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B. M. Crookston
Utah State University, brian.crookston@usu.edu

M. Rasmussen
Utah State University

E. Larsen
Utah State University

H. Kartchner
Utah State University

S. Dutta
Utah State University, som.dutta@usu.edu

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Predicting Density-driven Exchange Flows through the West Crack Breach of the Great Salt Lake Causeway with CFD and ANN

B.M. Crookston[1], M. Rasmussen[1], E. Larsen[2], H. Kartchner[2] & S. Dutta[2]
[1]*Department Civil and Environmental Engineering, Utah Water Research Laboratory, Utah State University, Logan, Utah, USA*
[2]*Department Mechanical and Aerospace Engineering, Utah State University, Logan, Utah, USA*
E-mail:brian.crookston@usu.edu

Abstract: *The Great Salt Lake is of environmental and economic value yet is threatened by various factors including drought and water diversion for irrigation purposes. Management efforts are required to preserve this saline lake; such efforts include accurately estimating the exchange flow through an opening in a railroad causeway that divides the lake. This study investigated two modeling approaches for predicting these discharges, a physics-based computational fluid dynamics model and a data-driven artificial neural network model. Good agreement was found between both models, and the advantages each provides to water management efforts are noted. Results indicate that, regardless of the modeling tool, accurate field data is invaluable when studying a hydraulic structure.*

Keywords: *Exchange Flow, CFD, ANN, Great Salt Lake.*

1. Introduction

Saline lakes are found on all seven continents and comprise approximately 44% of the volume of all lakes on earth (Messager et al. 2016; Williams 2002). Although historically perceived by some as unimportant, saline lakes and their associated wetlands are recognized for their biodiversity and valued habitat for many waterbirds (Pendleton et al. 2020; Zadereev et al. 2020). Many salt lakes also have thriving fishing, mineral extraction, and recreational industries (Demnati et al. 2017). Unfortunately, some saline lakes have been exploited for the abundant evaporitic minerals (e.g., sodium chloride, sodium carbonate, magnesium, potassium) that have a wide range of uses in medicine, manufacturing, chemical, agricultural, and construction industries (Waiser and Robarts 2009).

Of the various saline lakes scattered across the globe, the Great Salt Lake (GSL) is the largest saline lake in the western hemisphere and fourth largest in the world (Fig. 1a) (Arnow and Stephens 1990). As with other saline lakes, the GSL is currently under threat and requires additional conservation and management efforts. Threats to the GSL include climate shifts and irrigation demands that have reduced river inflow to the lake (Klotz and Miller 2010; Wine et al. 2019; Wurtsbaugh 2014; Wurtsbaugh et al. 2016, 2017). To highlight, in 2016 the GSL was below the historic low lake elevation of 1277.5 m and since then the lake elevation has further declined. Drought and flow diversion threaten an estimated economic output of over $1.3 billion via the mineral extraction, brine shrimp (*Artemia franciscana*) harvesting, and recreation industries (Bink 2021, Bedford 2005, Bioeconomics, Inc. 2012) and also the millions of migratory birds that use the GSL annually as a migratory staging area (Frank 2016).

When considering the past 100-years of the GSL, anthropogenic activities have permanently altered the lake in part from a rockfill railroad causeway (Fig. 1a,b,c) that was constructed (in 1956-1959) East-to-West that divided GSL into north and south sections (Great Salt Lake 1980). Construction of the causeway included two 4.6 m wide × 6.1 m high (15×20 ft) culverts with the purpose of providing flow exchange between the divided sections. The two sections quickly became physically and chemically different despite the culverts and the semi-porous causeway fill material (Madison 1970). Because 95% of freshwater flows into the GSL south of the causeway (Bear, Weber, and Jordan Rivers), the salinity of the northern section increased while the southern section became more dilute (Hahl and Handy 1969). In addition to salinity and the corresponding water density differences, a water surface gradient formed with a higher lake elevation in the southern section that has persisted even during periods of drought.

