canyon detention basin (insert).



Sections of the Dry Canyon Module	Steps in the Engineering Design Process
Introduction - Problem Statement: Flash flooding in Dry Canyon, a residential area.	Step 1 - Identify the problem: Establish objectives and required criteria.
Section 1 - Watershed Properties: Becoming familiar with Dry Canyon.	Step 2 - Synthesis: Define known and unknown quantities and constraints.
Section 2 - Precipitation: Investigating rain events in Dry Canyon.	
Section 3 - Runoff and Infiltration: Investigating storm runoff in Dry Canyon.	Step 3 - Analysis: Brainstorm solutions and choose one.
Section 4 – Inflow and Outflow Hydrographs: Establishing inflow to the detention basin in Dry Canyon and investigating its outflow.	Step 4 - Construction: Create something based on the chosen solution.
Section 5 – Modeling with HEC-HMS: Defining a design of the detention basin in Dry Canyon and establishing its outflow.	Step 5 - Testing & Evaluation: Test and modify the creation.

Figure 24. HDC Module Sections Defined Within the Engineering Design Process.

Table 3. HDC Module Activities Defined Within the Mathematical Modeling Process

Components of Mathematical Modeling Process	**Corresponding Activities in HDC**
Component 1: Identify The Problem	Presented within the module Introduction
Component 2: Make Assumptions And Identify Variables	1.3 Delineating a Watershed 2.3 Obtaining Historical Precipitation Data 2.4 Developing Precipitation Depth Duration and Frequency Information 2.5 Developing a Design Storm Hyetograph 3.4 Determining Soil Properties 3.5 Green-Ampt Method 4.3 Developing SCS Unit Hydrographs and Storm Hydrographs 4.4 Level Pool Routing
Component 3: Do The Math	2.3 Obtaining Historical Precipitation Data 2.4 Developing Precipitation Depth Duration and Frequency Information 2.5 Developing a Design Storm Hyetograph 3.4 Determining Soil Properties 3.5 Green-Ampt Method 4.3 Developing SCS Unit Hydrographs and Storm Hydrographs 4.4 Level Pool Routing
Component 4: Analyze And Assess The Solution	2.3 Obtaining Historical Precipitation Data 2.4 Developing Precipitation Depth Duration and Frequency Information 2.5 Developing a Design Storm Hyetograph 3.4 Determining Soil Properties 3.5 Green-Ampt Method 4.3 Developing SCS Unit Hydrographs and Storm Hydrographs 4.4 Level Pool Routing 5.3 Constructing a Storm Hyetograph and Hydrograph with HEC-HMS 5.4 Design of a Detention Basin with HEC-HMS
Component 5: Iterate	3.4 Determining Soil Properties 3.5 Green-Ampt Method 4.3 Developing SCS Unit Hydrographs and Storm Hydrographs 4.4 Level Pool Routing 5.3 Constructing a Storm Hyetograph and Hydrograph with HEC-HMS 5.4 Design of a Detention Basin with HEC-HMS
Component 6: Implement The Model	5.3 Constructing a Storm Hyetograph and Hydrograph with HEC-HMS 5.4 Design of a Detention Basin with HEC-HMS

This approach followed Greefrath's suggestions by integrating technological tools to support mathematical modeling throughout the module (Figure 24). Specifically, in the HDC module, students use an interactive map to help them better understand the geographic location and spatial context for the problem. They are guided through activities where they collect data from different online sources that also help them better understand the variables that impact the problem. These online sources are the same data sources as would be used by engineers solving this problem, so the students learn important data skills and the challenges of working with real data in an applied context. After doing the mathematics in an Excel spreadsheet, the students verify the mathematics using the HEC-HMS hydrologic engineering software. They use the results from these two digital tools to analyze and assess their solutions, iterating as needed (iterating is facilitated by the use of the digital tools), before presenting their final solution. In addition to integrating Greefrath's framework into the design of HDC, we also used it to examine students' perceptions of modeling in HDC. That is to say, we looked at their perceptions of mathematical modeling as expressed in comments from their use of HDC.

Methods

This study employed a qualitative design to understand how students across 5 years at two universities perceived mathematical modeling as implemented through the HDC module.

Context

From 2014 to 2018, the HDC module was implemented in undergraduate hydrology courses for engineering students at two institutions from different regions across the United States. The first implementation was delivered as a document. Subsequent implementations were delivered via the online user interface, accessible at https://hydroviz.org/Lessons/ Index/UT/DryCanyonFFP. Although the course instructors at each institution used the module in similar academic settings, the methods of implementation varied. Some instructors used the module as an independent assignment to be completed by the students out of class; meaning, no class time was dedicated to the module, it was not discussed in class, and no class time was devoted to working on the module in a computer lab. For some instructors, the module was discussed in class and some class time was devoted to working on the activities in an on-campus computer lab. Some instructors assigned the module in its entirety, while others assigned one or more sections at a time.

After each implementation, students were asked to complete a survey outside of class time regarding their perspectives of the module. For the purposes of this study, we analyzed responses to four open-ended questions included in the survey (see Appendix 2a). Using open-ended questions allowed for students to share their perceptions of HDC. Additionally, because these questions did not specifically prompt students to discuss mathematical modeling, any mention of aspects of mathematical modeling by the students served as evidence of their understanding of modeling. Although the overall modeling tasks remained the same within HDC, revisions were made to the module each year based on feedback from these surveys. The cycle of implement-assess-revise was performed for four iterations between 2014 and 2018. In all, 247 students participated in these surveys. Demographic data were not collected for the surveys. After the 2018 implementation, four students from the two institutions participated in interviews regarding their experiences. Three of these students were male and one was female. We chose to interview students in 2018 in order to gather more in-depth descriptions of the students' perceptions of the module. Although the surveys allowed us to capture data from many students, we found their responses to be rather thin. Engaging fewer students in semi-structured interviews allowed us to gather rich data by probing students for more detailed responses (Patton 2002).

Module Case Study: Dry Canyon

The HDC module is a case study that addresses the problem of potential flooding from Logan Dry Canyon. In the HDC module, students use the engineering design process along with mathematical modeling to design a detention basin for use in protecting an area of urban development from flooding. In doing so, students create a mathematical model to simulate the hydrologic processes involved in detention basin design.

This module was created and revised across the years with three main goals: (a) to create a module situated within a real-world context, requiring students to use mathematical modeling to solve an authentic hydrology problem; (b) to take advantage of digital tools used by engineers to support students' development of the mathematical and engineering skills needed in the workforce; and (c) to use student feedback in revisions to improve their learning experiences. Below we describe the module with regard to these three goals.

An Authentic Hydrology Problem Requiring Students to Model Mathematically. In August of 1977, a rather unusual rain event occurred near the city of Logan, Utah, which is located on the western edge of the Bear River Range, a northern extension of the Wasatch Range in the Rocky Mountains of the United States. Approximately 4 in. (100 mm) of rain fell in this area in less than 12 h, a rainfall record that has yet to be broken. As a result of this rain event, homes were flooded when a flash flood occurred in Dry Canyon, a small and rather steep valley without a perennial stream. However, despite this past flood, increased urban growth in the 1990's and 2000's resulted in multiple homes being constructed near the mouth of Dry Canyon. To protect these homes, a detention basin was constructed at the mouth of Dry Canyon in 2008 (Figure 25). A large stormwater drain was also constructed to carry outflow from the detention basin to Logan River. The HDC module was developed as a case study of the design of the detention basin and stormwater drain at the mouth of the Dry Canyon watershed. There are trade-offs between the size of the detention basin and size of stormwater drain that need to be examined during the design. Mathematical modeling can be used to evaluate these trade-offs by determining the hydrologic processes that result in peak flow rates.

