Comparison of the genetic algorithm and pattern search methods for forecasting optimal flow releases in a multi-storage system for flood control

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Abstract

This paper compares the well-known genetic algorithm (GA) and pattern search (PS) optimization methods for forecasting optimal flow releases in a multi-storage system for flood control. The simulation models used by the optimization models include (a) a batch of scripts for data acquisition of forecasted precipitation and their automated post-processing; (b) a hydrological model for rainfall-runoff conversion, and (c) a hydraulic model for simulating river inundation. This paper focuses on (1) demonstrating the application of the framework by applying it to the operation of a hypothetical eight-wetland system in the Cypress Creek watershed in Houston, Texas; and (2) comparing and discussing the performance of the two optimization methods under consideration. The results show that the GA and PS optimal solutions are very similar; however, the computational time required by PS is significantly shorter than that required by GA. The results also show that optimal dynamic water management can significantly mitigate flooding compared to the case without management.

Keywords: Flood control, Flood Management, Forecast, Optimization, Real-time

1. Highlights

1. We compare the performance of the genetic algorithm (GA) and pattern search (PS) methods for forecasting optimal flow releases in a multi-storage system for flood control.
2. The results of the GA and PS methods are very similar, however the run time required by PS is significantly smaller than that required by GA.
3. Dynamic water management according to the optimization results can help to significantly mitigate flooding compared to the case without management.
4. A key factor for flood control is to partially empty the storage systems before the rainfall event and during the initial rainfall period before the pre-specified inundation level at the control cross-section is exceeded.

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2. Introduction

Inland flooding produces more damage annually than any other weather event in the United States (NOAA 2016). It is expected that global warming along increasing trends in urban development will make the problem worse (NASA 2017). Multiple strategies to mitigate floods have been developed in the last few decades. In particular, flood mitigation at the watershed scale is receiving increasing attention (Kusler 2004, Flotemersch et al. 2016). Within this context, flood control can be improved by operating detention ponds, reservoirs and other storage systems in an integrated and coordinated manner according to precipitation forecasts (Leon et al. 2020). For instance, flood control can be improved by partially emptying wetlands ahead of (e.g., a few hours or a couple of days before) a heavy rainfall that would produce flooding. In this case, the storage made available by the early release would provide extra water storage during the heavy rainfall, thus mitigating floods.

Even though a few numerical frameworks were proposed for near real-time flood control (e.g., Wei and Hsu 2008, Vermuyten et al. 2020, Tang et al. 2020a), there are very few papers comparing the numerical performance of optimization algorithms. The present work compares the performance of the well-known genetic algorithm (GA) and pattern search (PS) for forecasting optimal flow releases in a multi-storage system for flood control. This paper is organized as follows: (1) the simulation and optimization models are briefly described; (2) the objective function and constraints are presented; (3) the case study is presented and discussed. Finally, the key results are summarized in the conclusion.

3. Model Description

A numerical framework for forecasting hourly flow releases in a multi-storage system for flood control needs to include an array of models intended for data acquisition of forecasted precipitation, landscape rainfall-runoff conversion, level-pool routing in storage systems, river inundation modeling and optimization. For each of these components, there are an array of options available in the literature. Below, it is briefly described the models used in the paper and the justification for their use.

3.1. Acquisition of precipitation forecast and conversion to DSS format

The acquisition of precipitation forecasts is obtained using our scripts that are provided in GitHub (see Appendix A). The scripts also include code to convert the data to DSS format, which is the file format used by HEC-HMS and HEC-RAS for storing time series data (such as precipitation and discharge over time) and other types of data (such as unit hydrographs, elevation-area curves, and elevation-discharge curves). As an illustration, Fig. 1 presents the precipitation forecast for the south east area of the United States. This figure depicts the precipitation forecast for April 13, 2020 and was generated using the code on April 08, 2020 (5 days lead time).

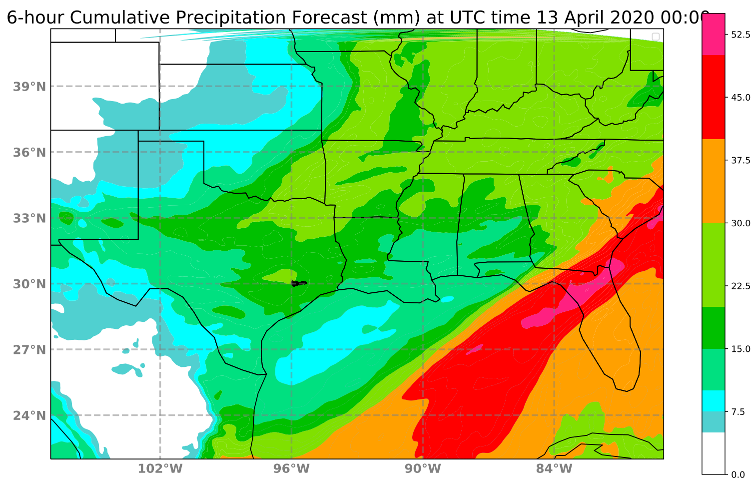

Figure 1. Precipitable water forecast generated with our Python script for the south east area of the United States. The scale of the precipitation is in mm and corresponds to 6-h cumulative precipitable water.

3.2. Hydrological and Hydraulic routing

As discussed in Leon et al. (2020), the U.S. Army Corps of Engineers' Hydrologic Modeling System (HEC-HMS) [Hydrologic Engineering Center 2017] is a good alternative for the hydrologic modeling and the U.S. Army Corps of Engineers' Hydrologic Engineering Center's River Analysis System (HEC-RAS) [Hydrologic Engineering Center 2016a, Hydrologic Engineering Center 2016b] is a good option for inundation modeling. The version of the models used herein are: HEC-HMS 4.3 and HEC-RAS 5.0.7.

3.3. Optimal schedules of flow releases in a multi-storage system

For forecasting optimal schedules of flow releases for flood control, an optimization solver is needed. The number of decision variables in the optimization is directly proportional to the number of storage systems and the number of time intervals (e.g., hourly releases) used in the optimization. For instance, if the number of storage systems is 20 and optimal schedules of flow releases are needed for a period of 5 days at hourly time intervals, the number of decision variables would be 2400 (5x24x20). Thus, a near real-time flood control framework requires an optimization solver suitable for large-scale problems. Herein, the performance of two state-of-the-art optimization solvers are compared and discussed within the context of flood control. Due to the availability of these solvers within the MATLAB optimization Toolbox (Chipperfield and Fleming 1995), this toolbox was used herein. The version of the MATLAB model used herein is MATLAB R2021a. The two used solvers are briefly described next.