The railroad causeway has been modified several times since construction to manage the lake and allow passage of flows between the northern and southern sections. To reduce flooding of Salt Lake City in 1984, a 91.4 m wide breach was constructed in the causeway near GSL's west shoreline (Gwynn and Sturm 1987) (Fig. 1b). This breach does not experience flows below a lake elevation of about 1,278.5 m (Baskin 2005). Deterioration of the culverts eventually resulted in their closure and abandonment (west culvert 2012, east culvert in 2013, (Waddell et al. 2014)) with a new breach and bridge, known as the West Crack Breach (WC Breach) added and completed in December 2016 to replace the culverts (Fig. 1c,d).

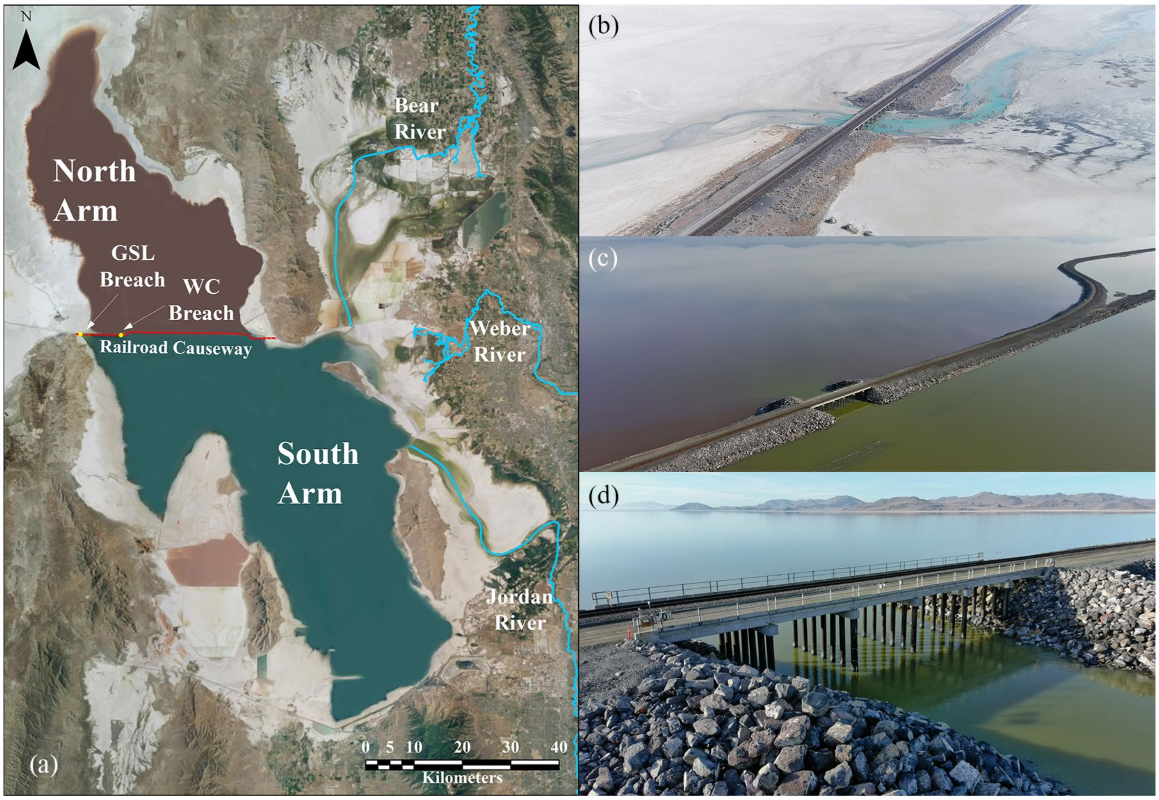

Figure 1. Overview of the Great Salt Lake located in Northern Utah, USA (circa 1984) (a); GSL's Lake-Side Breach constructed in 1984 to alleviate flooding (b), GSL's West Crack (WC) Breach (8 km east of the 1984 breach) in operation since January 2017 (c), with a view of the bridge over the WC Breach looking south-west (d).

