



Ensemble Based Forecasting and Optimization Framework to Optimize Releases from Water Supply Reservoirs for Flood Control

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Abstract

Water supply reservoir management is based on long-term management policies which depend on customer demands and seasonal hydrologic changes. However, increasing frequency and intensity of precipitation events is necessitating the short-term management of such reservoirs to reduce downstream flooding. Operational management of reservoirs at hourly/daily timescales is challenging due to the uncertainty associated with the inflow forecasts and the volumes in the reservoir. We present an ensemble-based streamflow prediction and optimization framework consisting of a regional scale hydrologic model forced with ensemble precipitation inputs to obtain probabilistic inflows to the reservoir. A multi-objective dynamic programming model was used to obtain optimized release strategies accounting for the inflow uncertainties. The proposed framework was evaluated at a water supply reservoir in the Hackensack River basin in New Jersey during Hurricanes Irene and Sandy. Hurricane Irene resulted in the overtopping of the dam despite releases made in anticipation of the event and resulted in severe downstream flooding. Hurricane Sandy was characterized by low rainfall, however, raised significant concerns of flooding given the nature of the event. The improvement in NSE for the Hurricane Irene inflows from 0.5 to 0.76 and reduction of the spread of PBIAS with decreasing lead times resulted in improvements in the forecast informed releases. This study provides perspectives on the benefits of the proposed forecasting and optimization framework in reducing the decision making burden on the operator by providing the uncertainties associated with the inflows, releases and the water levels in the reservoir.

Keywords ECMWF · flood control · Irene · ensemble · Dynamic programming

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1 Introduction

Reservoirs have been traditionally used for managing water resources for different objectives such as hydropower generation, flood control, water supply and recreation. Operation of reservoirs is affected by long-term stressors such as accelerated population growth (leading to an increased water demand) [Singh et al. 2014; Wisser et al. 2013], sedimentation [García-Ruiz et al. 2011; Graf et al. 2010] and aging infrastructure [Juracek 2015; Lane 2008]. Additionally, changing climatic conditions leading to an increased frequency of extreme weather events (flood and drought) are stressing the need to manage water resources on shorter timescales [Anderson et al. 2008; Hanak and Lund 2012; Ho et al. 2017; Lettenmaier et al. 1999; Rajagopalan et al. 2009; Vicuna et al. 2010].

Short-term management of reservoirs becomes proactive when inflow forecasts are available and this information can be effectively used to assist reservoir operations [Zavala et al. 2009]. Inflow forecasting is mainly performed using conceptual hydrologic models and data-driven models [Gragne et al. 2015]. Data driven approaches involve the use of artificial neural networks (ANN) [Adamowski 2008; Coulibaly et al. 2000; Kumar et al. 2015], automated regressive integrated moving average method (ARIMA) [Valipour 2012; Valipour et al. 2013], neuro-fuzzy techniques [Mehta and Jain 2009; Mukerji et al. 2009], genetic programming methods [Akbari-Alashti et al. 2015; Jothiprakash and Magar 2012] etc. However, data driven approaches have limitations in terms of dealing with non-stationarity, are less robust for short term forecasts and may sometimes diverge outside the range of the training set [Cannas et al. 2006; Gaume and Gosset 2003; Partal 2009].

In contrast to data driven approaches, conceptual hydrologic models fed with meteorological inputs provide better representation of catchment response [Che and Mays 2015; Todini 2007]. However, they are plagued by uncertainties arising from parametrizations of physical processes in meteorological models' resolution and initial conditions [Bartholmes and Todini 2005; Cuo et al. 2011; Krzysztofowicz 2001] and uncertainties in structure (e.g. lumped and distributed models), parameters and initial conditions of the hydrologic model [Gupta et al. 2005; Seo et al. 2006; Zalachori et al. 2012]. To account for the meteorological uncertainty, short-term hydrological forecasts are carried out by forcing a hydrologic model with ensemble of Numerical Weather Prediction (NWP) models [Buizza 2008; Cloke and Pappenberger 2009; Fan et al. 2014]. Ensemble streamflow forecasting is used in flood early warning systems [Bartholmes et al. 2009; Laugesen et al. 2011; Rabuffetti and Barbero 2005; Saleh et al. 2016; Thiemig et al. 2015; Verkade and Werner 2011] and are found to be viable for managing reservoir operations [Boucher et al. 2012; McCollor and Stull 2008; Ramos et al. 2007; Zhao et al. 2011].