3.3.1. *Genetic Algorithm (GA)*

The Genetic Algorithm (GA) solves constrained and unconstrained optimization problems based on a natural selection process that mimics biological evolution (Chipperfield and Fleming 1995). The GA repeatedly changes a population of individual solutions. At each generation, the GA randomly selects individuals from the current population and uses them as parents to produce children for the next generation. After several generations, the population is expected to evolve toward an optimal solution. The GA is recommended to solve problems that are not well suited for standard optimization algorithms, including problems in which the objective function is discontinuous, nondifferentiable, stochastic, or highly non-linear (Chipperfield and Fleming 1995). For more details about the genetic algorithm and its application to water resources the reader is referred to Wardlaw and Sharif (1999), Leon and Kanashiro (2010), Leon et al. (2014), Lerma et al. (2015), Yang et al. (2015), and Chen et al. (2016).

3.3.2. *Pattern Search (PS) Optimization*

The Pattern search method is an efficient algorithm for solving smooth and nonsmooth optimization problems (MathWorks 2020). At each iteration, the pattern search method searches a set of points, called a mesh, around the current point, looking for one where the value of the objective function is lower than the value at the current point. The Pattern Search method forms the mesh by (MathWorks 2020) (1) generating a set of vectors by multiplying each pattern vector by the mesh size and (2) adding the set of vectors to the current point, which is the point with the best objective function value found at the previous step. The set of pattern vectors is defined by the number of decision variables in the objective function (e.g., N) and the positive basis set. Two commonly used positive basis sets in pattern search algorithms are the maximal basis, with $2N$ vectors, and the minimal basis, with $N + 1$ vectors. For example, if there are two independent variables in the optimization problem, the default for a $2N$ positive basis consists of the following pattern vectors: v_1 = [0 1], v_2 = [1 0], v_3 = [0 -1] and v_4 = [-1 0]. The reader is referred to Kolda et al. (2006) for a description of the way in which the Pattern Search method forms a pattern with linear constraints. For more details about the pattern search algorithm the reader is referred to Lewis et al. (2007) and Abramson et al. (2009).

4. Objective Function and Constraints

4.1. *Objective Function*

A typical watershed may experience flooding only a few times per year. During flooding conditions, the water level at control cross-sections of the rivers and creeks should be maintained below the respective pre-specified maximum water level. A control cross-section can be specified, for instance, at densely populated areas. The maximum water level specified at a control cross-section corresponds to a level where inundation is imminent. The objective function f for flooding conditions can be written as follows:

$$f = \sum_{i=1}^{\mathrm{CS}} w_i \sum_{j=1}^{\mathrm{P}} \Big[(E_i)_j - (E_{max})_i\Big]^2 \tag{1}$$

where the summation in Eq. (1) is included for all $(E_i)_j > (E_{max})_i$ and "0" otherwise. In Eq. (1), CS and P are the number of control river cross-sections at which the water level constraint is checked and the number of time intervals (e.g., hourly flow releases) for each managed wetland, respectively. Also, $(E_i)_j$ is the water level at control river cross-section i and at time interval j (e.g., hour j), and $(E_{max})_i$ is the specified maximum water level constraint at control river cross-section i. Also, in Eq. (1), w_i is the weight of the importance of maintaining the water level in control river cross-section i. If the weights are equally important, all w_i can be set equal to 1.

4.2. Constraints

The optimization may be subject to linear equality ($\mathbf{A}_{eq}\ \mathbf{x} = \mathbf{b}_{eq}$) and inequality constraints ($\mathbf{A}_{ineq}\ \mathbf{x} \le \mathbf{b}_{ineq}$). The equality constraint needs to be specified when, for instance, a certain water level needs to be maintained in the wetlands at a given time. For brevity, let's consider only two wetlands and three time intervals (e.g., three decision variables for each wetland). For this case, the vector of decisions variables x would consist of 6 variables. If a certain water storage (S_{end}) needs to be maintaned at the end of the optimization, the matrix $\mathbf{A}_{eq}$ and vector $\mathbf{b}_{eq}$ would be defined as:

$$\mathbf{A}_{eq} = \begin{bmatrix} 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 \end{bmatrix}$$

$$\mathbf{b}_{eq} = \begin{bmatrix} (S_o - S_{end})_1/\Delta t + \Sigma I_1 \\ (S_o - S_{end})_2/\Delta t + \Sigma I_2 \end{bmatrix}$$

where $(S_o)_i$ is the initial storage at wetland i and ΣI_i is the sum of inflows that enters wetland i.

The optimization would also be subject to several linear inequality constraints. For instance, from the operational point of view, it may be desirable that the change of two consecutive flow releases are within a certain value. Mathematically, this means that the absolute value of the difference of two consecutive flow releases are within a certain value (e.g., c). Note that the absolute value is equivalent to two linear inequality constraints ($x_k - x_{k+1} \le c$ and $-x_k + x_{k+1} \le c$). Another inequality constraint can be defined to maintain the water storage in each wetland above a minimum wetland storage, which may be required for ecological purposes (S_{ecol}). Another inequality constraint can be defined to keep the water storage in each wetland below its maximum storage capacity (S_{max}). As an illustration, for the two wetlands and the three time intervals mentioned above, the matrix $\mathbf{A}_{ineq}$ and the vector $\mathbf{b}_{ineq}$ for the three aforementioned inequality constraints, in the presented order, can be written as:

$$\mathbf{A}_{ineq} = \begin{bmatrix} 1 & -1 & 0 & 0 & 0 & 0 \\ 0 & 1 & -1 & 0 & 0 & 0 \\ -1 & 1 & 0 & 0 & 0 & 0 \\ 0 & -1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 0 & 1 & -1 \\ 0 & 0 & 0 & -1 & 1 & 0 \\ 0 & 0 & 0 & 0 & -1 & 1 \end{bmatrix}, \mathbf{b}_{ineq} = \begin{bmatrix} c \\ c \\ c \\ c \\ c \\ c \\ c \\ c \end{bmatrix}$$