Due to the aforementioned differences in lake water surface elevation (ΔWSE) and density ($\Delta\rho$) between the northern and southern lake sections, a unique flow behavior occurs through the breach for the majority of the year. Waters flowed simultaneously in both directions (north and south); this density-stratified bi-direction flow is often referred to as a gravity-driven exchange flow. Such a hydraulic feature is known to occur in similar lake and ocean settings (Turner 1973). At the WC Breach, the bi-directional flow is characterized by a plunging current of northern water beneath a surface current of less-dense southern water. The less-dense south-to-north surface flow travels more than a kilometer north as it gradually expands laterally. The saltier north-to-south flow is mostly unmixed, passes beneath the surface flow, and connects to a deep brine layer in the southern section of the lake (Naftz 2017).

Predicting the exchange of flow and salt through the WC Breach is critical to current lake management and conservation efforts because salt concentrations in each section directly impact the environment and GSL industries/economies. Prior to the WC Breach, 1D computational hydraulic model of the original culverts were created to estimate discharge and salt exchange to support lake management efforts (Holley et al. 1976). Using this culvert model, the WC Breach was designed to duplicate (as closely as possible) the transfer of water previously provided by the culverts (HDR Engineering, Inc. 2018) but this model does not consider the WC Breach geometry and the resulting three-dimensional (3D) flow. Thus, a new model is needed to improve prediction accuracy. Therefore, what modeling tools might be suitable to improve discharge estimates through the Great Salt Lake Causeway WC Breach and how might viable tools be able to provide further insights into the bi-directional flow regimes as a function of lake conditions?

One common approach for simulating water interacting with a structure such as the West Crack Breach is a physics-based model, such as using computational fluid dynamics (CFD). Various open-source and proprietary CFD solvers have been used to study the interaction of water with control structures and bridges. For example, Crookston et al.

(2018) described the use of CFD to estimate discharge rating curves of piano key weirs. Similarly, Torres et al. (2021) presented the successful use of CFD models in free-surface flows over a weir and spillway to estimate a rating curve. Another study by Chanel and Doering (2008) compared CFD predictions with physical modeling of spillway flow with general success. CFD modeling has also been successfully applied to complex stratified and multiphase flows. Dutta et al. (2014) used CFD models to reveal particle trapping secondary currents in sewer conduits with single and multi-phase flows. Also, An et al. (2012) simulated particle-driven gravity currents that agreed well with similar laboratory experiments and Stancanelli et al. (2018) applied CFD models to analyze the classic lock exchange experiment.

Another approach for predicting discharge through a structure is to use a data-based model, such as machine learning models, which include artificial neural networks (ANN) and deep learning neural networks (DNN). This is a data-driven approach that, through regression and back propagation, formulates a predictive model. Such models are trained with specific data so that the key input parameters can be related to observed patterns in the dataset. Recently, ANN has been used for discharge prediction and flow behavior at a structure (Dutta et al. 2014; Khosravi et al. 2022a,b; Hassanpour et al. 2022; Salazar and Crookston 2019). ANN has also been used to study other fluid problems such as flood patterns (Tsakiri et al. 2018) and sediment loads (Gudino-Elizondo et al. 2019). Thus, in this study these two approaches were evaluated regarding the ability of each model to predict exchange flow rates through the West Crack Breach and provide insights into flow to support GSL management efforts.

In the current paper we present models developed using both the physics-based approach (CFD) and the data-driven approach (ANN), and discuss the scenarios under which a particular approach is advantageous.

2. METHODS

Field data for both modeling efforts relied on USGS data made available to Utah State University, which included monthly specific conductance σ, and velocity profiles, along with water surface elevations, wind speed, wind direction at (and around) the WC Breach. This data was supplemented by a Utah State University field campaign that included continual specific conductance measurements since November 2020 (Dutta et al., 2021), monthly TDS samples, and a temperature array located within the breach to identify the interface in the exchange flow. The USU field campaign also included an exploratory effort to help identify special variability of the flow field adjacent to the WC Breach to inform placement of CFD model boundaries. These field data were used for CFD model development, validation and for ANN model training and testing.

2.1. CFD Model

In this study, FLOW-3D™ by Flow Science, Inc.© was utilized to numerically simulate flow in the WC Breach (Flow Science Inc. 2022). The CFD software uses numerical methods to approximate the Reynold-averaged Navier-Stokes (RANS) equations that are solved with the Boussinesq assumption to simplify the compressible form of the RANS equations.