Studies have demonstrated the importance of ensemble streamflow forecast for short-term reservoir operations. Zhao et al. [2011] analyzed the effect of forecast uncertainty on a hypothetical, real-time reservoir operation by modelling the dynamic evolution of uncertainties involved in various forecast products. Their results showed that it was more valuable to consider the forecast uncertainty for reservoirs with smaller storage capacity as they were sensitive to forecast errors. A hydro-economic assessment of hydrologic forecasting systems carried out by [Boucher et al. 2012] quantified the benefits of ensemble forecasts for decision making in hydroelectricity production during a flood event.

Different optimization techniques can be used to capture the sequential and non-linear decision-making nature of reservoir operations. Dynamic Programming (DP) is conventionally used as a method to optimize single-reservoir operations given the availability of deterministic

inflows to the reservoir [Labadie 2004; Loucks et al. 2005; Yakowitz 1982]. To explicitly include the uncertainty information to make optimal decision under uncertainty, stochastic DP is preferred when dealing with ensemble forecasts [Eum et al. 2011; Galelli et al. 2014]. Studies have also used ensembles of inflow forecast and real-time model predictive control approach to improve operations of a single reservoir *Fernando Mainardi* Fan et al. [2016]; Schwanenberg et al. [2015] and multi-reservoir systems [Ficchi et al. 2016] leading to more robust decisions.

Despite the intensive research on the applications of optimization to reservoir systems, there is a gap in real-world implementation, specifically in terms of incorporating uncertainties and implementing real time operations during extreme weather events. The objective of this work was to develop an automated forecasting and optimization framework that addresses the gap by using a widely available semi-distributed hydrologic model to obtain short term ensemble-based forecasts of inflows and derive alternate reservoir operation rules to potentially mitigate flooding. A regional scale hydrologic model was forced with deterministic and probabilistic precipitation forecasts from the European Centre for Medium range weather forecasts (ECMWF) corresponding to two distinct precipitation events to obtain inflows to the reservoir. A multi-objective dynamic programming approach was used to optimize the releases from the reservoir. The Oradell reservoir in the Hackensack River basin in New Jersey was used as a test bed in this study. The two events were selected based on their severity, the operation of the reservoir during the events and the skill of the corresponding meteorological forecasts to assess the feasibility of the proposed approach at different lead times. This study seeks to provide a flexible, assistive tool to alleviate the complexity of operational decision-making of single purpose reservoirs that have to operate beyond the scope of traditional operational policies specifically during extreme weather events.

2 Materials and Methods

2.1 Study Area and Case Description

The study area covers the Hackensack River basin which is located mainly in the Hudson and Bergen counties in northeastern New Jersey in the United States. This area includes some of the most highly developed, urbanized areas as well as undeveloped marshlands known as the Hackensack Meadowlands. The flows in the upper areas of the Hackensack River basin above the Oradell dam are regulated by a four-reservoir system (Fig. 1).

The Oradell reservoir formed by the Oradell dam is the most downstream reservoir of the system and receives inflows from Pascack Brook at Westwood and Hackensack River at Rivervale. Flows along the Pascack Brook are altered by the Woodcliff Lake Reservoir and diversions for municipal supply. Similarly, as a part of the multi-reservoir system, DeForest Lake and Lake Tappan regulate the flow along the Hackensack River at Rivervale [Carswell 1976]. The Oradell reservoir is located approximately 1.6 km upstream from the town of New Milford and 6.4 km upstream from the city of Hackensack in Oradell, Bergen County, New Jersey (Fig. 1).

The reservoir has a maximum storage volume of $12.4 \times 10^6 \text{ m}^3$ for an elevation of 7.52 m NAVD88 [Baker III 1978] and the Oradell reservoir dam is classified as a high hazard dam i.e. in the event of its failure there would be significant loss of lives and property. The lower portions of the Hackensack river downstream of the dam are characterized by low density