$$\mathbf{A}_{ineq} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 \end{bmatrix}, \mathbf{b}_{ineq} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} I_1^1 \\ I_1^2 \\ I_1^3 \\ I_2^1 \\ I_2^2 \\ I_2^3 \end{bmatrix} - \begin{bmatrix} (S_{ecol} - S_o)_1/\Delta t \\ (S_{ecol} - S_o)_1/\Delta t \\ (S_{ecol} - S_o)_1/\Delta t \\ (S_{ecol} - S_o)_2/\Delta t \\ (S_{ecol} - S_o)_2/\Delta t \\ (S_{ecol} - S_o)_2/\Delta t \end{bmatrix}$$

$$\mathbf{A}_{ineq} = \begin{bmatrix} -1 & 0 & 0 & 0 & 0 & 0 \\ -1 & -1 & 0 & 0 & 0 & 0 \\ -1 & -1 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & -1 & 0 & 0 \\ 0 & 0 & 0 & -1 & -1 & 0 \\ 0 & 0 & 0 & -1 & -1 & -1 \end{bmatrix}, \mathbf{b}_{ineq} = \begin{bmatrix} -1 & 0 & 0 & 0 & 0 & 0 \\ -1 & -1 & 0 & 0 & 0 & 0 \\ -1 & -1 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & -1 & 0 & 0 \\ 0 & 0 & 0 & -1 & -1 & 0 \\ 0 & 0 & 0 & -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} I_1^1 \\ I_1^2 \\ I_1^3 \\ I_2^1 \\ I_2^2 \\ I_2^3 \end{bmatrix} + \begin{bmatrix} (S_{max} - S_o)_1/\Delta t \\ (S_{max} - S_o)_1/\Delta t \\ (S_{max} - S_o)_1/\Delta t \\ (S_{max} - S_o)_2/\Delta t \\ (S_{max} - S_o)_2/\Delta t \\ (S_{max} - S_o)_2/\Delta t \end{bmatrix}$$

where I_i^k indicates the inflow that enters wetland i at time interval k.

5. Case Study: A hypothetical eight wetland system in the Cypress Creek watershed, Houston, TX

The coupled optimization-simulation model is applied to the operation of a hypothetical eight wetland system in the Cypress Creek watershed, which is located in Houston, Texas (see Fig. 2). The characteristics of this watershed are described in Tang et al. (2020b). The Cypress Creek watershed, which has a total area of 8.33x10^8 m^2, experienced devastating floods during Hurricane Harvey in August 2017. The upper half of the Cypress Creek watershed was historically covered by wetlands and rice farms and as such, there are a multitude of existing levees that can be easily repaired to restore the function of wetlands (Tang et al. 2020b). To help in flood mitigation, Tang et al. (2020b) considered eight hypothetical wetlands (WL-300, WL-310, WL-330, WL-380, WL-390, WL-400, WL-410, WL-420) that are placed in the midstream portion of the watershed. These eight wetlands are depicted as yellow clouds in Fig. 3.

This case study considers a single control cross-section (Station 42006.23 in the Lower Reach of the Cypress creek River) to track the water level. The

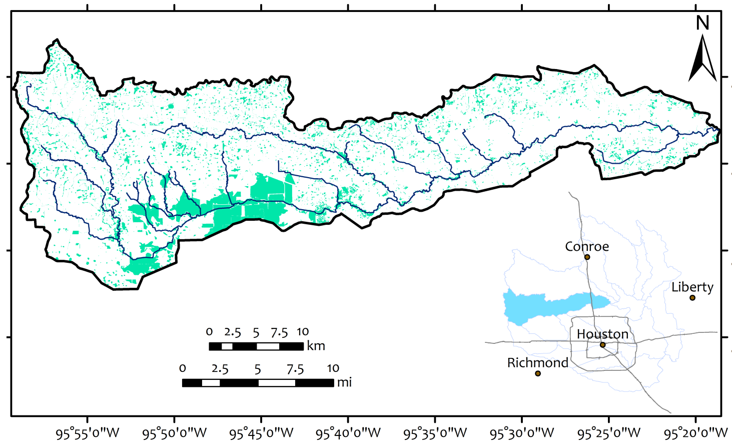

Figure 2. Geographical location of Cypress Creek watershed, TX

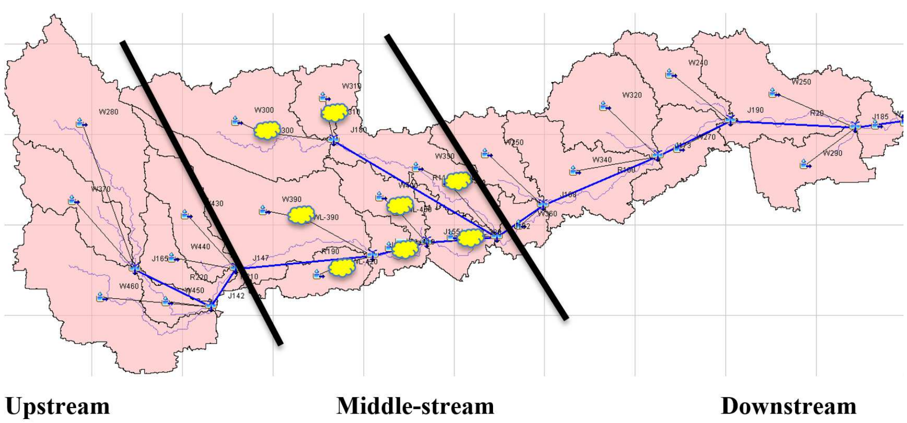

Figure 3. Cypress Creek Basin of HEC-HMS model displaying the schematics of eight hypothetical wetlands in midstream (yellow clouds)

maximum desired water elevation at this river station was set to 37 and 37.5 m. It is noted that according to Eq. (1), the objective function is the sum of the square of the difference between the water level in the control cross-section and the maximum desired water elevation. Thus, specifying a higher inundation level will result in less flooding and in more operation flexibility before and during the flood.

The flow chart of the fully coupled optimization-simulation model for forecasting optimal flow releases in a multi-storage system for flood control is presented in Fig. 4. As shown in this figure, the HEC-HMS and HEC-RAS models are prepared, validated, and linked offline. The linking consists on using the outflows of HEC-HMS (managed wetlands and unmanaged basins) as inflows for the HEC-RAS model via DSS filepaths. After the HEC-HMS and HEC-RAS models are specified, the user needs to specify the optimization parameters, the initial water levels in the managed wetlands and the initial flow conditions in the river. Then, for a given precipitation (historical or forecasted), the optimization model generates an schedule of outflows for each wetland at each generation in GA or at each iteration in PS. The schedule of wetland outflows is then used by HEC-HMS to update the water levels in the wetlands. Then, the outflows from HEC-HMS, which could be unmanaged flows (sub-basins without managed storage) or managed flows (sub-basins with managed storage), enter the streams in HEC-RAS. The water levels in the control cross-sections in HEC-RAS are used to evaluate the objective function given in Eq. (1). The linear inequality and equality constraints are satisfied at each generation or iteration in both, GA and PS. The process is repeated until the optimization stop criteria is satisfied. Once the optimization is completed, the process can be repeated for another precipitation. The Matlab and Python scripts for the coupled optimization-simulation are provided in GitHub (see Appendix B).

