Assessing Impacts of Flood Diversion on the Ecosystem of Brackish-Water Lakes through Simulation-Optimization Model

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Abstract: This study develops and evaluates a simulation-optimization approach to mitigate the environmental impacts of freshwater pulses in brackish-water lakes whilst maximizing flood diversion benefits. Lake Pontchartrain, located downstream of the Mississippi River, Mississippi, United States, is a brackish-water ecosystem threatened by reducing salinity concentrations due to freshwater pulses from the flood diversion project on the Mississippi River. An adaptive neuro-fuzzy-inference-system-based model was developed as a data-driven model for simulating salinity distribution at a representative station of Lake Pontchartrain. Then, the data-driven model was used as the simulator in the optimization system. Both single-objective and multi-objective particle swarm optimizations were used to find the optimal solutions. Results show that the data-driven model is robust at simulating the salinity time series in the brackish-water ecosystem of Lake Pontchartrain. The Nash–Sutcliffe efficiency index of the data-driven model between measured and modelled salinity is 0.85, which means the model is reliable for applying in further simulations. The proposed optimal solutions for the environmental management of the lake indicate that because of the magnitude of the volume of freshwater released, environmental impacts at this location cannot be optimized through varying the timing and volume of the releases. This work presents a novel contribution to science through developing an optimization framework for mitigating the impacts of flood management on changes in salinity in brackish-water systems.

Keywords: freshwater pulse; environmental impacts; salinity; Lake Pontchartrain; Bonnet Carré Spillway; neuro-fuzzy model; optimization

1. Introduction

The Mississippi River is one of the largest rivers in the world and has experienced many catastrophic floods. Due to the considerable potential flood damage at downstream areas, the Bonnet Carré Spillway was constructed between 1929 and 1931 to prevent flooding in New Orleans. This spillway diverts freshwater from the Mississippi River into Lake Pontchartrain and then into the Mississippi Sound. The environmental impacts of freshwater pulses on the saline ecosystem of the Mississippi Sound and Lake Pontchartrain from the Bonnet Carré Spillway have been highlighted in recent years [1–3]. In fact, freshwater pulses reduce the salinity of the ecosystem in the spatial and temporal scale to such an extent that marine organisms that need higher levels of salinity are threatened [4–7]. Simulating the potential impacts of freshwater pulses on changing salinity is a crucial tool for decision-makers and regional governments seeking to understand and balance environmental degradation in these valuable habitats.

In general, hydrodynamic models are useful tools because they use mechanistic, physics-based equations to simulate hydrodynamic conditions seamlessly throughout time and space. However, hydrodynamic models have some limitations which restrict their application in practical situations. For example, the computational time that is required
to run a hydrodynamic model is one of the significant problems when applying these models. In large domains and for long-term simulations, these models need considerable computational time and may not be a popular option for engineers who are interested in carrying out numerous simulations in a short time. Moreover, hydrodynamic models often require powerful computers, which are not available in all situations. Hence, alternatives to hydrodynamic modelling are useful in numerous applications.

Artificial intelligence (AI) methods have been applied in different branches of engineering in recent years [8]. The successful application of these methods in environmental engineering makes them a popular tool for a wide range of situations. One AI method is neural networks (NNs), which have been widely applied to hydrological systems. For example, feedforward neural networks (FNNs) have been used to simulate stream flow [9] and water quality [10]. Due to the inherent drawbacks of ANNs, such as interpretability and black-box behavior, neuro-fuzzy inference systems (NFIs) have been developed to improve conventional neural networks. Adaptive neuro-fuzzy inference systems (ANFISs) are an NFS in which a fuzzy inference system is used in the structure of the FNN model [11,12]. Previous studies corroborated the robustness of ANFIS-based models in modelling the water quality of rivers [13]. In studies of lacustrine systems, if the objective is to simulate the distribution of water quality, using hydrodynamic models and artificial intelligence (AI) models might demand the same computational sources. In other words, it cannot be generally claimed that AI models are computationally superior. However, if the objective of the study is to simulate water quality at a specific location, AI models are superior in terms of their computational requirements because hydrodynamic models solve partial differential equations through a computational mesh at small timesteps, while AI models only need to simulate water-quality parameters in a specific location over a specific time, without the need for time series solutions throughout a computational grid. In the present study, we use an ANFIS-based model to simulate the environmental impacts of freshwater pulses due to flood diversion on the saline ecosystem of Lake Pontchartrain.