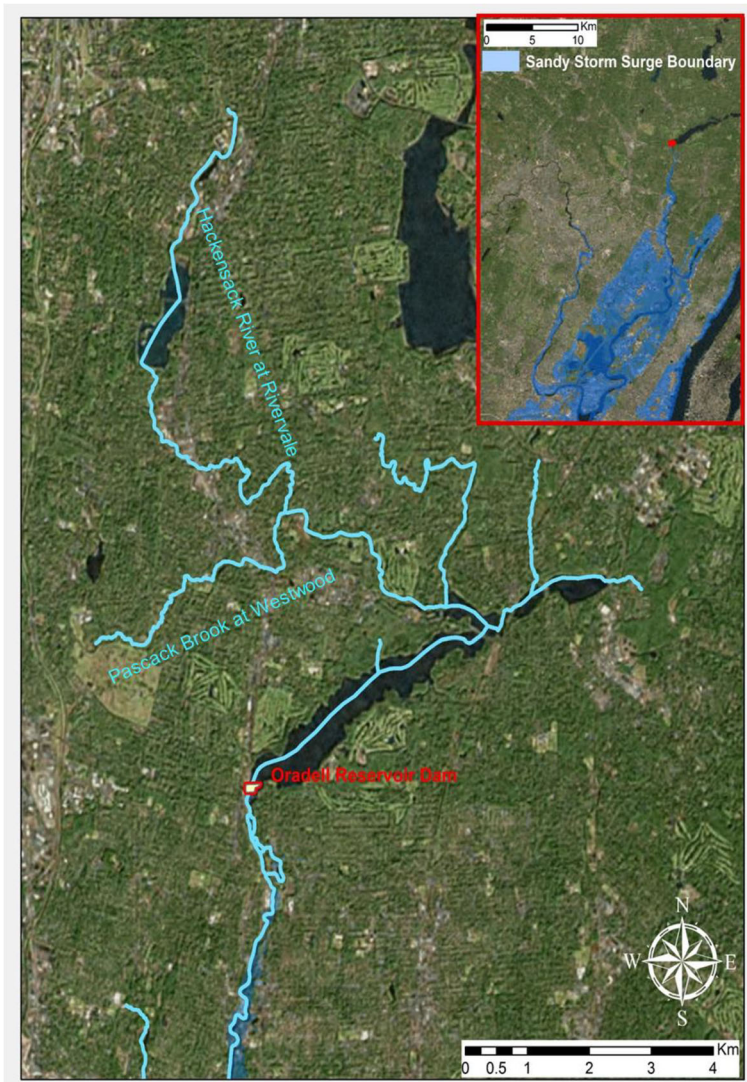


Fig. 1 Study area showing the Hackensack River basin, the hydrographic network, stations of interest and the Oradell reservoir

residential and commercial land use and are vulnerable to floods when the reservoir is at a high stage [EPA 2015; FEMA 2014].

The reservoir is operated with a primary objective of supplying water to Hudson and Bergen counties in New Jersey and is typically drawn down in summer when the customer demands increase and refills in the winter and spring through runoff and snowmelt. Hurricane Sandy which occurred between October 26–29, 2012 was selected due to the high magnitude of expected rainfall associated with the storm and the resulting press release approving the lowering of the North Jersey reservoirs [DEP 2012]. However, there were considerable differences between forecasted and observed precipitation over land that resulted from the uncertainties in the environmental steering flow and its interactions with the mid-latitude

trough [Munsell and Zhang 2014] resulting in no releases from the reservoir. The effect of this discrepancy was examined in the context of reservoir operations.

Hurricane Irene (August 27-30, 2011) was selected because of the unique meteorological characteristics associated with the event that inundated streams and caused the failure of numerous dams in New Jersey [Watson et al. 2013]. The Oradell dam overtopped during Hurricane Irene, despite the releases to increase the storage capacity.

2.2 Modelling and Optimization Framework Description

The framework diagram (Fig. 2) describes the steps used in modeling the streamflow and optimizing the reservoir operations. The hydrologic model was implemented using HEC-HMS, the parameters calibrated using the gridded precipitation data from the National Centers for Environmental Prediction (NCEP) North American Regional Reanalysis (NARR) [Mesinger et al. 2006] and validated using observations from the USGS gauging station located at Hackensack river at New Milford, Hackensack River at Rivervale and Pascack Brook at Westwood. A retrospective forecast of the inflows to the Oradell reservoir at different lead times for the three events was then performed using 51 member ensemble forecast from European Center of Medium Range Weather Forecasting (ECMWF) and one deterministic high resolution forecast (ECMWF-HRES) [Buizza et al. 1999].