The hydrologic model of the Cypress Creek watershed was created in HEC-HMS. The details of the HEC-HMS model construction, calibration and validation are discussed in Tang et al. (2020b). It is noted that the present paper used gridded precipitation instead of time series precipitation used in Tang et al. (2020b). For details of the gridded precipitation, the reader is referred to Bian et al. (2021). Our Python and Matlab scripts for obtaining gridded precipitation are provided in GitHub (see Appendix A). For the present demonstration, the eight hypothetical wetlands (WL-300, WL-310, WL-330, WL-380, WL-390, WL-400, WL-410, WL-420) have a total combined area of about 3.5% of the whole watershed area and each wetland has a maximum depth of 1 m. The hydraulic model of the major streams of the Cypress Creek watershed was created in HEC-RAS using the HEC-GeoRAS tool within ArcGIS. The details of the HEC-RAS model construction, calibration and validation are discussed in Tang et al. (2020b).

The optimization period considered in this case study is 14 days (336 hours) resulting in a total of 2688 optimal hourly flows for the eight wetlands. The optimization parameters specified for the GA are as follows: Population, 128; Function Tolerance, 1e-4. The optimization parameters specified for the PS are as follows: Initial mesh size, 0.5 m^3/s; maximum number of iterations, 1000;

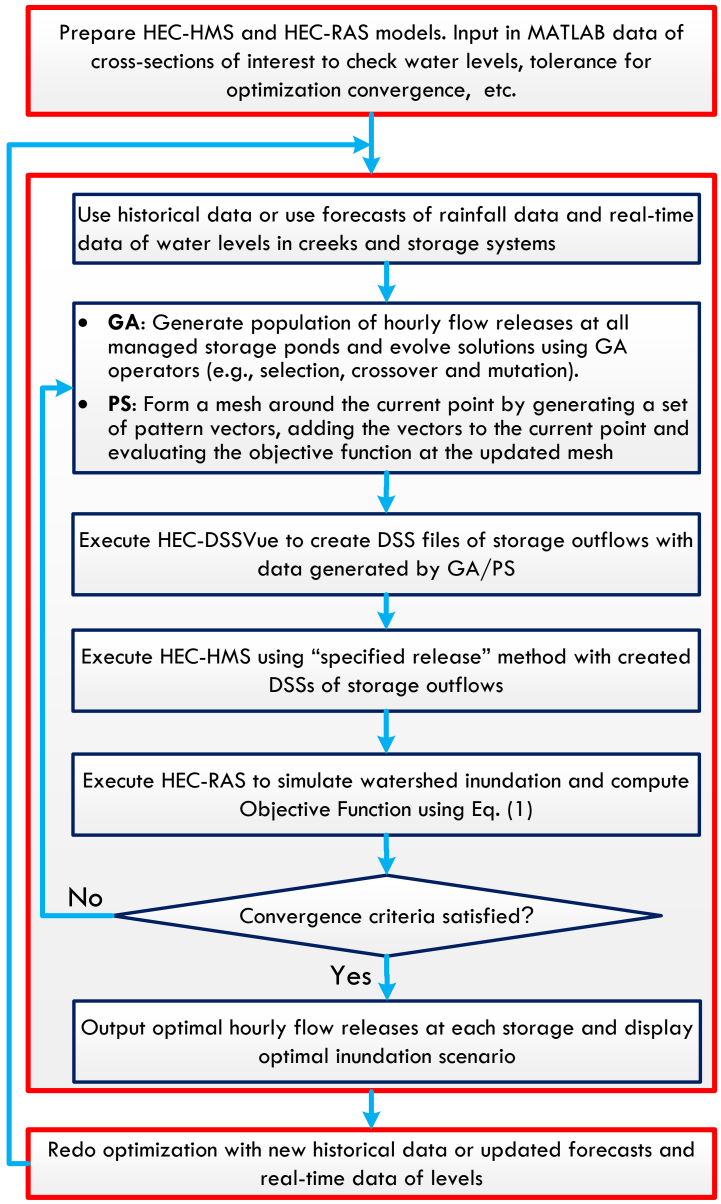

Figure 4. Flow chart of the integrated model for determining optimal flow releases in a multi-storage system for flood control

Mesh Tolerance, 1e-4; Function Tolerance, 1e-4. The lower limit for the flow releases at all eight managed wetlands was set to 0 m^3/s. The upper limit for the flow releases was set to 25, 12, 15, 15, 25, 10, 10, and 10 m^3/s for wetlands WL-300, WL-310, WL-330, WL-380, WL-390, WL-400, WL-410, WL-420, respectively. To speed up the computations, all HEC-RAS simulations are performed in a vectorized manner (e.g., HEC-RAS simulations are computed in parallel). Herein we have used 18 available processors in the 8th Generation Intel Core i7-8700 (18 parallel computations).

Equality and inequality constraints were specified for all eight wetlands. Two constraint scenarios were specified in the optimization. The first constraint scenario considered one equality constraint and two inequality constraints. The equality constraint specified that 72 hours (3 days) after the beginning of the optimization, which was also before the beginning of the rainfall event, the water level in all wetlands be at its ecological depth (assumed to be 0.3 m for all wetlands). The first inequality constraint is that the maximum change between two consecutive hourly flow releases is 5 m^3/s. The second inequality constraint specified that the water depth in each wetland needs to be maintained above the minimum ecological depth at all times. The second constraint scenario includes all constraints of the first constraint scenario plus a no overflow constraint. The no overflow constraint specified that the water depth in all wetlands at all times need to be maintained below the respective maximum wetland depth (1 m). This inequality constraint was set to avoid overflows at the wetlands.