Optimization models have been recommended for a wide range of water resources and environmental engineering problems [14]. Optimization models can balance the societal needs and environmental impacts of water resource projects. Linear programming (LP) and non-linear programming (NLP) have applied to a wide range of optimization problems in environmental and water resource engineering [15]. However, due to complexities of the non-linear objective functions, evolutionary optimization has been introduced as a robust and efficient method. Based on the nature of the problem, evolutionary optimization is applicable in the form of a single objective or multi-objective optimization, which provides different solutions for the problem [16].

The simulation and optimization of the impacts of freshwater pulses due to flood diversion projects on saline water ecosystems such as Lake Pontchartrain have not been extensively highlighted in the literature. There is likely a similar need for numerous cases around the world. Due to this research gap, the present study develops a novel ANFIS-based model to simulate the environmental impacts of freshwater pulses in the valuable ecosystem of Lake Pontchartrain. Moreover, an optimization model was developed for evaluating how the environmental impacts of the freshwater pulses should be managed. The present study opens new windows for applying simulation-optimization frameworks for managing the environmental degradations in estuaries due to water resource projects. The proposed framework is applicable for similar cases in which flood diversion projects have considerable impacts on the aquatic habitats of saline ecosystems.

2. Study Area and Problem Definition

Figure 1 shows the location of the Bonnet Carré Spillway, Lake Pontchartrain, and the Mississippi Sound near the Gulf of Mexico. The Bonnet Carré Spillway empties into Lake Pontchartrain, which then empties into the Mississippi Sound. Lake Pontchartrain is a shallow, large (1600 km²) estuarine lake, located in south-eastern coastal Louisiana. The Rigolets is a tidally influenced straight that connects Lake Pontchartrain with the
Mississippi Sound. The Mississippi Sound is located along the southern coast of Alabama and Mississippi, extending west into Southeast Louisiana. Barrier islands separate the Sound from ocean dynamics in the marine waters of the Gulf of Mexico.

Figure 1. The location of the Bonnet Carré Spillway, Lake Pontchartrain, and Mississippi Sound (the red circle shows the location of the representative station for developing the ANFIS-based model; the coordination system is UTM).

Brackish-water habitats of the Lake and Sound are threatened by freshwater flows that reduce salinity concentrations. The Bonnet Carré Spillway openings drastically alter the salinity of the Lake and the Sound through massive freshwater pulses. This spillway was constructed for mitigating the impacts of disastrous floods of the Mississippi River upon downstream urban and agricultural areas, by diverting flood flows to Lake Pontchartrain and into the Mississippi Sound. Several scientific studies have documented the ecological impacts of the spillway on the Lake and Sound. For example, the spillway has been shown to affect sediment, salinity, and phytoplankton in Lake Pontchartrain [1]. The population of oysters in the Mississippi Sound has also decreased due to freshwater entering via the Bonnet Carré Spillway [17].

Several stations managed by the United States Geological Society (USGS) measure salinity in the Lake and Sound. We selected the station USGS 301001089442600 Rigolets at Hwy 90 near Slidell, LA, for which the long-term data were available (from 2010 to 2020); this serves as a representative station for simulating the impacts of the freshwater pulses using the ANFIS-based model (shown in Figure 1 by a red point). In the present study, we focused on changing salinity in the Lake. While only the salinity in Lake Pontchartrain was evaluated in this study, the salinity in the Lake has implications for the Sound. However, data and analysis only involve the Lake. Table 1 displays the data sources used in this study.
Table 1. Data sources in the case study.

<table>
<thead>
<tr>
<th>Data Type</th>
<th>Spatial/Temporal Resolution</th>
<th>Source of Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Digital elevation model of catchment (spatial data)</td>
<td>30 × 30 m</td>
<td>USGS Earth Explorer Database</td>
</tr>
<tr>
<td>Soil map of catchment (spatial data)</td>
<td>Converted to 30 × 30 m</td>
<td>FAO Database</td>
</tr>
<tr>
<td>Land-use map of catchment (spatial data)</td>
<td>Converted to 30 × 30 m</td>
<td>National Land Cover Database, USGS</td>
</tr>
<tr>
<td>River flows used for calibrating/validating hydrological model</td>
<td>Daily recorded flows in hydrometric stations mainly at midstream and upstream of the catchment (2010–2020)</td>
<td>USGS water data for nation</td>
</tr>
<tr>
<td>Salinity (EC) data for the lake</td>
<td>Daily recorded data in the station USGS 301001089442600 Rigolets at Hwy 90 near Slidell, LA, (2010–2020)</td>
<td>USGS Database</td>
</tr>
<tr>
<td>Opening/closing data of flood gate</td>
<td>Daily recorded data of the flood gate (2010–2020)</td>
<td>Regional authority</td>
</tr>
</tbody>
</table>