Bathymetry data for CFD model geometry were compiled from HDR Engineering Inc. (2021) who provided data (from time of construction completion) for the entire excavated section of the WC breach. Supplemental data for the remaining portion of the numerical domain was provided by the USGS (Baskin 2005) or derived from topographic maps. The specific geometry of the bridge was created using bridge structural drawings (HDR Engineering, Inc. 2016).

The CFD modeling in this study had 1) a sectional model phase and 2) a full-width model phase. Phase 1 was of a single-cell width through the center of WC Breach and allowed for an efficient initial study of mesh size, governing equations, boundary conditions, numerical methods for consideration in Phase 2. The Sectional mesh boundaries were assigned as an overlap boundary and pressure types for the E/W and N/S bounds, respectively. Pressure boundaries required input for both fluid elevation and ρ. Grid convergence with 8 different cell sizes was performed and focused on minimal changes in the velocity profile at the USGS measurement locations with numerical velocity probes assigned at locations identical to the USGS acoustic doppler velocimeter (ADV) measurements. In this study, four turbulence schemes provided by FLOW-3D were considered: k-ε, Renormalized Group k-ε (RNG- k-ε), k-ω, and Large Eddy Simulation (LES) (Flow Science, 2008). The four turbulence schemes were tested in Phase 1 considering different model coefficients, and the results indicated better performance by the LES and k-ω, which were then considered in Phase 2.

The following density evaluation options by the FLOW-3D solver considered herein include: 1) density as a function of hydraulic parameters (i.e., temperature, etc.), 2) a first-order approximation, and 3) a second-order monotonicity preserving approximation. Although a fourth option was available (a constant uniform density) it was not considered appropriate for this study.

For Phase 2, the computational mesh was expanded in the east and west directions. In order to continue the grid convergence study, a nested block approach was adopted with two primary or main mesh blocks to represent the north and south sections of the lake with an overlap boundary condition within the WC Breach. Similar to Phase 1, additional boundary conditions were assigned pressure conditions with *WSE* and ρ inputs (Fig. 2). Nested blocks with refined cell size were centered at the WC Breach due to the primary focus of discharge estimation and available velocity data. The total number of computational cells was limited to a maximum of around 25 million due to computing power limitations (four well-equipped desktop machines). To obtain mesh independence in the 3D domain, three mesh configurations were tested with a 2:1 cell size ratio between blocks: 1) 0.3 m cells without a nested mesh block, 2) with a nested 0.15 m mesh block around the breach, and 3) with both a 0.15 m mesh block around the breach and a smaller 0.08 m mesh block. Multiple simulations were performed to determine the appropriate grid size, turbulence closure, density modules, etc. More details can be obtained in Rasmussen (2022) and Dutta et al. (2021).