The typical convergence process for the GA and PS are shown in Figs. 5 and 6, respectively. After the stopping criteria of the GA and PS is satisfied, our framework automatically generates a plot for the best optimal solution for each managed wetland. Each plot includes the optimal trace of outflows, the corresponding time trace of the water surface elevation and storage in the wetland, and the time trace of total inflow, wetland spill flow and total outflow (spill flow + managed outflow). A plot produced for wetland WL-390 with GA and PS for inundation elevation of 37.5 m and for the first constraint scenario is shown in Figs. 7 and 8, respectively. As shown in Figs. 7 and 8, the pattern of outflows produced with both algorithms are very similar. As also shown in these figures, the optimization releases water from the wetlands before the rainfall and during the initial rainfall period. This initial rainfall period corresponds to the period before the control cross-section is about to be inundated.

Four optimization conditions were simulated. The conditions were obtained by utilizing two inundation elevations at control cross-section 42006.23 (37 and 37.5 m) and the two aforementioned constraint scenarios. Figs. 9 - 12 show the time traces of the water elevation and discharge at the control cross-section for the above mentioned optimization conditions for the best solutions obtained with the GA and PS methods and those without any water management. Overall, the optimization aims to release water from the wetlands before the rainfall and during the initial rainfall period. This initial rainfall period corresponds to the period before the control cross-section is about to exceed the pre-specified level of inundation. During the later rainfall period, there is no significant change in the objective function and as such no significant flood mitigation.

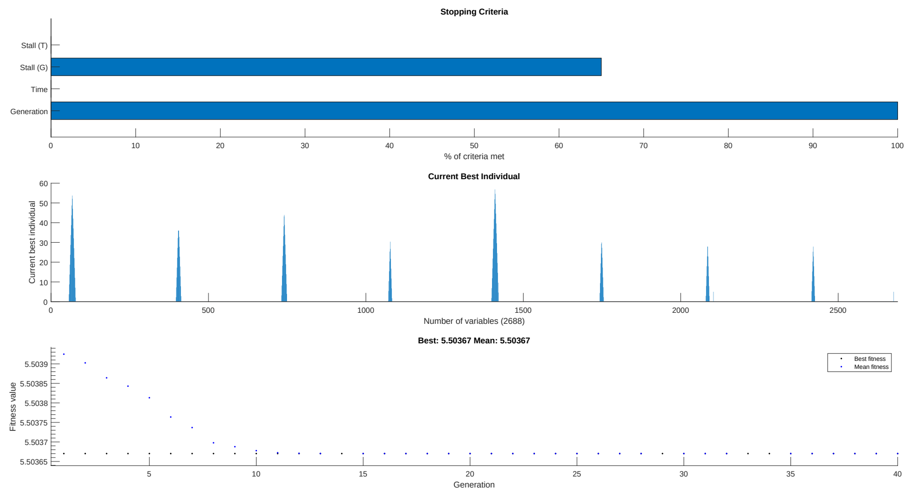

Figure 5. GA typical convergence process for optimal schedule of storage outflows

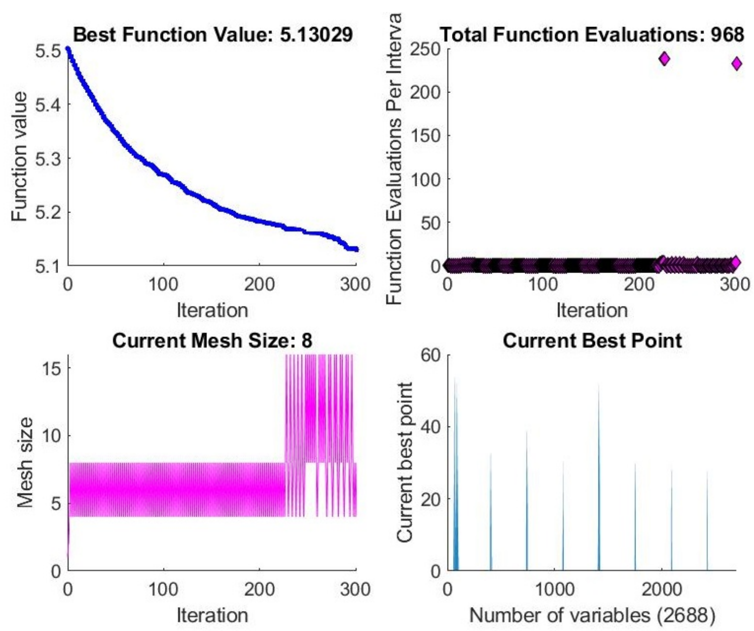

Figure 6. PS typical convergence process for optimal schedule of storage outflows

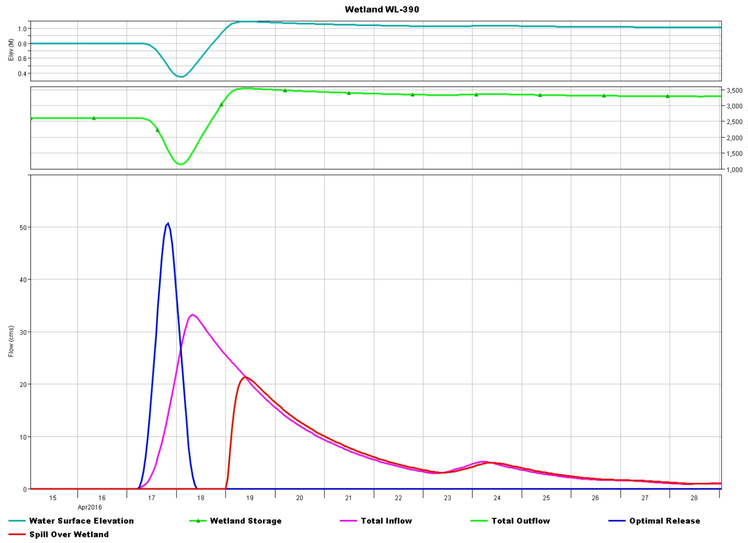

Figure 7. Optimal trace of outflows for wetland WL-390 obtained using GA. This plot also shows the corresponding time trace of the water surface elevation and storage in the wetland, and the time trace of total inflow, wetland spill flow and total outflow (spill flow + managed outflow) [Assumed inundation elevation = 37.5 m and first constraint scenario.]