3. Methodology

Two models were developed in the present study, as follows:

1. An ANFIS-based model, in which the simulations were carried out for the representative station.
2. An optimization model of Lake Pontchartrain in which reducing salinity due to freshwater pulses was minimized whilst the flood diversion benefits are maximized. The ANFIS-based model was used in the structure of the optimization model.

3.1. ANFIS-Based Model

A simple structure of the ANFIS model is displayed in Figure 2 with two inputs. As a brief description on the structure of ANFIS-based models, this network includes five layers: The first layer is the input membership functions or the effective inputs in the model. The fixed nodes in the second layer compute the output as a product of all incoming signals. The next layer computes the normalized firing strength of each rule. The firing strength of a fuzzy rule is obtained by multiplying the input membership grades. By passing this value to the membership grade of the output to the corresponding fuzzy set, we compute the final output of the model.

![Figure 2. Simple structure of ANFIS-based data-driven model with two inputs and one output.](image-url)
We tune adaptive parameters in the next layer to train the model and obtain the output of the model. Finally, a single node in the last layer is able to calculate the summation of all incoming signals. The membership function is computed for the input of \( X \) by

\[
\mu_{A_i}(X) = \frac{1}{1 + |(x - c_1)/a_1|^2N_1} \tag{1}
\]

where \( a_1, N_1 \) and \( c_1 \) are changeable premise parameters. \( \mu_{B_i}(Y) \) are computed similarly. Then, the membership functions should be multiplied by

\[
w_i = \mu_{A_i}(X)\mu_{B_i}(Y) \quad (i = 1, 2) \tag{2}
\]

The nodes of the fourth layer apply the average \( w \) used as a weighting factor. As an example of fuzzy rules, if-then rules are definable as follows (in which \( A \) and \( B \) are linguistic labels, and the terms \( p, q \) and \( r \) are changeable consequent parameters):

**Rule 1:** If \( x \) is \( A_1 \) and \( y \) is \( B_1 \), then \( f_1 = p_1x = q_1y + r_1 \).

**Rule 2:** If \( x \) is \( A_2 \) and \( y \) is \( B_2 \), then \( f_2 = p_2x = q_2y + r_2 \).

The training method of ANFIS-based models is effective; however, it requires selecting an appropriate training method for developing a successful data-driven model. Training an ANFIS-based model was originally devised as an optimization problem in which finding the optimal coefficients of the network was the aim. The hybrid algorithm (backpropagation + least square) is an appropriate and conventional method to train ANFIS-based models. Hence, we trained the data-driven model via this algorithm. More details regarding the training algorithms are provided in the literature [18].

Selecting the best combination of inputs is the most important step in the development of a data-driven model. In the present study, initial iterations of trial and error were used to find the best combination of inputs in the data-driven model. In the selection process of the inputs, several steps were considered, as follows:

1. A long list of effective parameters was provided based on previous studies and expert opinions regarding the effective factors for assessing salinity in estuary ecosystems.
2. Factors which have minor effects on salinity were deleted from the list, because machine-learning models can work as a surrogate model by considering the major effective parameters. In other words, major parameters were selected as the shortlist.
3. Several initial models were developed from different combinations of the inputs. Then, the accuracy of the model and the computational costs were considered to select the best combination of inputs used for developing the final model.

Moreover, different types of ANFIS-based models were tested. Finally, the ANFIS model was finalized based on details shown in Table 2. The number of iterations used by the hybrid algorithm for training the model was 10,000, to ensure optimal weights for the neural network.