Integrating Digital Tools Used by Engineers. The sections of the HDC module are organized in conjunction with the steps of the design process for the detention basin (Figure 24). Sections 1–4 are dedicated to data acquisition and analysis by hand and with Excel spreadsheets, while Section 5 includes computer modeling using HEC-HMS (Figure 25) and the analysis of computer modeling outputs. Each section of the HDC module introduces topics in hydrology that pertain to the design of a detention basin and includes one or more activities that walk students through the mathematical modeling process (Figure 24). The activities were designed to mimic, as closely as possible, the process an engineer would go through to produce a hydrologic model for the purpose of designing a detention basin as well as teach the needed material just in time and in the context of this problem. To achieve this and also produce realistic results, publicly available data were used whenever possible from agencies such as the United States

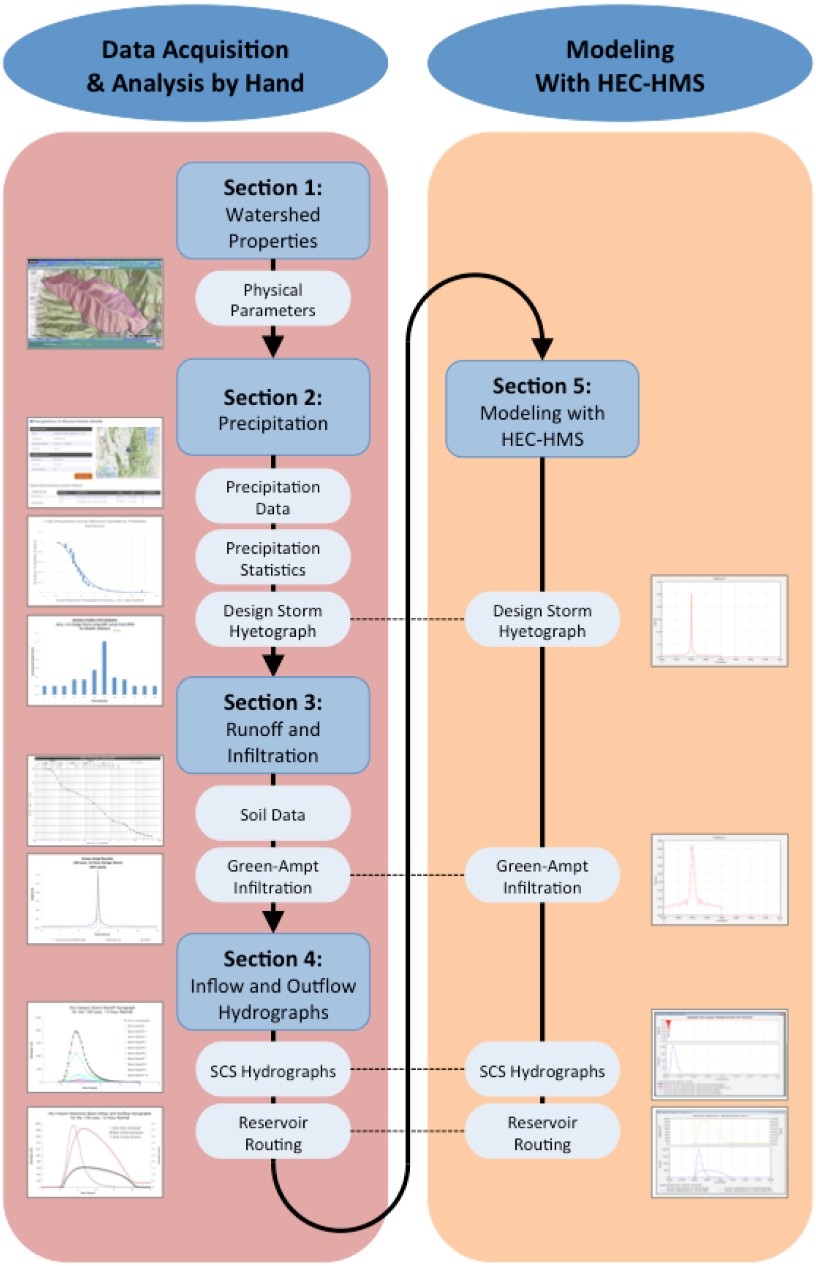


Figure 25. Flow diagram of the sections and activities within HDC. The sections are represented by blue rectangles and the activities are the white bubbles. Dashed lines indicate components of the modeling process that are performed both by hand or in Excel and modeled in HEC-HMS.

Geological Survey, National Climatic Data Center, and National Oceanic and Atmospheric Administration. In addition, students design their detention basin using HEC-HMS, which is the same modeling software used by the consulting firm that designed the actual detention basin constructed in Dry Canyon. Each activity in the HDC module is dependent on information and knowledge from previous module activities. For example, students delineate the boundary of the watershed in the first activity using StreamStats, an online tool accessed through the United States Geological Survey website. In this activity, students click on the outlet location in an online map and the tool delineates the watershed draining to that location. This reinforces for the students what a watershed is and its relationship to its outlet, without them needing to tediously draw lines based on map contours. The second activity walks students through obtaining precipitation data from the National Climate Data Center database for the area defined in the first activity. The students then use Excel to perform the mathematical operations necessary to transform the data into a usable form. These mathematical tasks include averaging from the 15 min intervals of the original data to 30 min, 1 h, 2 h, and so on, and identifying the annual maxima of these new intervals for use later in the statistical analysis of annual maximum precipitation intensity, duration, and frequency.

Using Student Feedback to Make Revisions. Student survey results and instructor feedback helped guide the development and evolution of the HDC module. Several iterative modifications were made to (a) make the case study more authentic and real-world, (b) help students narrow their results to feasible outcomes in order to keep them on track with their detention basin design, (c) help students better analyze the data and synthesize their final results, and (d) avoid the use of black box style tools.

Make the Case Study More Authentic. In an effort to make the case study more authentic, detailed background and supporting text was added to each section of the module. In order to expose the students to real-world resources, students were required to work with publicly available datasets and generally accessible tools used by practicing engineers. For example, students obtain raw data from publicly available datasets and preprocess that data within module activities rather than them being given clean data to use.

Help Students Narrow their Results. Quizzes were added at important milestone points for students to check their results and progress and to provide them intermediate feedback on estimates or assumptions, with the expectation that this would keep students from obtaining incorrect results while working through the module. This helped keep the students on track with their design goals by having them verify that their calculation results were within a realistic range.

Help Students Synthesize their Final Results. Based on student feedback that doing the assignment was ‘easy’ but understanding the ‘what’ and ‘why’ was difficult, summary questions were added after each activity to help the students synthesize important results in the form of a written synopsis. The synopses are meant to help the students integrate relevant information from previous activities in order to see the big picture of where they currently are in the design and modeling process and where they are going with the final design of their detention basin.

Avoid the Use of Black Box Tools. Originally, students were expected to create their own spreadsheets. This proved too difficult and time consuming, so preprogrammed Excel spreadsheet templates were added along with screencasts for support in completing and understanding the calculations within the templates. However, these templates also proved too difficult for students to follow (too black box) and students still had difficulty grasping the meaning behind the calculations, even with the help of the screencasts. Therefore, the templates were replaced with other spreadsheets that are less prescriptive and require students to build their own functions. In addition, initially the spreadsheet calculations and HEC-HMS results were not consistent and results between the two were thus not comparable. Student feedback suggested that they were not understanding the connection between the hand calculations and Excel results and the HEC-HMS results. Therefore, the module was restructured to have results from Excel and HEC-HMS be comparable if done correctly. This served to connect the separate learning of the mathematics describing individual processes and the modeling components involving hand calculations and Excel spreadsheets (sections 1–4) with the capstone section (5) which is dedicated to modeling all the hydrologic processes together in HEC-HMS. Activities in the last section were modified to produce HEC-HMS model outputs that mimic, for the purposes of comparison, the outputs completed by hand calculation and Excel spreadsheet in previous activities.