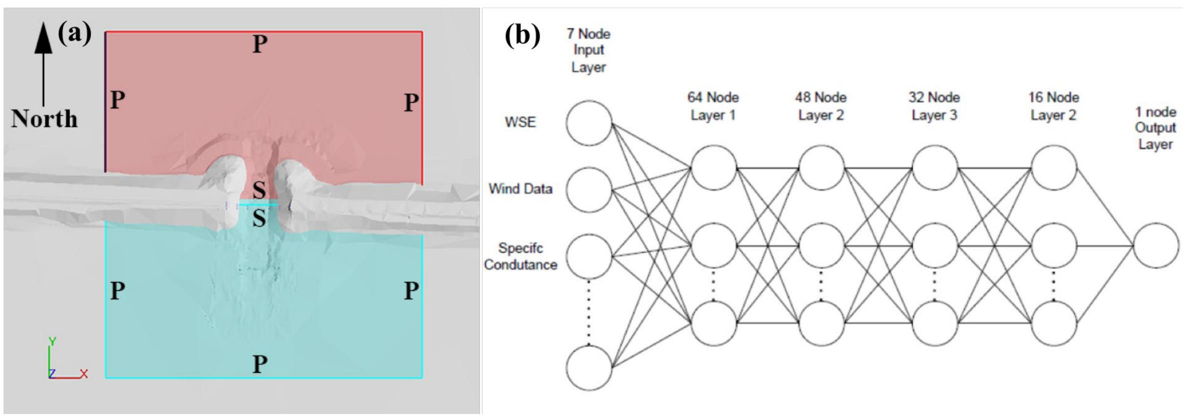

Figure 2. The computational domain for the CFD model with the boundary conditions, where P referring to a pressure boundary (water surface elevation) with assigned density and S referring to an internal overlap boundary (a) and structure of the most accurate ANN model with 4 hidden layers (b). The inputs and output layers have seven and one nodes respectively.

2.2. ANN Model

The ANN model developed herein (see Fig. 2b) used data measured by USGS. For the study, the feed forward network architecture was chosen, along with back-propagation (BP) for learning. These methods have been successful in the past for hydraulic structure (Dutta et al., 2014). Two separate networks were trained, both having the same inputs, but one predicting North-to-South (NS) flow and the other predicting the South-to-North (SN) flow. Three inputs for the model are related to water surface elevation, North of the breach, South of the breach and at the breach. One of the main drivers of the exchange flow is density difference between the North and South sides of the breach, which primarily depends on the salinity of the water. The salinity of N and S sides of the breach is accounted in the model using measured specific conductance value. The final two inputs of the ANN models are wind-speed and wind-direction at the breach. During low wind speeds, records show that wind does not have a substantial effect on the dynamics of the flow at the breach. During high-wind speeds, it can force all the flow through the breach to move south or north, depending on the wind-direction. Thus, it was important to include the wind data to make the model more robust. After pre-processing and cleaning the data, the final data set had 27,204 entries. This was divided into training (21763 entries), testing (2721 entries) and validation (2720 entries) data set. The final network architecture was developed through a process of refining the attributes of the network. The first stage of development was through the layer structure of the network. The number of layers and the size of those layers were varied through multiple tests to find the best performing network. The networks were evaluated on the training data that they presented. The training and evaluation loss values were compared during model training. With the depth and width of the network determined, the batch size of the data used was changed to find the optimal amount of data required for the network before adjusting the weights. Batch sizes ranging from 12-40 were used to visualize the effect batch size had on the training of the model. Each network was tested at 50 and 150 epoch lengths to view the trend that prolonged training had on the network's performance.

3. RESULTS

3.1. CFD Results

Within the WC Breach and north of the railroad is a submerged berm. The berm is intended for management efforts by serving as a control structure for buoyancy-driven flows moving north-to-south. Depending on current or anticipated conditions, the berm could be modified with construction equipment by removing submerged causeway materials or by adding additional materials, thus increasing or lowering the crest elevation of the berm. The CFD model results indicate that indeed the north-to-south flows are influenced by this submerged berm (see Figs. 3 and 4) and that either a lowering of the lake elevation or a raising of the berm would decrease such flows. As an additional detail the flows in the streamwise or y direction can exceed 1 m/s with a densimetric Froude number of about 0.7. The CFD results clearly show this denser saltwater plunging beneath the less-dense south-to-north flows (see Fig. 4) as was observed in the Utah State University field campaign for a July 2021 condition.