As displayed in Table 2, one of the important inputs of the model is the total watershed inflow to the Lake, which varies on a daily scale. Some hydrometric stations were able to measure the inflow from the rivers. However, total inflow was not recorded. Hence, it was necessary to simulate the total inflow to the Lake for use in the structure of the data-driven model. We applied the soil and water assessment tool (SWAT) to simulate total watershed inflow to the Lake during the simulated period (the simulation period is 2010–2020 on a daily scale). This continuous hydrological model has been extensively applied for simulating catchments [19]. Thus, it is a reliable model in this regard. The methodology of the SWAT model has been fully addressed in the literature; more details documenting the SWAT model are out of the scope of the present study. Figure 3 shows the workflow using SWAT in the present study, in which the model was initially applied to develop a hydrological model in one of the sub-basins of Lake Pontchartrain. In this sub-basin, the outflow had been recorded in a daily scale. Hence, the SWAT model was calibrated and validated for this sub-basin. Then, calibrated coefficients were applied for the Lake basin to simulate the total inflow in the simulated period. According to the
recommendations in the literature, the Nash–Sutcliffe efficiency index (NSE) was utilized to measure the goodness-of-fit of the model in the calibration and validation processes [20]. The NSE for the calibration and validation period was 0.82, which demonstrates the reliability of the SWAT model to simulate the total inflow of the Lake. According to the literature, if NSE is more than 0.5, the hydrological model may be considered reliable. The maximum NSE is 1, which means the model and observations are identical. However, a perfect model is not possible practically. Figure 4 displays two samples of the inputs of the SWAT in the Lake basin, including the digital elevation model of the basin and the slope map generated by the SWAT. Moreover, Figure 5 shows the normalized total inflow of the Lake and the normalized opening rate of the flood control spillway (freshwater pulse rate). It should be noted that all the inputs of the data-driven model were used in the normalized form to achieve the best results. In the optimization model, we focused on one of the major floods in which the flood diversion spillway was completely open (displayed as a blue square in Figure 5). Moreover, Figure 5 shows the flood volume compared with the Lake volume, which indicates the flood volume compared with the total volume of the Lake is significant. In other words, Figure 5 demonstrates the potential impact of freshwater pulses on the saline ecosystem due to considerable volumes of flood flow to the Lake ecosystem.

Table 2. Main characteristics of ANFIS-based model (all inputs and outputs are in normalized form).

<table>
<thead>
<tr>
<th>Inputs</th>
<th>Number of Membership Functions MFs (Inputs)</th>
<th>Type of MFs (Inputs)</th>
<th>Outputs</th>
<th>Number of MFs (Output)</th>
<th>Type of MFs (Output)</th>
<th>Clustering Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Three inputs of EC to the model (recorded in the station): average EC in Steps t-1 to t-9, average EC in Steps t-1 to t-6, average EC in Steps t-1 to t-3</td>
<td>5</td>
<td>Gaussian</td>
<td>EC in time step t 5</td>
<td>Linear</td>
<td>Subtractive clustering</td>
<td></td>
</tr>
<tr>
<td>Three inputs of inflow to the model (simulated by SWAT): average inflow in Steps t-1 to t-9, average inflow in Steps t-1 to t-6, average inflow in Steps t-1 to t-3</td>
<td>5</td>
<td>Gaussian</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Three inputs of opening rate of flood control spillway to the model: average opening rate in Steps t-1 to t-9, average opening rate in Steps t-1 to t-6, average opening rate in Steps t-1 to t-3</td>
<td>5</td>
<td>Gaussian</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 3. Flowchart of coupled SWAT and SWAT-CUP used to simulate outflow of the catchment.
impact of freshwater pulses on the saline ecosystem due to considerable volumes of flood
flow to the Lake ecosystem.

Figure 3. Flowchart of coupled SWAT and SWAT-CUP used to simulate outflow of the catchment.

(A) Delineated catchment of the Lake in SWAT, (B) digital elevation model and (C) slope map as the samples of the inputs in the SWAT.

Figure 4. (A) Delineated catchment of the Lake in SWAT, (B) digital elevation model and (C) slope map as the samples of the inputs in the SWAT.
Figure 4. (A) Delineated catchment of the Lake in SWAT, (B) digital elevation model and (C) slope map as the samples of the inputs in the SWAT.

Figure 5. (A) Simulated inflow to Lake Pontchartrain in SWAT and (B) opening rate of flood control spillway (major lines in the graphs are the years and minor lines are the months).