Data Collection

In order to better understand student perceptions of mathematical modeling in the HDC module between 2014 and 2018, we collected survey and interview data.

Student Surveys. Following each implementation of the HDC module, students were asked to answer survey questions about their experience using the module. The student surveys were administered online using Google Forms. Students were allowed approximately one week to respond to the survey outside of class time and after completion of the module. Approximately 64% of students enrolled in the courses completed the survey (total number of surveys, n = 247). Results from the survey were then used to evaluate module content, make necessary revisions, and inform the design and evolution of the online student user interface. For the purposes of this study, we used the open-ended questions from the survey which allowed students to broadly share their perceptions of what they found beneficial or not about HDC, thus not all comments generated were applicable to modeling (see Appendix 2a).

Student Interviews. The second author conducted four interviews with students, representing both universities, in the spring of 2018 after the semester had ended. All the interviews lasted between 21 and 29 min. She used a semi-structured interview approach, in which she asked all four participants the same questions but also used a variety of probing questions to gather more information based on their responses. The semi-structured interview questions are included in Appendix 2b. These interviews were transcribed verbatim.

Data Analysis

All survey and interview data were organized by year and uploaded to Dedoose (SocioCultural Research Consultants 2017). The first two authors reviewed the survey and interview response data. In the first read through, comments describing student perceptions of mathematical modeling were separated from the rest of the comments. We considered Greefrath’s (2011) framework and the components of mathematical modeling described in the GAIMME report (COMAP and SIAM 2019) and included any comments that addressed making assumptions, gathering data, determining values for variables, analyzing and assessing the solution, iterating, or implementing the model in reality, mathematics or technology. Next, two a priori codes (Saldaña 2013), “beneficial” or “non beneficial,” were applied to generally describe students’ perceptions of mathematical modeling in HDC. Then open codes (Saldaña 2013) were applied to these excerpts. Once all excerpts were coded, we read through the excerpts within an open code to look for congruity (i.e., that all excerpts within a code seemed to represent that code in a similar way) and repetitive open codes were condensed. Examples of repetitive open codes that were condensed at this point in the data analysis include “designing the detention basin”, “the last section”, “the design part at the end”, and “thinking about the design”. Lastly, open codes were categorized into broader themes to describe students’ perceptions of mathematical modeling in HDC. Statistics in the form of percentages were calculated for each of these themes using the total number of excerpts for a theme divided by the total number of surveys recorded (n = 247), not the total number of surveys that mentioned mathematical modeling. Therefore, the percentages reported indicate the percent of students who mentioned each theme out of all participants, not out of the subset of participants who mentioned mathematical modeling, and so the numbers will necessarily be smaller than if they were calculated from the smaller set. Given that the surveys did not specifically ask about mathematical modeling, any mention of some aspect of mathematical modeling by a student without prompting is noteworthy.

Findings

We found, subject to the limitation that these are perceptions from not all students, that students perceived the use of mathematical modeling in HDC in four primary and intersecting ways: (a) HDC allowed students to be a part of the modeling process, (b) using technology in HDC helped students to understand what they were doing in mathematical modeling, (c) using technology in HDC helped students to develop their skill set, and (d) difficulties with the technology and/or modeling decisions they had to make in the modeling activities were in some cases barriers that interfered with students' ability to learn. To preserve student voices, all quotes presented in the findings are in the students' words, without correction for grammar, spelling, or punctuation.

HDC Allowed Students to Be Part of the Modeling Process

Various technologies allowed students to participate in the entire design and modeling process. Approximately 20% (n = 50) of the student surveys were coded as "Modeling - Beneficial - Being part of the process." This means that, without being asked specifically about the modeling process in HDC, 20% of the students who responded to the survey mentioned that some aspect of the HDC module allowed them to be part of the modeling process in a beneficial way. Positive survey feedback included comments about being involved in a "real-world" project, a "case study," or "real engineering" where the students could engage in the design and modeling process, "the whole process ... from start to finish" (student survey 2014). "I think the most beneficial part of this assignment was helping me realize how real engineering is done. It's not all canned equations" (student survey 2016). Another student responded that a benefit of HDC was "Seeing how to take the given Data and how to use it. Finally real life work" (student survey 2017). These comments reflect the students' perspectives of the entire HDC module and do not necessarily pertain to specific sections or activities within HDC or the students' ability to learn hydrology or the modeling process. However, many of these comments also expressed that the culminating activities using HEC-HMS software pulled together the hydrology concepts they had learned in class. "HEC-HMS was very beneficial, it ... helped understand everything coming together and how each part was important" (student survey 2016). Another student commented: "I really felt the HEC-HMS portion of the analysis really pulled together my knowledge of hydrology" (student survey 2014). The last section of HDC wraps up the mathematical modeling process, the students implement their model, and complete their detention basin design.

Some students also made comments describing "ah-ha" moments. For example, one student from 2014 discussed how modeling a step of the design process in Excel allowed them to better understand the mathematics behind the process. Another student commented in 2014:

> I did learn that i suck at mathematical modeling. i also learned about what a catchment would actually be. i learned about hydrologic system management and floodplain analysis. i also learned that i wouldn't know where to begin trying to actually perform either of those. Someone was asking me questions about a neighborhood being constructed nearby and i couldn't actually answer a single question. it was pretty embarrassing.

Although this student's overall perception was that they "suck at mathematical modeling," this comment reveals an understanding of using mathematical modeling and knowledge of principles of hydrology to consider the needs in the design process.

Using Technology in HDC Helped Students Understand Mathematical Modeling

Of the students surveyed, 17.4% (n = 43) indicated that the use of technology helped them understand the design and modeling process, interpret their results, and learn the hydrology material. Some students' comments revealed their interest in being involved in a project that brought together multiple technologies: "Being able to see how all of these programs work with on one project was very interesting" (student survey 2014). Using technology also enabled students to explore various parameters and observe the resulting outputs at different points in the design and modeling process. "Changing the time lag / Curve Number for the different soil classes - helps you understand more deeply why you get the results you were given based off characteristics" (student survey 2016). The activities in the final section especially allowed them to see how everything from the HDC module came together in the design of their detention basin. "The last section I found to be the most beneficial because I was using everything I learned in the class and applying it to a program and I was able to have a visual on what was happening" (student survey 2015). Students were also encouraged to compare results amongst themselves. "I also liked comparing my results to other classmates' results. Seeing how different soil types affected everything was kind of neat" (student survey 2015). Some also compared their results to the actual design of the constructed detention basin. One student commented that it was beneficial: "Using HEC-HMS for constructing hydrological Model and comparing different studies with figuring out the reasons for different results" (student survey 2014). Some students also seemed to appreciate having to use their critical thinking skills and make independent decisions. They were not handed the inputs and not only had to find the appropriate data but use their judgment when data were missing. “The portion of the assignment that gave me the least amount of confidence but that taught me the most was the interpretation of the data and the necessity of using our engineering judgment to decide what kind of flow we should design for” (student survey 2014). Using the technology in HDC to understand how different inputs affected the model was one of our main goals for students.

Using Technology Helped Students Develop their Skill Set

Exposure to current technologies, real-world applications, and gaining practical skills rather than simply classroom knowledge was an opportunity that 30% (n = 73) of the students surveyed thought was beneficial and would be an advantage they might have over other graduates. Some students’ comments suggested that they found the real-world context of HDC and the opportunity to use tools used by practicing engineers engaging. “I think that it as a tool was kind of cool to see that this is a utility used in real engineering” (student interview 2018). In this interview the student directly connected the HEC-HMS tool to their future work as a practicing engineer. Overwhelmingly, the positive feedback on technology was related to the students’ interest and excitement about learning a tool used by engineers in industry. However, some also learned the limitations of technology: “I learned a lot from the excel assignments ... and that you can’t take everything for face value” (student interview 2018). This comment suggests that, although this student may have had difficulty with the spreadsheets, the student questioned the process and therefore the spreadsheet calculations rather than blindly accepting them as model output.