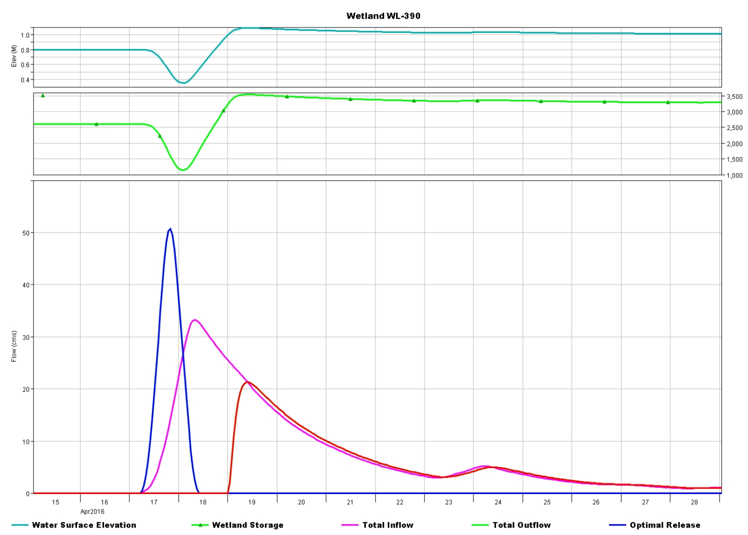

Figure 8. Optimal trace of outflows for wetland WL-390 obtained using PS. This plot also shows the corresponding time trace of the water surface elevation and storage in the wetland, and the time trace of total inflow, wetland spill flow and total outflow (spill flow + managed outflow) [Assumed inundation elevation = 37.5 m and first constraint scenario.]

This is because during most of this period, the wetlands are full and the river is flowing near maximum capacity.

The results in Figs. 9 - 12 indicate that the results produced by the GA and PS are very similar, however the computational time required by PS is significantly smaller than that required by GA. For instance, the results in Fig. 9 required a runtime of 16 hr for the PS and about 5 days for the GA. The results also show that the simulation without water management exceed more significantly the specified inundation level (37 or 37.5 m) and for longer periods of time.

For the same inundation level (37 or 37.5 m), the results for the two aforementioned constraint scenarios are also very similar. It is clear that in the second constraint scenario, the flow releases at the managed wetlands will be continuous even during the entire rainfall period, however the total outflow (flow release + spill flow) for both constraint scenarios are essentially the same. Thus, the results are very similar.

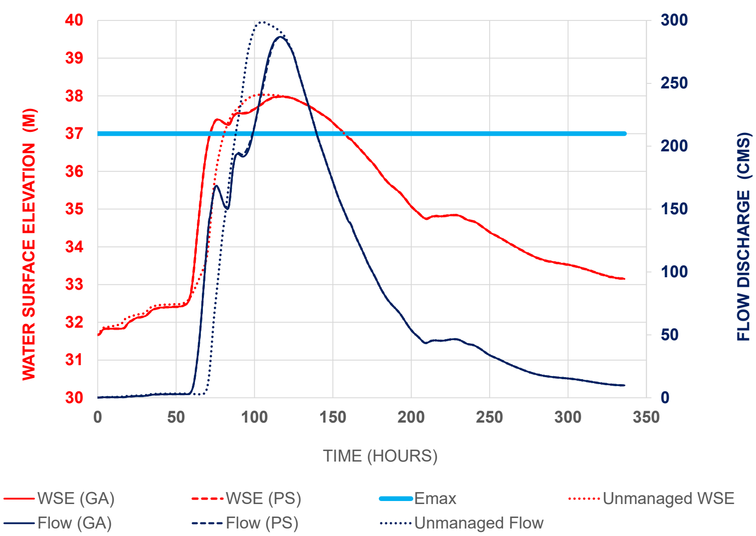

Figure 9. Time traces of water elevation and discharge at the control cross-section (Station 42006.23) for best solutions obtained with GA and PS methods and those without management [Assumed inundation elevation = 37 m and first constraint scenario.]

6. Conclusions

This paper compares the performance of the well-known genetic algorithm and pattern search methods for forecasting optimal flow releases in a multi-storage system for flood control. This framework combines HEC-HMS, HEC-RAS, the MATLAB Optimization Toolbox, and a batch of scripts to integrate these models. All scripts used are made available in GitHub (see Appendices A and B). The case study is illustrated using the operation of a hypothetical eight

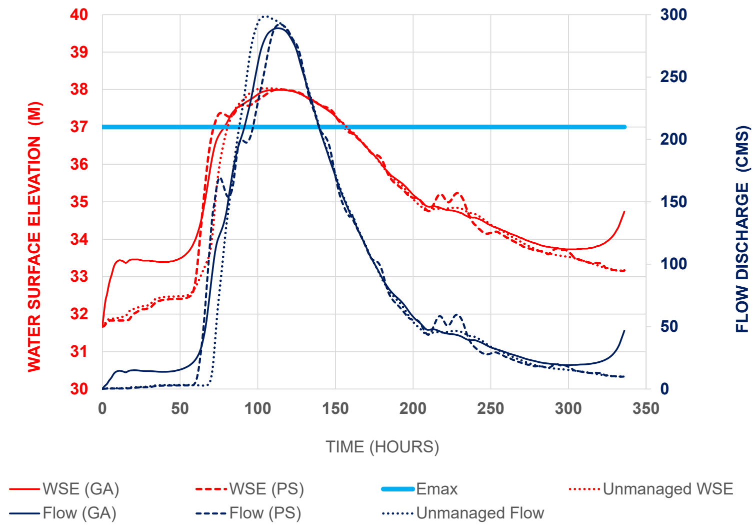

Figure 10. Time traces of water elevation and discharge at the control cross-section (Station 42006.23) for best solutions obtained with GA and PS methods and those without management [Assumed inundation elevation = 37 m and second constraint scenario.]

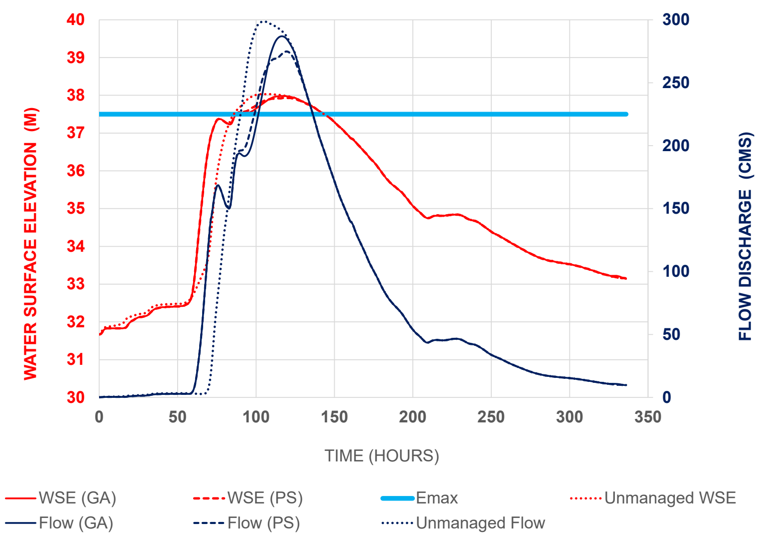

Figure 11. Time traces of water elevation and discharge at the control cross-section (Station 42006.23) for best solutions obtained with GA and PS methods and those without management [Assumed inundation elevation = 37.5 m and first constraint scenario.]