Two indices—NSE and the root-mean-square error (RMSE), as displayed in the following equations—were applied for assessing the robustness of the ANFIS-based model [21]:

\[
RMSE = \sqrt{\frac{1}{T} \sum_{i=1}^{T} (O_i - M_i)^2} \tag{3}
\]

\[
NSE = 1 - \frac{\sum_{i=1}^{T} |M_i - O_i|}{\sum_{i=1}^{T} |O_i - O_m|} \tag{4}
\]

\(O_i, M_i\) and \(O_m\) are the observed data, modelled data in each measured point and average of the observed habitat suitability in each microhabitat, respectively. The maximum NSE is 1, which indicates that the model is perfect, and the simulated results and
observations are identical. If the NSE is more than 0.5, the performance of the model is deemed acceptable.

3.2. Optimization Model

We developed an optimization model in which two objectives were defined. First, minimize the reduction of salinity in the Lake due to freshwater pulses from diverted floods. Second, maximize the benefits of the flood diversion project. These two objective functions are shown in Equations (5) and (6). In these equations, the ideal opening rate (IR) assumes that the spillway is closed (zero flow). The optimal opening rate (OR) is the proposed opening rate in the optimization model in which flood mitigation and salinity management are simultaneously considered. The ideal salinity concentration (IS) is the simulated salinity in the Lake in which the flow of the spillway is zero. The optimal salinity concentration (OS) is the proposed salinity concentration in the optimization model in which flood mitigation and salinity management are simultaneously considered. It should be noted that the optimization model alters the amount of flow from the spillway and release timing, by finding an optimal solution in the simulated period.

We focused on one of the major floods in the case study (which occurred in 2011) for the optimization model. It is necessary to discuss how the ideal salinity concentration and ideal opening rate of the flood spillway were defined in the optimization model. Ideal salinity concentration was computed in each time step by the ANFIS-based model in which the flood spillway was considered completely closed. Moreover, the ideal opening rate in each time step was defined based on the actual condition in the flood diversion structure for the simulated flood event in 2011.

\[
\text{Minimize}(\text{OF1}) = \sum_{t=1}^{T} \left( \frac{IS_t - OS_t}{IS_t} \right)^2 \tag{5}
\]

\[
\text{Minimize}(\text{OF2}) = \sum_{t=1}^{T} \left( \frac{IR_t - OR_t}{IR_t} \right)^2 \tag{6}
\]

We applied multi-objective particle swarm optimization to solve the multi-objective problem (Equations (5) and (6)). The flowchart for this method is displayed in Figure 6. More details regarding this algorithm can be found in the literature [22]. Furthermore, we combined two functions into one objective function, as displayed in Equation (7). This function was used for solving the problem via single-objective particle swarm optimization. It should be noted that we applied two forms of the optimization problem (i.e., single-objective and multi-objective modes) for comparing the performances of the algorithms. Equation (7) was solved by the single-objective particle swarm optimization:

\[
\text{Minimize}(\text{OF(single objective model)}) = \sum_{t=1}^{T} \left( \frac{IR_t - OR_t}{IR_t} \right)^2 + \left( \frac{IS_t - OS_t}{IS_t} \right)^2 \tag{7}
\]

The developed optimization model is beneficial in terms of the environmental management of flood diversion projects in the Sound ecosystem. Using a multi-objective model is beneficial in terms of visualizing the trade-offs between the purposes. In contrast, using a single-objective model is beneficial in terms of reducing computational complexities.

4. Results

Figure 7 displays the simulated salinity from the ANFIS-based model and the recorded data at the representative station of the Lake. The performance of the data-driven model is robust. The NSE for the ANFIS-based model is 0.85, which means the model is reliable. RMSE is 2177.6 and corroborates the robustness of the ANFIS-based model. However, the ability of the ANFIS-based model to simulate the peak points of the salinity time series is weaker.
Figure 6. Multi-Objective Particle Swarm Optimization (MOPSO) flowchart [22].
Minimizing the impact of freshwater pulses on the salinity of the Lake was carried out using two optimization models, including single-objective optimization and multi-objective optimization. In other words, we developed two functions which were used in the multi-objective optimization, while the aggregated form of the functions was applied in the single-objective optimization. The non-dominated solutions from the multi-objective optimization are displayed in Figure 8. The minimum difference between Objective 1 and Objective 2, shown in Figure 8, was considered the best solution. Figure 9a shows the salinity concentration under the best solutions proposed by both optimization models as well as the observed condition (opening rate of spillway: 94%) and the ideal condition (opening rate of spillway: 0%). Figure 9b shows the actual spillway opening rate along with the opening rate proposed by the best solutions from both optimization models. The performance of the optimization models is not similar across all time steps. However, the performance of both optimization models is generally similar for the simulated flood in 2011. It should be noted that the simulated flood was a major flood in which the impact of freshwater pulses on the salinity of the Lake was considerable. In Figure 9a, the remarkable difference between the observed salinity (opening rate of spillway: 94%) and the ideal condition (opening rate of spillway: 0%) demonstrates the significant impact of freshwater pulses on changing salinity.