Gathering and assembling information through the use of databases and websites included in HDC, which are not typically taught or used in class, was also a noted benefit by some students. For instance, one student commented that "The most beneficial part of the assignment for me was using databases and other resources as this may help in the future in case I would need to look for information while doing a job" (student survey 2016). Similarly, another student mentioned:

> I found using the websites to find information on the soil, characteristics of the basin, and find precipitation data for design storms to be the most instructive. In the book problems we learn to solve problems given the parameters but this gives us a chance to learn how to find the parameters in the first place, which can be difficult to do well. (student interview 2014).

This student compared the process of working through book problems to the HDC activities. Like so many other student comments, this student appreciated the opportunity to learn a new part of the problem-solving process, gathering the information and determining whether it is necessary or correct as opposed to using what is simply given in a book problem. Not only did these students recognize that using the web and other resources to gather model inputs and parameters was a new skill, they appreciated having to do it.

Difficulties with Technology and Modeling Decisions Interfered with Students' Ability to Learn

Although many students noted the positive experiences they had with mathematical modeling in HDC, 36% (n = 89) of students indicated that they were not able to fully understand the modeling because of (a) glitches in the technology, (b) technology as a black box, or (c) they had to make estimates or assumptions but they did not fully understand the implications of those estimates.

Glitches in Technology. Approximately 10% (n = 25) of students mentioned broken web links within the HDC activity instructions. "Some of the web links were out of data and required figuring out where the required data had moved" (student survey 2014). Other students described their struggles becoming familiar with new programs. One student mentioned the least beneficial aspect of HDC was "the HMS part becausei felt i was fighting with the program more than learning the material" (student survey 2016). A struggle that researchers and engineers face, but that was new to many students using HDC, is that retrieving data can be frustrating and time consuming. "Waiting for days to receive the NOAA files needed to come via email was kind of ridiculous. There's got to be a better way to make those available" (student survey 2017). Most of these comments highlight hurdles that are common in the real world but that become easier with more experience.

Technology as a Black Box. One idea that emerged from 21% (n = 52) of students was that technology acted as a black box, suggesting that the Excel spreadsheets, which calculated the necessary values with pre-programmed formulas, did not clarify the mathematical calculations for them. Some students focused more on inputting the right numbers than on considering the output of the model. "Sometimes hard to understand what we were doing... Since the spreadsheets did all calculations, it was hard to understand what actually just happened in the spreadsheet" (student survey 2016). Some students expressed that they did not understand what was happening in the spreadsheet, even though the spreadsheet directly aligned with the model calculations. "I can Google and YouTube what I need to do in Excel, it was just trying to understand what the question was and how it translated into Excel" (student interview 2018). Although there were some complaints about the activity instructions lacking enough detail, a surprising number of students suggested there was too much guidance in the instructions yet not enough clarity in helping them understand the results. “Overall, the directions were very clear. One could easily do the assignment, just understanding what happened seemed difficult...” (student survey 2016). “I’m fairly comfortable using Excel. I just felt like a lot of times it was follow a pretty well-defined instruction, procedure set, and punch data in. So it just felt like maybe the material was kind of taking a back seat to Excel’s functionality...” (student interview 2018). The digital tool that some students felt supported their understanding of the mathematical model the least were the Excel spreadsheets.

Estimates and Assumptions. About 15% (n=38) of the students expressed frustration with their lack of experience with the processes and activities like those in HDC and therefore doubted their judgment and assumptions, which made their estimates feel like guesswork. “The only thing that was somewhat confusing was the estimated values that was allowed. I felt as if we had too much choice in what values we could use” (student survey 2014). “It was difficult not knowing the best answer. Many times I felt like I was just making assumptions...” (student survey 2016). Some students also found it frustrating when their results differed from other classmates’ or from the professional design of the basin constructed at the mouth of the canyon. “I had a hard time when I got drastically different results from the professional analyses. I know they have a lot more details, but it’s hard to be confident about your work when it’s so far off” (student survey 2014).

Discussion

This case study of the flood detention basin at the mouth of Dry Canyon provided an opportunity to both update the teaching approach in undergraduate engineering hydrology courses and integrate technology in the courses (Baher 1998; Brogan et al. 2016; Kollöffel and de Jong 2013; Koretsky et al. 2011; NSF 2008). It also proved to be an opportunity to put effort toward reform in hydrologic education, especially as is needed at the undergraduate level (CUAHSI 2010). The result is the HDC module, an online hydrology education module centered on case-based, data- and simulation-driven learning as described earlier. The HDC module is a tool that continues to be used at multiple institutions and has served as a foundation for the development of other similar learning modules. The findings from this study highlight more than just what worked or did not work with the HDC module. These findings can inform future teaching and learning innovations that seek to combine mathematical modeling and engineering content: (a) situating mathematical modeling problems within real-world contexts and presenting students with authentic engineering problems aids students in learning new content; (b) incorporating digital tools used by engineers can help students be a part of the mathematical modeling process; and (c) instructors should take student feedback into account in revisions to curriculum materials.

In developing the HDC module, we adopted an improvement-focused evaluation model (Posavac and Carey 2003) with an iterative design process that included multiple cycles of implement, assess, and revise. Once the original module was designed, it was tested in classes at two universities. The first implementation and each one thereafter were successful in the sense that the students were able to complete the module, gain knowledge in engineering hydrology, give feedback on their experience using the module, and we were then able to assess and revise the module so that a newer and more refined version could be used in the next implementation.

The instructors for each course in which the module was implemented used the module differently, which was helpful in testing the module's flexibility but complicated the process of assessing year-to-year changes. Even when the same instructor used the module more than once, it was used differently each subsequent time. Although it would have been helpful to include a wider variety of students and courses in the implementations, the variety we encountered proved difficult enough to assess and then respond to in revisions. However, it was helpful to include students in the implementation from universities including those unfamiliar with Dry Canyon and the Logan area and who were also taught by instructors not associated with the design team for the module.

The responses to the open-ended questions were quite informative and therefore had a large impact on what changes were made to the module over time. The evolution of the module was essentially driven by the responses to these open-ended survey questions and various comments made by students, both in person and within the survey, along with the work turned in by the students and instructor feedback. In hindsight, it may have been more helpful to observe students while using the module (e.g., in the classroom, the computer lab, or while working in groups) and also interview them while they were working through it rather than after they completed it and moved on to the next course subject. It likely would have been most helpful to have a comparison group that did not use the module at all and compare what and how they were able to learn with the students who used the HDC module (Creswell and Guetterman 2019). However, that was not a feasible option for the courses taught at the institutions involved. Therefore, rating the effectiveness of the module is subjective and comes down to whether or not the instructor feels it worked for them: their curriculum, their teaching methods, and their students.

Our findings indicated that students who participated in HDC said that the digital tools allowed them to be a part of the mathematical modeling process, helped them understand what they were doing in mathematical modeling, and/or helped them develop their skill set. These types of positive interactions between the learner and the content are important in changing the students' perspectives and possibly their beliefs about mathematical modeling (Gosmire et al. 2009). However, it is important to note that this study did not examine students' engagement, beliefs, affect, or motivation. Rather, we asked students to describe their experiences with the HDC module. In many cases they were recounting their experiences more so than describing their engagement. Nevertheless, we viewed their perspectives as important insight into the ways in which they interacted with HDC which could possibly shed light on their beliefs. Many students also felt that the technology and/or modeling decisions they had to make in HDC interfered with their ability to learn. The first finding, that HDC allowed students to be a part of the modeling process, is in alignment with Greefrath's (2011) description of modeling using digital tools, whereby digital tools can help students in every component of the mathematical modeling process. This finding highlights the importance of using digital tools not only to do the mathematics, but throughout the modeling process in engineering.