2.3 Meteorological Datasets

2.3.1 North American Regional Reanalysis (NARR)

NARR precipitation dataset, corresponding to the three events was used to calibrate the hydrologic model. High-quality precipitation observations are assimilated into the atmospheric analysis to create a long-term, dynamically consistent, high-resolution climate dataset. The temporal resolution of NARR dataset is 3 hours and the spatial resolution is 32 km [Mesinger et al. 2006]. NARR datasets have also been successfully used to calibrate the parameters of the

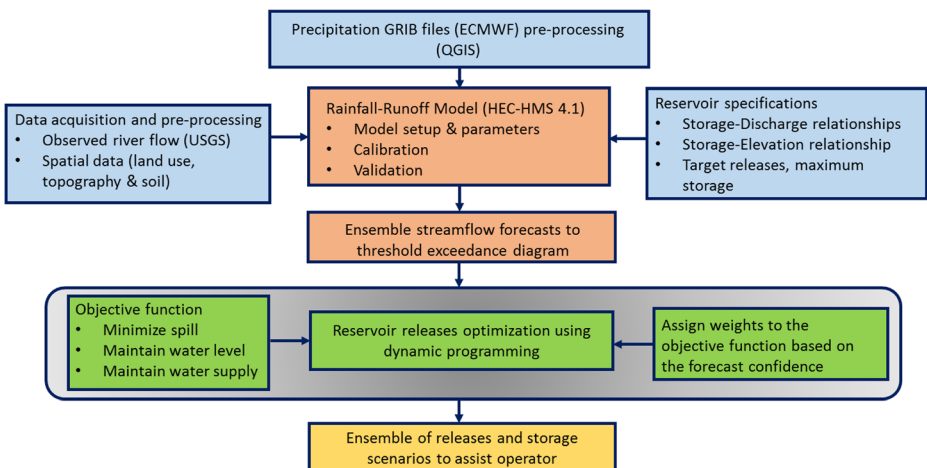


Fig. 2 Hydrologic modeling and reservoir optimization framework

hydrologic models [Choi et al. 2009] in data scarce regions with limited number of precipitation gauges [Solaiman and Simonovic 2010; Trubilowicz et al. 2016].

2.3.2 European Center for Medium Range Weather Forecasts (ECMWF)

The retrospective streamflow forecasts were obtained by forcing a hydrologic model with precipitation inputs from 51 ECMWF ensemble members and one high-resolution model ECMWF-HRES [Hagedorn 2008; Molteni et al. 1996]. An ensemble of 50 ECMWF members was obtained by perturbing the initial conditions of the control forecast to simulate the effect of initial condition uncertainty. ECMWF ensemble has a spatial resolution of 0.25° while the ECMWF-HRES has a spatial resolution of 0.125° with a temporal resolution of 3-hours. Previous studies have extensively addressed the skill and the advantages of ECMWF for hydrologic studies including forecasting reservoir inflows for managing water resources [Boucher et al. 2011; Ramos et al. 2007]. A total of 52 precipitation fields were obtained from the Meteorological Archival and Retrieval System (MARS) for 26th, 27th and 28th August 2011 for Hurricane Irene and 26th, 27th and 28th October 2012 for Hurricane Sandy.

2.4 Hydrologic Model Description and Datasets

Inflows to the Oradell reservoir was modeled using the latest Hydrologic Engineering Center's Hydrologic Modelling System (HEC-HMS), version 4.2 [USACE 2016]. HEC-HMS is developed by the US Army Corps of Engineers and has been used extensively in modeling streamflow [Halwatura and Najim 2013; Saleh et al. 2016; Yang and Yang 2014; Zhang et al. 2013] and simulating inflows to reservoirs [Che and Mays 2015; Shoghli et al. 2016; Uysal et al. 2016]. The model structure was defined using empirically derived parameters to describe the infiltration losses, the runoff, baseflow and routing [Feldman 2000; Kull and Feldman 1998]. The initial and constant loss method was selected to account for the infiltration losses [Halwatura and Najim 2013; Huizinga 2014]. The interception i.e. the absorption of precipitation by surface cover and depression storage were represented using the initial loss parameter. The constant rate represented the constant precipitation loss occurring during the event [HEC 2000a]. The Clark Unit hydrograph method was used to calculate the runoff transformation and the groundwater contributions to streamflow were included in the model using the initial flow and recession constants [Maidment 1992].

The Geographical information system (GIS) data was imported to HEC-HMS using the HEC-GeoHMS 10.2 extension [Fleming and Doan 2013; Johnson et al. 2001]. The topography was obtained from the USGS Nation Elevation Dataset (NED) [Gesch et al. 2002]. The Hackensack River basin was delineated into sub-basins based on the flow direction and accumulation derived from the DEM using HEC-GeoHMS. The GIS data was used to derive parameters such as the storage co-efficient and the percent imperviousness of the sub-basins. The baseflow recession constants for each sub-basin were used to represent the falling limb of the hydrograph.