Figure 7. The results of the ANFIS-based model (major lines are the years and minor lines are the months in the graph).

Figure 8. Trades-off between objectives in MOPSO.
Additional simulations were conducted to investigate how changing the percent opening rate of the spillway changes salinity in the Lake. Figure 10 shows the results of altering the rate of opening on the salinity concentration of the Lake.

Figure 9. (a) Salinity concentration (observed means recorded salinity concentration in the Lake, ideal means ideal salinity concentration (IS), PSO means optimal salinity (OS) proposed by particle swarm optimization and MOPSO means optimal salinity (OS) proposed by multi-objective particle swarm optimization), (b) flood mitigation (actual opening rate is the same as ideal opening rate (IR), PSO means optimal opening rate (OR) proposed by particle swarm optimization and MOPSO means optimal opening rate (OR) proposed by multi-objective particle swarm optimization).

Figure 10. Salinity concentration changes under different opening rates of the floodgate for the simulated flood.
In Figure 11, the salinity concentration under the actual condition and ideal condition (closed spillway) is shown consecutively for all flooding days in the simulated period (2010–2020). Based on this figure, the significant impact of the freshwater pulses on the salinity concentration of the Lake is undeniable. In other words, the impact of the flood diversion project on salinity is non-negligible during all the floods that occurred over the ten-year period of study.

![Figure 11](image)

**Figure 11.** Simulated salinity concentration under the ideal condition (closed gate) and actual condition in consecutive order for all flooding days of the simulated period (2010–2020).

5. Discussion

According to the results of the optimization models, the optimal solution proposed by either single-objective or multi-objective optimization is not robust enough for minimizing the environmental impacts of the flood diversion project in the Lake. In other words, the observed salinity and the optimal solutions are similar, which means the optimization model is not able to reduce the environmental impacts of freshwater pulses in the Lake. According to Figure 9b, the opening rate proposed by the two optimization models, when compared with the actual condition, indicates that the single-objective model has the better performance in terms of operation of the spillway, because opening and closing of the spillway incurs costs. Based on the analysis of the results, the optimization model did not reduce the average opening rate of the spillway in the simulated period. One potential reason for optimization failing to find a solution is the large volume of freshwater passing through the system. Figure 10 shows that even small opening rates (i.e., minor floods) change the salinity concentration in the Lake considerably. In other words, the size of the freshwater pulses from the spillway, even during minor openings, dramatically influences the salinity of the Lake. In the case study, minor openings carry a huge amount of water, which means optimizing the impact of freshwater pulses is not possible under an optimization model.

Several studies have investigated the impacts of the Bonnet Carré Spillway on the salinity of Lake Pontchartrain and the Mississippi [23–25]. However, to date, there are no studies that have attempted to optimize the flood prevention and ecological damage trade-off by varying the timing and magnitude of spillway openings. More analysis of the results would be helpful for investigating why the optimization model is not more useful in the case study.

It should be noted that numerical hydrodynamic models are generally applied in the simulation of coastal regions. Hence, it will be useful to compare the developed data-driven model with conventional hydrodynamic models in the discussion. This is particularly advantageous for engineers who are selecting the best models to use in future projects. Both data-driven and hydrodynamic models have inherent advantages and weaknesses, which should be highlighted for the readers. Data-driven models need a rich database for training and testing, which is not available in all cases. In this case study, recorded data
were available for a period of ten years (2010–2020), which made it possible to develop a robust data-driven model. However, availability of data for a longer period would enhance the robustness of the model. It should be noted that for developing the data-driven model, the availability of salinity data in the representative station targeted by the simulation is essential. In contrast, a hydrodynamic model does not require robust data at the representative station. In fact, the availability of data at the boundaries of the domain (boundary conditions) and some limited data at other points—for calibrating and validating the model—is adequate. However, data-driven models do not need the salinity time series at the boundary condition locations. Hence, it is recommended to select the best model based on the availability of data in the representative stations and the boundary conditions of the Lake.