Incorporating digital tools and technology into engineering curricula not only addresses many of the desired changes in hydrology and water resources engineering education, but also aids students in understanding processes and learning new material. The HDC module includes authentic context and real-world, problem-based activities, as recommended by Faulkner et al. (2019). Student survey feedback supporting both our first and second findings suggest that the familiarity of the HDC context and the case-study perspective of the problem allowed students to be a part of the process and better understand the mathematical modeling involved. Some student comments further support that mathematical modeling is more effective and meaningful to the student when they are familiar with the context (Crawley et al. 1994) yet are pushed to use their critical thinking when solving problems within the mathematical modeling process. Moreover, these findings regarding student perspectives shed insight into their interactions with the module and informed revisions we made to the HDC module.

Both Crawley et al. (1994) and Moussavi (1998) pointed out that mathematical modeling is a necessary component for engineering students to remain competitive in a global market and, as graduates, these students should be prepared to apply current technology as an engineer in industry. In addition, engineers often work with existing models to interpret situations and to predict and design solutions (Alpers 2011; Bissell and Dillon 2000). The HDC module exposes students to real-world applications and allows them to blend practical skills along with classroom knowledge. Survey feedback shows that not only are these modeling skills valued by the students, but so is the exposure to additional digital tools, such as HEC-HMS, Excel, online databases, and other web-based tools.

However, some students also felt that difficulties with technology and/or modeling decisions they had to make, but where they did not feel prepared or had insufficient information, interfered with their ability to learn. Technical glitches can create problems when using digital tools and technology in learning (Hill 2002; Song et al. 2004). Student feedback included complaints of a variety of technical glitches with HDC, such as out of date web links, slow websites, as well as an inability to find the correct button or model input. Most technical glitches are avoidable but require constant maintenance, which can be a hurdle for the instructor. Another technical hazard highlighted by student survey feedback was that technology sometimes acted as a black box, that the HDC activities sometimes felt too plug-n-chug, or that students obtained answers that seemed correct but that they did not understand the process behind calculating the answer. Some of these complaints may be attributable to students' experience, or lack thereof, with a tool or process, which influences the students' perception of its usefulness and contribution to overall learning (Clarke III et al. 2001). However, as mentioned previously, Merwade and Ruddell (2012) cautioned against creating these types of "black box" tools which would make the concepts and modeling less apparent. Based on these findings and feedback from students, we revised HDC to replace the pre-programmed Excel templates with other sheets that are less hard-wired and allow students to build their own functions. We also added more checking-in quizzes to provide students with intermediate feedback on estimates or assumptions they make during the modeling process to assist the student in avoiding the accumulation of erroneous decisions or answers. Additionally, other real-world resources were integrated, including a watershed delineation web tool.

We do not have a direct assessment of how helpful the HDC module was in supporting student learning, as anonymous surveys could not be cross-referenced with student performance in the module. However, the general appreciation for working with authentic tools on a real world problem expressed by many of the students suggests that the innovations we made to this module were beneficial. The comments by students about their struggles with assumptions and their implications do need to be addressed though. It would be better for students to leave this module with greater confidence in their ability to execute this sort of mathematical modeling based design in the real world, than is evident in their responses. This could be addressed by providing a bit more guidance at places in the module where the students had trouble, to limit their confidence being undermined. Students' general areas of difficulty can be identified when assessing their work and addressed during classroom lecture. Nevertheless, capturing student perceptions on this, through questions asking students to identify areas of difficulty may be a useful addition to future student surveys.

Limitations

The limitations of this study are attributable to data collection methods and also revisions within the HDC module. Two different types of data were collected over the 5 years of this study: (a) student survey data in 2014–2017 and (b) student interview data in 2018. Although the line of questioning was similar between these two formats, the data are not completely comparable. In addition, response rates for the student survey changed from year to year as participation requirements changed; some instructors required that students participate in the survey while other instructors allowed participation to be completely voluntary. Each year, the HDC module content and interface was revised based on feedback from students. In particular, additional Excel supports were added each year from 2014 to 2018. This was responsive teaching but also means that technology was integrated to support mathematical modeling differently across the years.

Implications

Our findings are in line with others' (Baher 1998; Brogan et al. 2016; Greefrath 2011; Kollöffel and de Jong 2013; Koretsky et al. 2011), that technology has the potential to enhance students' understanding of and skills with mathematical modeling. Engineering course instructors should consider integrating technology, especially tools used by practicing engineers, such as HEC-HMS and spreadsheet work, into mathematical modeling problems in their courses. The HDC module erred in some ways, creating complex spreadsheets that were perceived as black boxes, and which resulted in students processing the spreadsheets mechanically rather than being pushed to understand the calculations within the process. Instructors should strive to balance the detail provided in packaged models, like preconstructed spreadsheets, with having students construct their own spreadsheets and/or calculating their own solutions. Similarly, instructors should be sure to frame questions on the output that technology is producing to push students to think critically and interpret the outputs, not just report them and move on.

Our findings are also consistent with literature that real world authentic problems enhance student engagement that benefits learning (Freeman 2014; Habib and Deshotel 2018; Herrington and Herrington 2007). The student perception findings and positive feedback with respect to the real world case study aspect of HDC support this. The HDC module was framed to help students think critically about the links between how hydrologic processes work and real world ramifications. They learned and modeled hydrologic processes just in time, motivated by this real world context, and were stretched in their critical thinking skills to put their knowledge together in synthesizing a design. Some of the comments they made about challenges and uncertainties reflect that, on occasion, they perceived being stretched too far. It is our perception, as engineering educators, that this is good, but developing ways to evaluate this, perhaps using a survey of perceptions over time that quantified this, would be beneficial.

This study examined engineering students' perceptions of mathematical modeling incorporated as part of an online module that embedded technological tools. Future research should examine how students interact with modeling by collecting data throughout such a module, including student work and interviews. Moreover, future research could assess students' ability to engage in mathematical modeling for students who participated in such a module and for students who did not, to see if the skills learned transfer to a new situation.

Although engineers typically graduate with strong computational skills, mathematical modeling skills are still sometimes lacking. And yet these skills are equally as important, both within students' engineering coursework and also their competitiveness once entering the job market. Multiple engineering education researchers have stated that mathematical modeling should be more central to engineering curricula (Crawley et al. 1994; Faulkner et al. 2019; Gainsburg 2006). Further supporting this, based on our findings, students' perceptions of mathematical modeling are mostly positive. By including more opportunities for students to engage in mathematical modeling in their coursework, not only will students' understanding of mathematical modeling change, they will become more familiar and comfortable with the modeling process and essential technology and gain the necessary associated critical thinking skills.

As engineering instructors consider course design, and especially as they consider creating online modules, the teaching and learning innovations we employed in the HDC module, and the findings from this study, can inform their work. Instructors should consider: (a) situating real-world problems in authentic contexts requiring students to model mathematically to find a solution, (b) integrating technologies and digital tools used by engineers to model mathematically and solve engineering problems, and (c) using an improvement-focused evaluation model to take student consideration into account when revising their module.

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References

Alpers, B. (2011). The mathematical expertise of mechanical engineers: Taking and processing measurements. In G. Kaiser, W. Blum, R. Borromeo Ferri, & G. Stillman (Eds.), Trends in teaching and learning of mathematical modelling (pp. 445–456). Springer.