The storage in the reservoir was simulated using two different routing methods contained within HEC-HMS. The Specified Release routing method was used to calibrate and validate the model. This method models the storage in the reservoir when the outflow discharge is known for each time interval of the simulation. Thus, the storage can be tracked at each time interval using the known inflows, outflows and conservation of mass. The calibration procedure is further discussed in section 3.1.

The Outflow Curve Routing method was used to obtain the inflows to the reservoir and to represent the reservoir using storage-discharge-elevation relationship. Using the observed initial elevation, HEC-HMS uses the level-pool routing model to calculate the outflow from an impoundment that has a horizontal water surface. The model recursively solves the one-dimensional approximation of the continuity equation by discretizing time and breaking the total analysis into equal intervals [HEC 2000b].

$$I_{avg} - O_{avg} = \frac{\Delta S}{\Delta t} \tag{1}$$

Where I_{avg} is the average inflow during time interval, O_{avg} is the average outflow during the time interval Δt and ΔS is the storage change.

2.5 Multi-objective Dynamic Programming

The ‘dp_multi’ function within the R package ‘reservoir’ was used to return the optimal sequence of releases [Turner and Galelli 2016]. Table 1 depicts the cost functions associated with these objectives, the parameters of the cost function and the problem constraints.

D is the target release, R_t , E_t and S_t are the controlled release, spill and storage at time step t respectively. τ is the penalty cost exponent and greater the penalty exponent the greater the hedging i.e the cutback on releases to maintain amenity for future water supply [Celeste and Billib 2009; Turner and Galelli 2016]. The volumetric capacity V was set to 0.98 which translates to 98% of the reservoir capacity. The inputs to the dynamic programming model were the inflow time series, the initial storage in the reservoir which was based on the initial water level and the depth-storage-area relationship and the target releases (Table 2). The storage and releases were discretized to 1000 and 10 uniform states respectively. The storage was discretized to a higher value to assist the interpolation of the reservoir volume to the water levels. The release was discretized arbitrarily assuming releases every 10 hours over the 120-hour forecast horizon.

The optimal sequence of releases for the input flow time series were obtained by minimizing the sum of penalty costs to maintain a target water supply, minimize spill and maintain a target water level using the backwards recursive procedure to solve Eq. (2).

$$f_t(S_t) = \min\{C_t(S_t, Q_t, R_t) + f_{t+1}(S_{t+1})\} \tag{2}$$

Where S_t is the storage at the reservoir, Q_t is the current period inflow, R_t is the release decision to minimize the current period cost C_t plus the future cost expectation $f_{t+1}(S_{t+1})$.

Table 1 Cost function, weights, exponents and constraints of the multi-objective dynamic programming model

	Maintain water supply	Minimize Spill	Maintain amenity
Cost function	$\left(\frac{D-R_t}{D}\right)^\tau$	$\left(\frac{E_t}{Quantile(Q,0.95)}\right)^\tau$	$\left(\frac{S_t - V * capacity}{V * capacity}\right)^\tau$
Weights	0.4	0.3	0.3
Exponents (τ)	2	2	2
Constraints	$0 \leq D \leq 2 * D$		$0 \leq S_t \leq 0.98 * capacity$

Table 2 Types of reservoir parameters, model inputs/parameters and the data sources

Reservoir parameters		Model input/parameter	
Parameter	Type	Input/parameter	Type
Reservoir capacity	definite, from Baker III (1978)	Inflow time series	determinate, from hydrologic model
Surface area at max depth	definite, from Baker III (1978)	Storage & release discretization	user defined, package default
Initial storage	definite, NWIS	Target releases	user defined, operator experience

3 Results

3.1 HEC-HMS Model Implementation and Calibration

Pascack Brook at Westwood and Hackensack River at Rivervale were modeled as two sub-basins and the excess inflows to the reservoir was modeled as a separate ungauged sub-basin. Observed elevations at the Oradell reservoir, the streamflow observations at the outlets of the two sub-basins and the observed outflow at the Hackensack River at New Milford were obtained from the USGS gauge stations.

Observed inflow to the reservoir was back calculated using the reverse level pool routing technique with a central difference scheme to reduce oscillations arising from the uncertainties in observed reservoir water levels, gate positions and observed discharge downstream of the reservoir [D'Oria et al. 2012; Zoppou 1999].