One of the significant advantages of the hydrodynamic models is their capability to simulate the spatial distribution of the salinity in the Lake, which can be helpful for environmental policy makers. Conversely, the data-driven model is only able to generate the data at the selected point or points.

It should be noted that updating and improving the models is another technical issue in model evaluation. The ANFIS-based model is updated or enhanced using additional data. In contrast, the hydrodynamic model is improved by refining boundary conditions and meshes and enhancing calibration and validation.

The computational cost is another aspect to consider when choosing a model to simulate the impact of freshwater pulses on brackish-water ecosystems. The computational cost is an important limitation for using hydrodynamic models in our case study and similar cases. In fact, a fine mesh, and small-time steps (on the order of seconds) are required for developing robust hydrodynamic models. Accordingly, these models require considerable time and memory for computing the results. It should be noted that selecting an appropriate time step is critical in hydrodynamic models because large time steps generate instability in the model. In contrast, the computational costs of the ANFIS-based model are less than those of hydrodynamic models. Hydrodynamic models [26] require days to simulate salinity. However, the ANFIS-based model can be trained in less than an hour. Hence, the data-driven model was superior in terms of computational cost for simulating salinity in this case study.

The ANFIS-based model was not able to simulate peak points of the salinity time series properly, which is a significant weakness for this model. Previous studies have confirmed this conclusion, finding that ANFIS-based models are generally unable to simulate peak points of a time series [27]. As a general recommendation, it is advantageous to apply hydrodynamic as well as data-driven models when simulating environmental impacts, and to use results from both models for making decisions on environmental policies.

Adding other system drivers is another technical point to be considered in this case study or similar cases. For example, climate change might alter the potential impacts of freshwater pulses on the marine ecosystem. Data-driven models such as the ANFIS-based model are advantageous in this regard because this study (as well as some previous studies) corroborates the flexibility of ANFIS-based models to simulate the impacts of climate change on ecological processes [28]. However, simulating the spatial change in salinity distribution due to climate change would require a hydrodynamic model.

We applied the ANFIS-based model in the present study. However, many other types of data-driven models or neural network models are available for this purpose and used in other ecological simulations [29]. Generally, data-driven models are categorized as regression models. In the present study, we used the ANFIS-based model as a regression model to simulate the salinity in the selected station. However, other types of neural networks such as feed-forward neural networks or recurrent neural networks can be applied to the same case study. Furthermore, classification models such as support vector machines can be used in future studies. The training method of machine-learning models is effective in producing reliable outputs. In the present study, we applied a hybrid algorithm in the training of the ANFIS-based model. However, we recommend testing other training
methods in future studies, to select the best models. It should be noted that utilizing a decision-making system is helpful for selecting the best training algorithm, which should be highlighted in future studies. Due to complexities of the environmental impacts of freshwater pulses, it is also recommended to apply population- or individual-based models of target species to obtain a clearer understanding of ecological impacts of freshwater pulses (more details regarding individual- and population-based models can be found in the literature [30,31]).

In the present study, we developed a novel form of optimization in which the environmental impacts in the Lake due to freshwater pulses and the benefits of the flood diversion project are balanced. This case study shows that because of the magnitude of the volume of freshwater released, environmental impacts cannot be optimized through varying the timing and volume of the releases. However, this method may be applicable in other studies of smaller rivers and diversions. The output of the present study will help policymakers in the Mississippi River Basin to understand the environmental impacts of flood diversions.

6. Conclusions

The present study developed a data-driven model to simulate the impact of freshwater pulses on salinity in the saline ecosystem of Lake Pontchartrain. The ANFIS-based model was utilized to simulate the impact of freshwater pulses on the salinity at a representative station of Lake Pontchartrain from which recorded salinity data for a long-term period were available. Moreover, an optimization model was developed to balance the environmental degradation due to freshwater pulses in the saline ecosystem of the Lake and the benefits of the flood diversion project. Based on the results, the ANFIS-based model was generally robust for simulating the salinity time series in the representative station of the Lake. However, the ANFIS-based model is not robust enough for simulating the peak points in the salinity time series in the Lake. Results of the optimization model indicated that no appropriate solution is available for mitigating the environmental degradation of freshwater pulses in the Lake due to the large amounts of freshwater, even during minor Mississippi River flood diversions.

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