Alpers, B. (2017). The mathematical modelling competencies required for solving engineering statics assignments. In G.A. Stillman, W. Blum, & G. Kaiser (Eds.), Mathematical modelling and applications: Crossing and researching boundaries in mathematics education (pp. 189–99). Springer.

Baher, J. (1998). How articulate virtual labs can help in thermodynamics education: A multiple case study.

FIE '98. 28th Annual Frontiers in Education Conference. Moving from 'Teacher-Centered' to 'Learner-Centered' Education. Conference Proceedings (Cat. No.98CH36214). https://doi.org/10.1109/FIE.1998. 738764.

Bissell, C., & Dillon, C. (2000). Telling tales: Models, stories, and meanings. For the Learning of Mathematics, 20(3), 3–11.

Blum, W., & Leiß, D. (2007). 5.1 - How do Students and Teachers Deal with Modelling Problems? In C. Haines, P. Galbraith, W. Blum, & S. Khan (Eds.), Mathematical Modelling (pp. 222–231). Woodhead Publishing. https://doi.org/10.1533/9780857099419.5.221.

Bordogna, J. (1998). Tomorrow's civil systems engineer – the master integrator. Journal of Professional Issues in Engineering Education and Practice, 124(2), 48–50.

Bourget, P. G. (2006). Integrated water resources management curriculum in the United States: Results of a recent survey. Journal of Contemporary Water Research & Education, 135(1), 107–114.

Brogan, D., McDonald, W., Lohani, V., Dymond, R., & Bradner, A. (2016). Development and classroom implementation of an environmental data creation and sharing tool. Advances in Engineering Education, 5(2), 1–34.

Clarke III, I., Flaherty, T. B., & Mottner, S. (2001). Student perceptions of educational technology tools. Journal of Marketing Education, 23(3), 169–177.

Consortium for Mathematics and Its Applications (COMAP) & Society for Industrial and Applied Mathematics (SIAM). (2019). GAIMME: Guidelines for Assessment and Instruction in Mathematical Modeling Education (2nd Ed.). Philadelphia: Society for Industrial and Applied Mathematics.

Consortium of Universities for the Advancement of Hydrologic Science, Inc. (CUAHSI). (2010). Water in a dynamic planet: A five-year strategic plan for water science. Cambridge: CUAHSI.

Crawley, E. F., Greitzer, E. M., Widnall, S. E., Hall, S. R., Mcmanus, H. L., Hansman, J. R., Shea, J. F., & Landahl, M. (1994). Reform of the aeronautics and astronautics curriculum at MIT. Journal of Engineering Education, 83(1), 47–56.

Creswell, J. W., & Guetterman, T. C. (2019). Educational research (6th ed.). New York: Pearson.

English, L. D. (2009). Promoting interdisciplinarity through mathematical modelling. ZDM, 41(1), 161–181. https://doi.org/10.1007/s11858-008-0106-z.

Faulkner, B., Earl, K., & Geoffrey, H. (2019). Mathematical maturity for engineering students. International Journal of Research in Undergraduate Mathematics Education, 5(1), 97–128. https://doi.org/10.1007/ s40753-019-00083-8.

Ferguson, L. (2012). Understanding calculus beyond computations: A descriptive study of the parallel meanings and expectations of teachers and users of calculus. In S. Brown, S. Larsen, K. Marrongelle, & M. Oehrtman (Eds.), Proceedings of the 15th annual conference on research in undergraduate mathematics education (pp. 187–201). Portland, Oregon.

Freeman, S. (2014). Active learning increases student performance in science, engineering, and mathematics. Proceedings of the National Academy of Sciences of the United States of America, 111(23), 8410–8415. Gainsburg, J. (2006). The mathematical modeling of structural engineers. Mathematical Thinking and

Learning, 8(1), 3–36. https://doi.org/10.1207/s15327833mtl0801_2.

Gosmire, D., Morrison, M., & Van Osdel, J. (2009). Perceptions of interactions in online courses. MERLOT

Journal of Online Learning and Teaching, 5(4), 609–617.

Greefrath, G. (2011). Using technologies: New possibilities of teaching and learning modelling – overview. In

G. Kaiser, W. Blum, R. Borromeo Ferri, G. Stillman (Eds.), Trends in teaching and learning of

mathematical modelling, ICTMA 14 (pp. 301–304). Springer.

Habib, E., & Deshotel, M. (2018). Towards broader adoption of educational innovations in undergraduate water resources engineering: Views from academia and industry. Journal of Contemporary Water

Research & Education, 164(1), 41–54.

Habib, E., Ma, Y., & Williams, D. (2012). Development of a web-based hydrologic education tool using

Google Earth resources. In S.J. Whitmeyer, J.E. Bailey, D.G. De Paor, & T. Ornduff (Eds.), Google Earth and Virtual Visualizations in Geoscience Education and Research (pp. 431–439). Geological Society of America. https://doi.org/10.1130/2012.2492(33).

Herrington, A. J., & Herrington, J. A. (2007). What is an authentic learning environment? In: L. A. Tomei (Eds.), Online and distance learning: Concepts, methodologies, tools, and applications (pp. 68–77). Information Science Reference.

Hill, J. R. (2002). Overcoming obstacles and creating connections: Community building in web-based learning environments. Journal of Computing in Higher Education, 14(1), 67.

Howe, C. W. (2008). A creative critique of U.S. water education. Journal of Contemporary Water Research & Education, 139(1), 1–2.

Kollöffel, B., & de Jong, T. (2013). Conceptual understanding of electrical circuits in secondary vocational engineering education: Combining traditional instruction with inquiry learning in a virtual lab. Journal of Engineering Education, 102, 375–393. https://doi.org/10.1002/jee.20022.

Koretsky, M., Kelly, C., & Gummer, E. (2011). Student perceptions of learning in the laboratory: Comparison of industrially situated virtual laboratories to capstone physical laboratories. Journal of Engineering Education, 100(3), 540–573. https://doi.org/10.1002/j.2168-9830.2011.tb00026.x.

Ledley, T. S., Prakash, A., Manduca, C. A., & Fox, S. (2008). Recommendations for making geoscience data accessible and usable in education. Earth & Space Science News, 89(32), 291.

Maiorca, C. & Stohlmann, M. (2016). Inspiring students in integrated STEM education through modeling activities. In C. R. Hirsch & A. R. McDuffie (Eds.), Mathematical modeling and modeling mathematics (pp. 153–161). National Council of Teachers of Mathematics.

McDade, S. A. (1995). Case study pedagogy to advance critical thinking. Teaching of Psychology, 22(1), 9– 10.

Merwade, V., & Ruddell, B. L. (2012). Moving university hydrology education forward with community-based geoinformatics, data and modeling resources. Hydrology and Earth System Sciences, 16(8).

Middleton, J. A., Jansen, A., & Goldin, G. A. (2017). The complexities of mathematical engagement: Motivation, affect, and social interactions. In J. Cai (Ed.), Compendium for research in mathematics education (pp. 667–699). Reston: National Council of Teachers of Mathematics.

Moore, M. J. (1993). Three types of interaction. In K. Harry, M. John, & D. Keegan (Eds.), Distance education: New perspectives (pp. 19–24). Routledge.

Moussavi, M. (1998). Mathematical modeling in engineering education. FIE '98. 28th Annual Frontiers in Education Conference. Moving from 'Teacher-Centered' to

'Learner-Centered' Education. Conference Proceedings (Cat. No.98CH36214) https://doi.org/10.1109/FIE.1998.738891.

National Science Foundation. (2008). Fostering learning in the networked world: The cyberlearning opportunity and challenge. Report of the NSF Task Force on Cyberlenaring. https://www.nsf.gov/pubs/2008/ nsf08204/nsf08204.pdf

Patton, M. Q. (2002). Qualitative research and evaluation methods (4th ed.). Los Angeles: SAGE Publications

Posavac, E. J., & Carey, R. G. (2003). Program evaluation: Methods and case studies (6th ed.). Upper Saddle River: Prentice Hall.