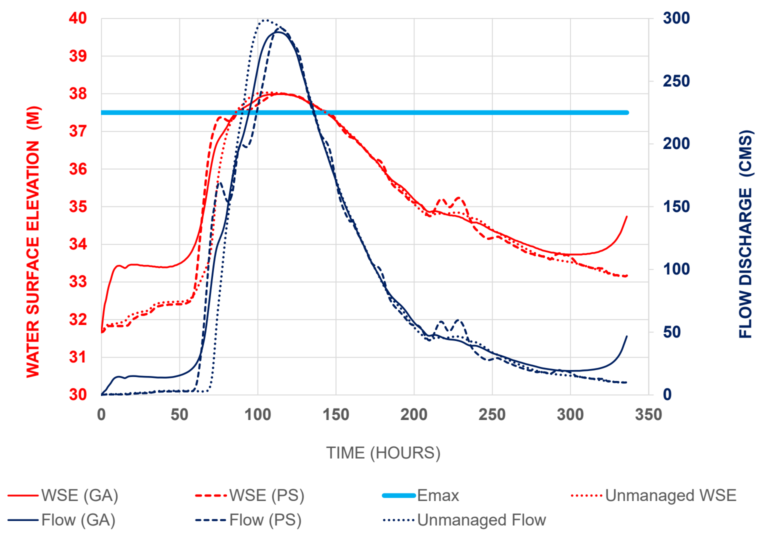

Figure 12. Time traces of water elevation and discharge at the control cross-section (Station 42006.23) for best solutions obtained with GA and PS methods and those without management [Assumed inundation elevation = 37.5 m and second constraint scenario.]

wetland system in the Cypress Creek in Houston, Texas. The key results are as follows:

1. The results produced by the genetic algorithm (GA) and pattern search (PS) methods are very similar, however the computational time required by PS is significantly smaller than that required by GA.
2. In general, the results show that the dynamic water management according to the optimization results can help to significantly mitigate flooding compared to the case without management (e.g., uncontrolled water release of wetlands).
3. The results without any water management exceed more significantly the maximum water level at the control cross-section and for longer periods of time.
4. A key factor for flood control is to partially empty the storage systems before the rainfall event and during the initial rainfall period. This initial rainfall period corresponds to the period before the pre-specified inundation level at the control cross-section is exceeded. During the later rainfall period, the optimization doesn't play a significant role because the wetlands are full and the river is flowing near maximum capacity.

7. Software and Data Availability

All scripts used in this paper are made available in GitHub (see Appendices A and B).

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Appendix A: Automated Acquisition of Precipitation Forecast and conversion to DSS for its use in HEC-HMS

The acquisition of precipitation forecast and the automated conversion of the acquired data to DSS format is performed using a batch of scripts available at https://web.eng.fiu.edu/arleon/Code_Precip_Forecast_DSS.html and the GitHub repository https://github.com/artuleon/Automate-Precipitation-Forecast.git

The acquired precipitation is the bias-corrected Global Forecast System (GFS) for a lead time of 5 days (today's time is April 04 of 2021) and a time interval of 6 hours. The acquired data is automatically projected to the Cypress Creek Watershed. The precipitation map for a lead time of 5-days is shown in Fig. 13. This file is automatically generated in the folder "\Forecast_GFS" with the name "precip_plot.pdf". The DSS file is automatically generated in the folder "\Forecast_GFS" with the name "GFS.dss". The script "Forecast_GFS.py" re-samples the precipitation to a 1000 m × 1000 m grid cell and 1 hour time interval. An example of gridded precipitation converted to DSS for its use in HEC-HMS is shown in Fig. 14.

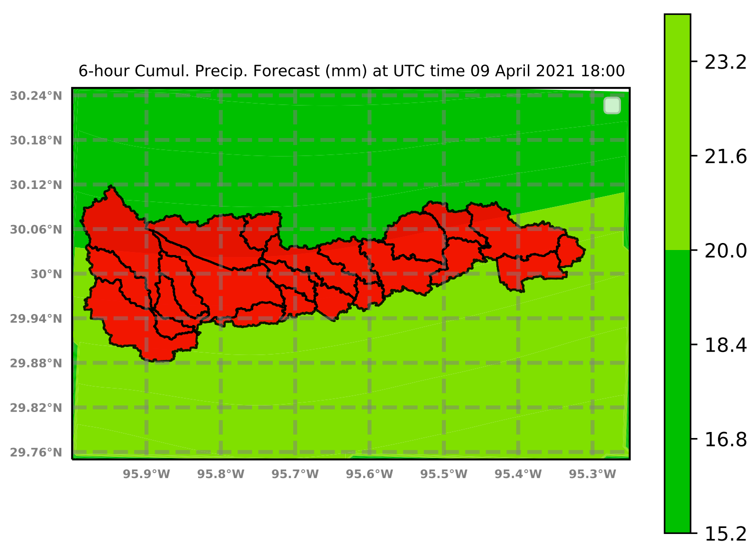

Figure 13. Snapshot of bias-corrected Global Forecast System (GFS) acquired by Python and projected to the Cypress Creek Watershed

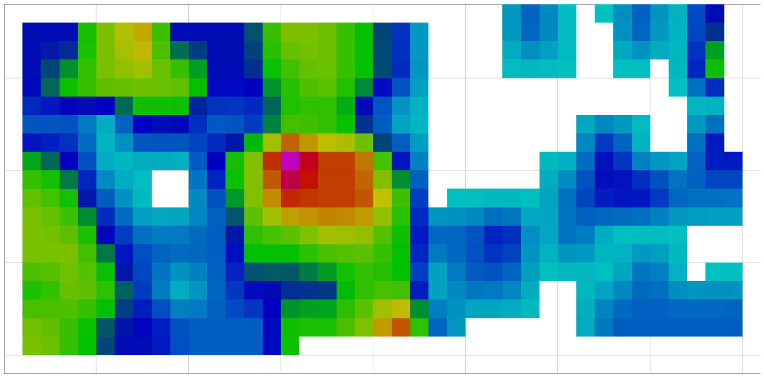

Figure 14. Snapshot of gridded precipitation converted to DSS for its use in HEC-HMS.