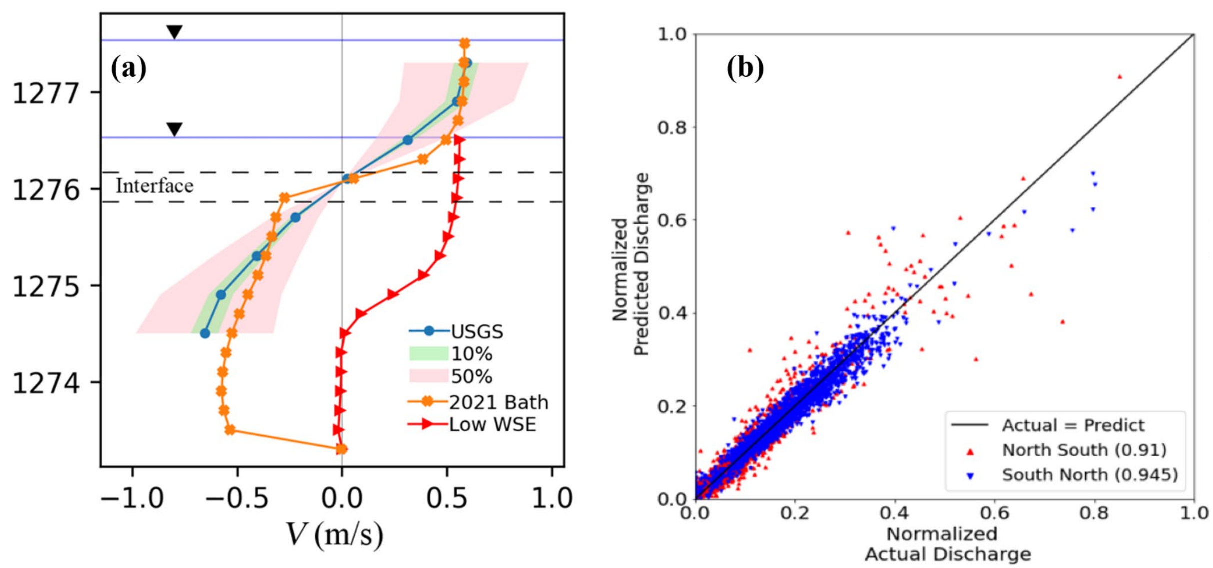

Figure 3. Velocity profile (velocity versus elevation (meters) from USGS compared to CFD results for a specific event in July 2021, and the location of the exchange flow interface via the temperature array (a); and normalized actual versus predicted discharge for the testing data-set using the ANN model (b). Note that if lake levels continue to drop the model predicts a significant decrease in north-to-south flows. The ANN model NSE coefficient is 0.91 for N-S flow and 0.945 for S-N flow.

Such results demonstrate that various combinations of water surfaces, densities, and lake elevations can be used to formulate a head-discharge rating curve through the breach. For additional details of other validation events and results, please see Rasmussen (2022). This study demonstrates that a simple empirical rating curve could be formulated and then incorporated into a hydrologic model of the Great Salt Lake Basin for management efforts. Furthermore, this modeling tool provides two specific advantages:

1. Hypothetical hydraulic scenarios can be simulated
2. Geometric modifications to the breach can be simulated for design purposes.

Specifically, this validated model can be used to consider current drought conditions at the lake and scenarios with even lower lake elevations. Therefore, simulations were performed such as a 0.6 m drop in lake elevation, as shown in Fig. 5. Portions of the lakebed are now exposed and discharges from north-to-south are further reduced. The CFD model also allows exploring any output hydraulic variable at any location within the domain for consideration of potential geometric modifications to the submerged berm. As shown in Fig. 6, sections in the transverse or x direction were taken in the breach at 150 m spacing with (a) located furthest north and (g) furthest south. At the location of the USGS ADV uplooker, CFD results are compared to the USGS field data (see Fig. 3a). Note the significant change in velocity for a reduced water surface elevation.