Prince, M. (2004). Does active learning work? A review of the research. Journal of Engineering Education, 93(3), 223–231.

Radzi, N. M., Abu, M. S., & Mohamad, S. (2009). Math-oriented critical thinking skills in engineering. 2009 International Conference on Engineering Education (ICEED). https://doi.org/10.1109/ICEED.2009. 5490579.

Ruddell, B. L., & Wagener, T. (2015). Grand challenges for hydrology education in the 21st century. Journal of Hydrologic Engineering, 20(1), [A4014001]. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000956.

Saldaña, J. (2013). The coding manual for qualitative researchers (2nd Ed.). Los Angeles: SAGE

Publications.

Shea, J. E. (1997). An integrated approach to engineering curricula improvement with multi-

objective decision modeling and linear programming. [doctoral dissertation, Oregon State

University].

SocioCultural Research Consultants. (2017). Dedoose (Version 7.5.9) [Web application for manag-

ing, analyzing, and presenting qualitative and mixed method research data]. https://www.dedoose.com

Song, L., Singleton, E. S., Hill, J. R., & Koh, M. H. (2004). Improving online learning: Student perceptions of useful and challenging characteristics. The Internet and Higher Education, 7(1), 59–70.

Stillman, G. A., Kaiser, G., Blum, W., & Brown, J. P. (2013). Mathematical modelling: Connecting to teaching and research practices–the impact of globalisation. In Teaching mathematical modelling: Connecting to research and practice (pp. 1-24). Springer.

Suh, J. M., & Seshaiyer, P. (2017). Modeling mathematical ideas: Developing strategic competence in elementary and middle school. Blue Ridge Summit: Rowman & Littlefield.

U.S. Army Corps of Engineers Hydrologic Engineering Center, USACE. (n.d.) Hydrologic Engineering Center Hydrologic Modeling System HEC-HMS [Computer Software]. https://www.hec.usace.army.mil/ software/hec-hms/

Wagener, T., Sivapalan, M., Troch, P. A., McGlynn, B. L., Harman, C. J., Gupta, H. V., Kumar, P., Rao, P. S. C., Basu, N. B., & Wilson, J. S. (2010). The future of hydrology: An evolving science for a changing world. Water Resources Research, 46(W05301). https://doi.org/10.1029/2009WR008906.

Appendix 2a. Survey Questions

The open-ended questions included in our analysis were:

1. What part of the assignment did you find the most beneficial, instructional, or constructive? Why?
2. What part of the assignment did you find the least beneficial, instructional, or constructive? Why?
3. Give an example of when you felt the directions for the assignment were clear and helpful.
4. Give an example of when you felt the directions for the assignment were not clear and not helpful. Having finished the assignment, what might have made the directions more clear and helpful?

Appendix 2b: Semi-Structured Interview Protocol

The following are potential questions for the interviews:

1. Tell me about your experiences in your hydrology/engineering course using the module this semester.
2. How did your professor use the HydroViz Dry Canyon materials?
3. What went well with the HydroViz Dry Canyon module?
4. What could have gone better with the HydroViz Dry Canyon module?
5. How did your experiences as a learner differ during the HydroViz Dry Canyon module as compared to the rest of the course instruction?
6. What suggestions do you have to improve HydroViz Dry Canyon?

CHAPTER 5

SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

The research presented in this dissertation addresses important gaps in our understanding of the GSL and the current changes it is undergoing, in addition to enhancing student learning of hydrologic processes within the GSL Basin. The goal of this dissertation was to contribute to furthering the understanding of hydrology within the GSL Basin to support scientifically based decision making in the interest of more sustainable management of the basin and its terminal lake.

Chapter 2 presents an analysis and visualization of the full historical salinity data record for the GSL. The purpose of this work was to examine the distribution of salinity and the occurrence and extent of the deep brine layer (DBL) across space and time for use in future planning and management of the lake. Specifically, based on the analysis of UGS and USGS datasets over an extended period, the intent was to more comprehensively understand the following questions:

1. How does salinity change within the lake?
2. How does the DBL fluctuate in time, space, and concentration?
3. How does surface salinity relate to average salinity and the DBL?
4. How does salt move between the north and south arms?
5. How has the total salt mass changed over time?

While prior work has, to some extent, addressed some of these questions, there was a need for a more holistic analysis of GSL salinity over the full record. The work presented in Chapter 2 more fully documents the changes in salinity, stratification, and the intermittency of the DBL, and sharpens our understanding of the answers to these questions.

The results in Chapter 2 show positive correlation between the average salinity in each arm of the GSL such that their salinities rise and falls in unison. Apart from flooding events, the north arm of the lake is homogeneous throughout the water column and consistently at or near a saturation salinity of approximately 275 g/L. In the south arm, salinities fluctuate, and the lower portion of the water column is prone to stratification. The upper portion of the water column in the south arm, above approximately 1272.5 m (4175 feet), is nearly homogeneous with surface salinities at or slightly below the average salinity of the south arm, which tends to remain around 125 g/L, although it was closer to 200 g/L shortly after the railroad causeway was constructed in 1959 and may currently once again be increasing.

The DBL appears in data from sample sites where the depth extends below 1272.5 and thus that are spatially within the 1272.5 m contour. It occurs only when causeway exchange supports flow from the north to south arms and has a salinity of approximately 150–250 g/L. Based on our salinity and salt mass results, similar information from separate sites suggests that salinity trends can be tracked using fewer sampling sites and higher sampling frequencies in time and depth. I also found that the average dissolved salt mass is negatively correlated between the two arms, such that the north arm mass increases as the south arm mass decreases and vice versa. These changes in salt mass reflect net movements of salt through the causeway, from south to north when lake WSE is going up and from north to south when lake WSE is going down. In addition, I show that the GSL has experienced a drop in total salt mass by more than 30% since the peak lake WSE in 1986. This salt loss is driven by mineral extraction processes that have removed approximately 1.177 billion metric tons (1.297 billion US tons) since 1986.

Chapter 2 contributed to the understanding of the distribution of salt and the occurrence and extent of the DBL by establishing a time series of salt concentration within GSL with respect to depth, delineating the DBL in time and space, comparing salinity at the lake's surface and at depth, and improving the understanding of salinity responses to causeway flow changes. Future recommendations pertaining to the work in Chapter 2 include continued exploration of flow through the causeway, particularly with respect to adjusting the berm elevation, and more detailed investigation of the salt mass precipitate on exposed lakebed and shores. Research in these areas would address remaining uncertainty about salt mass exchange between the lake arms and the contribution of precipitated salt to total salt mass within the lake.

The research in Chapter 3 investigated GSL volume changes along with evaporation and precipitation hindcasts as inputs to a water mass balance to reconstruct the full historical record of inflows to GSL from 1847-2022. The overall goal was to establish the magnitude of streamflow reductions as an indicator of how development of water resources, and therefore human consumptive water use, has impacted streamflow. With much of the decline in GSL WSE being attributed to human consumptive water use (Wurtsbaugh et al., 2017), there is a need to quantify lake input reductions over the GSL Basin. There have been recent efforts to estimate consumptive use for the GSL Basin by summing up various detailed uses and return flows, but thus far these estimates are disparate. Constructing a complete estimate of consumptive use using this method is a challenge because data for uses and return flows for the GSL Basin are often estimates, not measurements, and datasets spanning the full historical record (i.e., 1847 to 2022) are not available. The work reported in this dissertation used an alternative approach based on overall lake level and volume changes to quantify the total volumes of GSL input reductions.