Appendix B: Coupled simulation-optimization model for forecasting optimal flow releases in a multi-storage system for flood control

Our scripts for the coupled optimization-simulation used in this paper can be found at https://web.eng.fiu.edu/arleon/Code_Flood_Control_DSS.html and the GitHub repository https://github.com/artuleon/Flood_Control_DSS

References

Abramson, M., Audet, C., Dennis, J., Le Digabel, S., 2009. Orthomads: a deterministic mads instance with orthogonal directions. SIAM Journal on Optimization 20, 948–966. doi:10.1137/080716980.

Bian, L., Leon, A.S., Tang, Y., 2021. Effect of location and storage volume of wetlands on flood mitigation. Journal of Water Management. To be submitted.

Chen, D., Leon, A.S., Gibson, N.L., Hosseini, P., 2016. Dimension reduction of decision variables for multireservoir operation: A spectral optimization model. Water Resources Research 52, 36–51.

Chipperfield, A.J., Fleming, P.J., 1995. The matlab genetic algorithm toolbox, in: IEE Colloquium on Applied Control Techniques Using MATLAB, pp. 10/1–10/4. doi:10.1049/ic:19950061.

Flotemersch, J.E., Leibowitz, S.G., Hill, R.A., Stoddard, J.L., Thoms, M.C., Tharme, R.E., 2016. A watershed integrity definition and assessment approach to support strategic management of watersheds. River Research and Applications 32, 1654–1671. URL: http://dx.doi.org/10.1002/rra.2978, doi:10.1002/rra.2978. rRA-15-0132.R1.

Hydrologic Engineering Center, 2016a. HEC-RAS, River Analysis System, Hydraulic Reference Manual. Version 5.0. U.S. Army Corps of Engineers, Davis, California.

Hydrologic Engineering Center, 2016b. HEC-RAS River Analysis System User's Manual - Version 5.0. U.S. Army Corps of Engineers, Davis, California.

Hydrologic Engineering Center, 2017. Hydrologic Modeling System (HEC-HMS) User's Manual - Version 4.2.1. U.S. Army Corps of Engineers, Davis, California.

Kolda, T., Lewis, R., Torczon, V., 2006. A generating set direct search augmented lagrangian algorithm for optimization with a combination of general and linear constraints doi:10.2172/893121.

Kusler, J., 2004. Multi-objective wetland restoration in watershed contexts. Technical Report. Association of State Wetland Managers. Berne, NY. URL: https://www.aswm.org/pdf_lib/restoration.pdf.

Leon, A.S., Kanashiro, E., 2010. A new coupled optimization-hydraulic routing model for real-time operation of highly complex regulated river systems, in: Watershed Management Conference: Innovations in Watershed Management Under Land Use and Climate Change, ASCE-EWRI, Madison, Wisconsin, USA. pp. 213–224.

Leon, A.S., Kanashiro, E., Valverde, R., Sridhar, V., 2014. Dynamic framework for intelligent control of river flooding: Case study. Journal of Water Resources Planning and Management 140, 258–268. doi:10.1061/(ASCE)WR.1943-5452.0000260.

Leon, A.S., Tang, Y., Qin, L., Chen, D., 2020. A matlab framework for forecasting optimal flow releases in a multi-storage system for flood control. Environmental Modelling and Software 125, 104618. URL: http://www.sciencedirect.com/science/article/pii/S1364815218312453, doi:https://doi.org/10.1016/j.envsoft.2019.104618.

Lerma, N., Paredes-Arquiola, J., Andreu, J., Solera, A., Sechi, G.M., 2015. Assessment of evolutionary algorithms for optimal operating rules design in real water resource systems. Environmental Modelling and Software 69, 425 – 436.

Lewis, R., Shepherd, A., Torczon, V., 2007. Implementing generating set search methods for linearly constrained minimization. SIAM J. Scientific Computing 29, 2507–2530. doi:10.1137/050635432.

MathWorks, 2020. Matlab optimization toolbox. The MathWorks, Natick, MA, USA.

NASA, 2017. Earth Observatory: How Will Global Warming Change Earth? URL: https://earthobservatory.nasa.gov/Features/GlobalWarming/page6.php.

NOAA, 2016. U.S. Climate Resilience Toolkit: Inland Flooding. URL: https://toolkit.climate.gov/topics/coastal-flood-risk/inland-flooding.

Tang, Y., Leon, A.S., Kavvas, M.L., 2020a. Impact of Dynamic Storage Management of Wetlands and Shallow Ponds on Watershed-scale Flood Control. Water Resources Management: An International Journal, Published for the European Water Resources Association (EWRA) 34, 1305–1318. URL: https://ideas.repec.org/a/spr/waterr/v34y2020i4d10.1007_s11269-020-02502-x.html, doi:10.1007/s11269-020-02502-.

Tang, Y., Leon, A.S., Kavvas, M.L., 2020b. Impact of Size and Location of Wetlands on Watershed-Scale Flood Control. Water Resources Management: An International Journal, Published for the European Water Resources Association (EWRA) 34, 1693–1707. URL: https://ideas.repec.org/a/spr/waterr/v34y2020i5d10.1007_s11269-020-02518-3.html, doi:10.1007/s11269-020-02518-.

Vermuyten, E., Uytven, E.V., Meert, P., Wolfs, V., Willems, P., 2020. Real-time river flood control under historical and future climatic conditions: Flanders case study. Journal of Water Resources Planning and Management 146, 05019022. doi:10.1061/(ASCE)WR.1943-5452.0001144.

Wardlaw, R., Sharif, M., 1999. Evaluation of genetic algorithms for optimal reservoir system operation. Journal of Water Resources Planning and Management 125, 25–33.

Wei, C.C., Hsu, N.S., 2008. Multireservoir real-time operations for flood control using balanced water level index method. Journal of Environmental Management 88, 1624 – 1639. URL: http://www.sciencedirect.com/science/article/pii/S0301479707003088, doi:https://doi.org/10.1016/j.jenvman.2007.08.004.

Yang, T., Gao, X., Sellars, S.L., Sorooshian, S., 2015. Improving the multi-objective evolutionary optimization algorithm for hydropower reservoir operations in the california orovilleâ€“thermalito complex. Environmental Modelling and Software 69, 262 – 279.