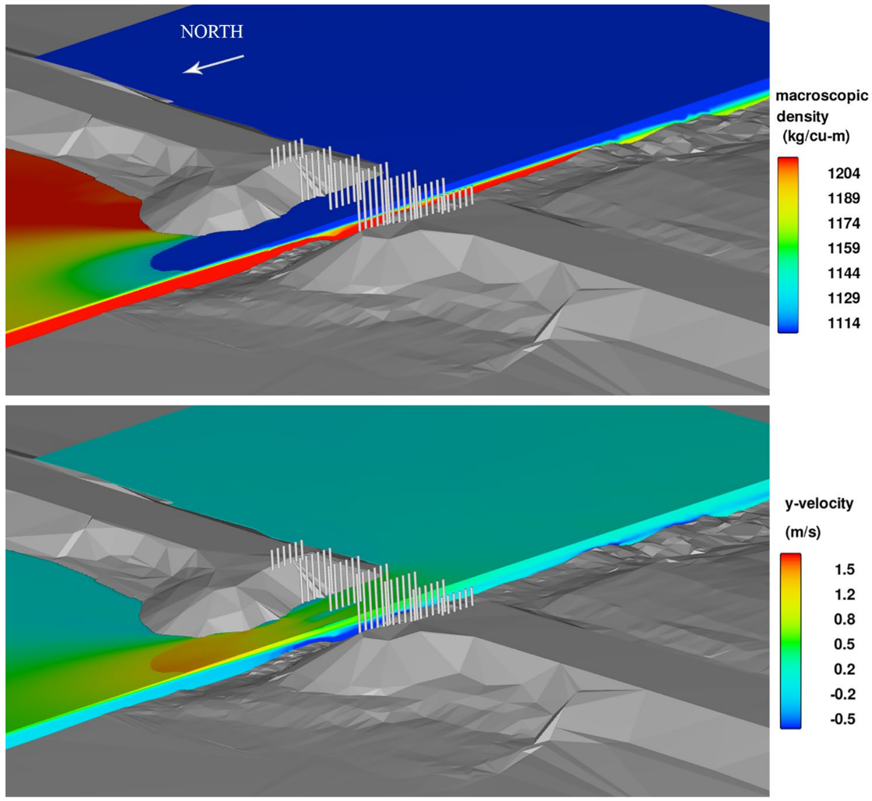

Figure 4. Water density section and velocity gradient in streamwise direction through the WC Breach for the July 2021 event, with surface jet expanding laterally and the lower brine layer traveling south with the velocity section through the WC Breach for July 2021 event.

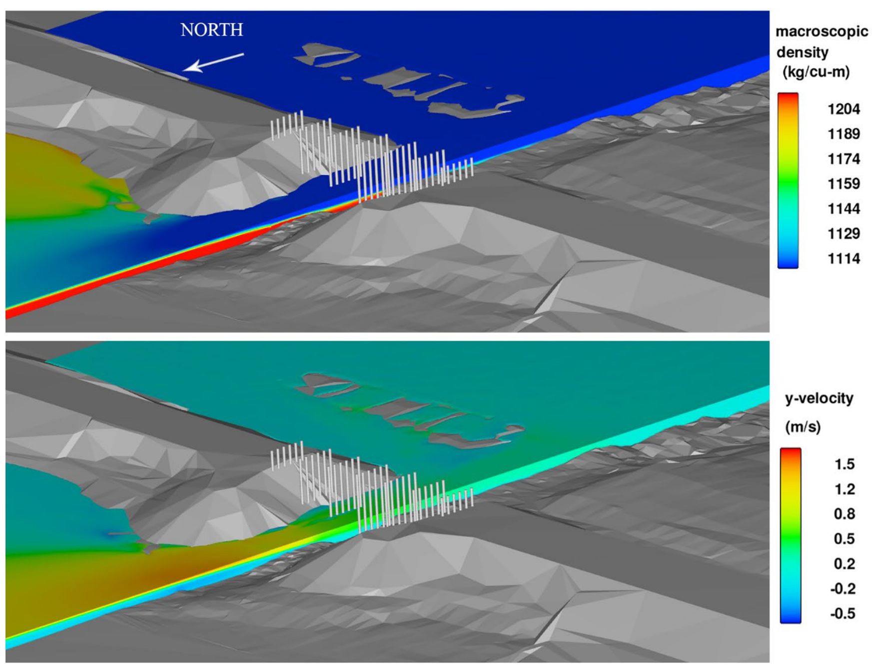

Figure 5. Potential drought scenario if the July 2021 field conditions included lake elevations lowered by 0.6 m.