The results in Chapter 3 include hindcasts for annual evaporation and precipitation depths over the lake and inflow volume to the lake, from which the annual inflow was reconstructed using a water mass balance. Two methods were used to estimate precipitation, resulting in a range for consumptive use of 1.65-2.5 km^3/yr and the associated lake level decline of 2.45-4.43 m. The hindcast of evaporation depth over the lake is consistent with previous mass balance estimations for the years 1950-2010 but was extended to include the entire 1847-2022 period. A bias may be present in the hindcast of precipitation using the runoff ratio due to its dependency on measured streamflow that includes consumptive use. This bias would be more pronounced in earlier years, when the GSL Basin was just being settled and consumptive use were relatively small. The reconstructed inflow using this hindcast precipitation is low and, therefore, the better estimate of consumptive use in the GSL Basin is closer to 2.5 km^3/yr and lake level decline is closer to 4.43 meters.

Chapter 3 contributed to the understanding of how human consumptive water use affects the GSL by establishing the magnitude of streamflow reductions over the historical record of GSL WSE. Future recommendations pertaining to the work in Chapter 3 include investigation of more reliable precipitation datasets, more detailed research on nearshore surface runoff, and continued exploration of the effects of climate change on streamflow and runoff. Research in these areas would address obvious uncertainties in precipitation and evaporation depths over the lake and also those due to ungaged inflows and the complex processes occurring within and near the lakebed.

Chapter 4 presents an innovative online module that concurrently develops students' mathematical modeling skills and their knowledge of the fundamentals of hydrology, rainfall-runoff processes, and engineering design. The study in this chapter applied a student-centered approach by including hands-on and active learning techniques through the use of an online educational module. The module leads students through a series of data- and modeling-driven activities to design the dam and outlet structure for a flood detention basin. In an effort to update the teaching approach for the required undergraduate hydrology course in the civil and environmental engineering degree programs at two United States universities, the module was incorporated into the curriculum. However, it was also developed with the intention that it could be a stand-alone learning tool.

The study in Chapter 4 examined how 251 students at two United States universities perceived mathematical modeling as implemented through the online module over a 5-year period. It was found that: (a) the module allowed students to be a part of the modeling process; (b) using technology, such as modeling software and online databases, in the module helped students to understand what they were doing in mathematical modeling; (c) using the technology in the module helped students to develop their skill set; and (d) difficulties with the technology and/or the modeling decisions they had to make in the module activities were in some cases barriers that interfered with students' ability to learn. Based on these findings, it is recommended that instructors create modules that: (a) are situated within a real-world context, requiring students to model mathematically to solve an authentic problem; (b) take advantage of digital tools used by engineers to support students' development of the mathematical and engineering skills needed in the workforce; and (c) use student feedback to guide module revisions.

References

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*. doi: 10.1038/ngeo3052.

CURRICULUM VITAE

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EDUCATION

PhD, Civil Engineering - Water Engineering, Utah State University, Logan, UT **2023**

- Dissertation: Surface Water Hydrology within the Great Salt Lake Basin
- Advisor: David Tarboton, Utah Water Research Laboratory
- Studied Physical Oceanography at the University of Alaska from 2011-2012

MS, Civil Engineering - Water Engineering, Utah State University, Logan, UT **2011**

BS, Mechanical Engineering, University of Minnesota, Twin Cities, Minneapolis, MN **1999**

WATER RESOURCES ENGINEERING PROJECTS and PAPERS

Great Salt Lake: salinity variability and inflow depletions **2015-2023**

Quantified the variability of salinity and movement of salt in time and space, the occurrence and extent of the deep brine layer, and the decline of salt mass within the Great Salt Lake.

- "The Salinity of the Great Salt Lake and Its Deep Brine Layer," published in Water, 2023.

Developed a novel method to hindcast historical lake inflows based on lake level in order to estimate streamflow depletions and the associated lake level decline due to basin-wide human consumptive water use.

- "Evaluating Variations in Great Salt Lake Inflow to Infer Human Consumptive Water Use, A Volume Reconstruction Approach," in prep for submittal to Water Resources Research, 2023.

Hydrology Education: online learning platform development **2014-2018**

Created a problem-based hydrology learning module focused on rainfall-runoff processes and design of a flood detention basin.

- "Engineering Students' Perceptions of Mathematical Modeling in a Learning Module Centered on a Hydrologic Design Case Study," published in International Journal of Research in Undergraduate Mathematics Education, 2021.

Arctic Streams: heat fate and transport **2009-2011**

Examined the extent and variability of water and nutrient storage and export in an arctic stream through qualitative analysis of observational data.

- "Variability of In-Stream and Riparian Storage in a Beaded Arctic Stream," published in Hydrological Processes, 2012.

Developed an instream temperature model that includes various heat fluxes, simplified vertical exchange between stratified layers, and attenuation of shortwave radiation.

- "Modelling In-Pool Temperature Variability in a Beaded Arctic Stream," published in Hydrological Processes, 2012.

PROFESSIONAL EXPERIENCE

Research Assistant **2013 – Present**
Utah Water Research Laboratory, Utah State University Logan, UT

- Hydrologic research within the Great Salt Lake Basin in support of scientifically based decision making and more sustainable management of the basin and its terminal lake.
- Data analysis and modeling using R, Python, FORTRAN, ArcGIS, HEC-HMS, and GoldSim.
- Authored grant proposals focusing on hydrodynamic modeling of lake processes.

Research Assistant **2011 – 2012**
University of Alaska, Fairbanks Fairbanks, AK

- Research and fieldwork on ocean circulation, hydrography, and sea ice dynamics in the arctic.
- Collection and analysis of field data from conductivity-temperature-depth sensors, upward looking sonars, and fluorometers using autonomous underwater vehicles, moorings, drifters, and shipboard towing and casting.

Research Assistant **2008 – 2011**
Utah Water Research Laboratory, Utah State University Logan, UT

- Research and fieldwork investigating heat fate and transport in an arctic stream and ecological stream habitat and fisheries monitoring in southern Idaho.
- Data analysis and modeling using R, VBA, ArcGIS, HEC-RAS, and PHABSIM.
- Fieldwork including weir design and installation, development of stage-discharge relationships, tracer studies, boat electrofishing, fish processing (identifying, weighing, counting, tagging), aquatic macroinvertebrate collection (benthic and drift), physical habitat surveys, and measurement of stream stage, discharge and geometry, water surface elevation, temperature, conductivity, and meteorological variables.

Project and Application Engineer **2002 - 2007**
GE Water and Process Technologies Minnetonka, MN

- Estimated costs, prepared bids, and designed water treatment equipment for large bottlers.
- Managed shop assembly and assisted technicians with troubleshooting and system start-ups.
- Conducted training seminars for both external customers and internal employees.

Public Health Engineer **2005 - 2006**
Minnesota Department of Health Saint Paul, MN

- Reviewed plans and specifications and conducted inspections of public water supply systems.
- Assessed innovative technologies and educated public on MDH codes and standards.

Design Engineer and Project Manager **2000 - 2002**
Northstar Fire Protection Eagan, MN

- Prepared and submitted bid packages, performed system designs, and managed the installation of fire sprinkler systems throughout the Twin Cities.
- Notable projects include the Milwaukee Road Depot and adjoining buildings, the Ameriprise Financial Center, and the Waste Management glass recycling center.

COMPUTER EXPERIENCE

Programming: R, Python, MATLAB, FORTRAN, VBA, JavaScript, HTML
Software: ArcGIS, AutoCAD, GoldSim, SAP, MS Office
Modeling: HEC-HMS, HEC-RAS, PHABSIM, Custom Models (Project-Based)

VOLUNTEERING

Nordic Ski Instructor **2008-2011**
Nordic United Logan, UT

Nordic Ski Coach **1997 –2007**
Saint Paul Public Schools Saint Paul, MN