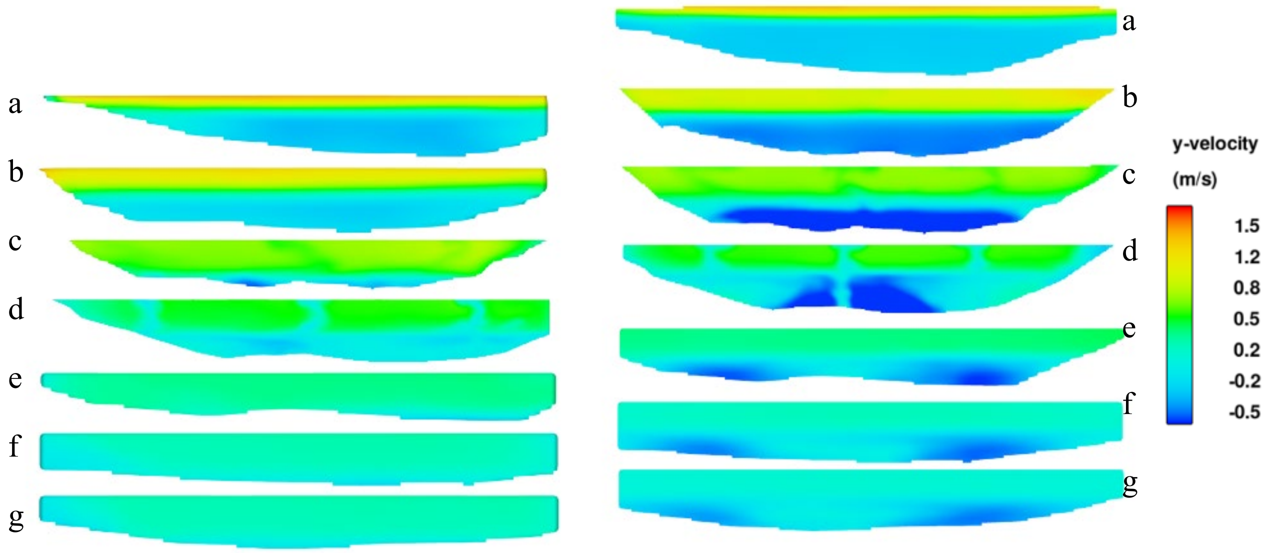

Figure 6. Sections through the WC Breach plotted by streamwise velocity for the July 2021 field event. Worsened lake conditions with a reduced water surface of 0.6 m (left) as compared to actual lake elevations (right). The cross-sections plotted start north of the breach, and go towards the south at a 12 m interval. The streamwise velocity clearly show the weakening of the N-S flow with lowering of the lake elevation.

3.2. ANN Results

Different architectures of the ANN model was trained and the model that performed the best for the testing data-set has been presented here. The ANN with a 7-64-48-32-16-1 architecture (see Fig. 2.) was found to be the most accurate while predicting N-S and S-N flow. The Nash–Sutcliffe efficiency (NSE) coefficient (R^2) for predicting N-S and S-N flow was found to be 0.91 and 0.945, respectively. The corresponding percent bias for the model was –3.65 and 0.84 for N-S and S-N respectively. This means, the ANN model is relatively bias free. Though, the N-S prediction was found to have negative bias, indicating that the ANN model is underestimating the flow compared to observed discharge values. As part of the ANN model development effort, a linear regression model was also developed. In congruence with the expectations, the linear regression model was found to have a substantially lower NSE coefficient ($R^2 \sim 0.8$), compared to the ANN model.

4. CONCLUSIONS

Various modeling tools are available to support water resources management efforts, which includes physics-based models and data-driven models. In this study, CFD and ANN models were used to predict a complex flow behavior at the West Crack Breach in the railroad causeway at the Great Salt Lake. The general flow pattern is an exchange flow or a density-driven bidirectional flow where the denser water from the northern section plunges and flows south, while the less-dense southern water flows at the surface towards the north. Both modeling efforts required field data. The CFD model was able to accurately simulate field conditions and is able to simulate hypothetical scenarios such as different hydraulic conditions or different geometric configurations, both of which are of high interest to the State of Utah. The simulated July 2021 event, had about 1% difference for N-S flow prediction and about 18% for S-N flow prediction, compared to field measurements. The ANN model was also able to accurately predict flows through the breach and is computationally inexpensive, allowing incorporation into a hydrologic model of the basin. It also informs managers what field data is needed for prediction efforts and what field conditions may cause discharges to increase or decrease. However, the ANN model is limited to the range of training data and therefore is not suitable for extrapolation such as predicting performance under future climatic shifts.

5. ACKNOWLEDGMENTS

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