The model HEC-HMS model was run on 2 X 2 km standard hydrologic grid resolution at hourly time steps [Maidment and Djokic 2000] with the NARR precipitation data. The specified release routing method in HEC-HMS was used to calculate the storage in the reservoir using the total observed discharge at the Hackensack River at New Milford. The hydrologic parameters at the three sub-basins were modified based on visual comparison with streamflow observations at the two gauged sub-basins and the observed reservoir elevations to produce a best-fit model. The simulations showed reasonable fit between model and observed discharge at the two-selected gauged sub-basins and the water level at the reservoir.

3.2 Forecast Uncertainty

The Outflow Curve routing method was used to calculate the outflows from the reservoir using the storage-elevation relationship. The inflow forecasts were analyzed visually and using Nash Sutcliffe Efficiency (NSE) and Percent bias (PBIAS) to assess predictive power of hydrologic models and the uncertainty at different lead times, arising from the meteorological forecasts. This analysis was performed to assess the spread of peak magnitude and the forecast consistency as the peak of event approaches.

Figure 3 depicts the forecast assessment for Hurricane Irene to understand the propagation of meteorological uncertainties through the hydrologic model to uncertainties in inflows. The skill of the forecasts was assessed at lead times of 72, 48 and 24h by comparing the ensemble-based inflow forecasts with the backcalculated inflows. The reforecast issued 72h prior to the event, was characterized by a high spread in the ensemble members, specifically, the magnitude and time of the peak of inflow forecasts. There was a delay in peak of the simulated

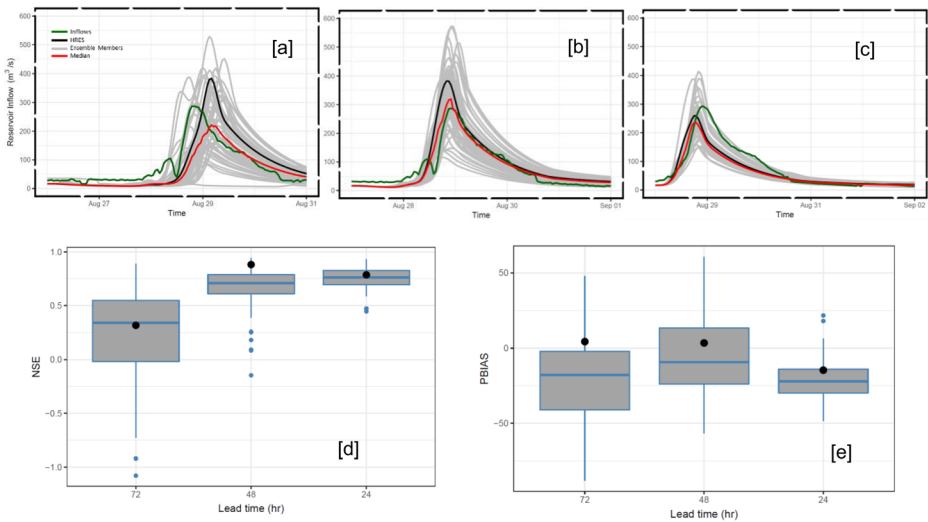


Fig. 3 Ensemble inflow forecasts compared to inflow calculated using the reverse pool routing methodology (backcalculated inflows) at lead times of 72, 48 and 24 h from the observed peak. The models' performance is represented by the Nash-Sutcliffe efficiency and the PBIAS at different lead times. The metrics show the median, interquartile range of the ensemble forecast and the high-resolution forecast

hydrographs by approximately 8–12 hours for both the ensemble and the deterministic high-resolution forecasts (Fig. 3a). The spread in the forecasted ensemble members was also evident from Fig. 3d, e where the interquartile range of the NSE was from 0 to 0.6 with a median of 0.4 and the interquartile range of the PBIAS was from 0 to -45% with a median PBIAS of 12%.

The inflow forecast issued 48h prior to the event, exhibited a lower peak spread compared to the spread from the forecast issued on 26th August 2011 (Fig. 3a, b). The delay in the peak timing was reduced with the deterministic forecast and the median agreeing well with the backcalculated inflow. The decreased interquartile range (0.6 to 0.8) and increase in the NSE was also indicative of the improvement in the skill and decrease in the forecast spread (Fig. 3d). The PBIAS increased with the median PBIAS of -5% with an interquartile range of -25% to 20% (Fig. 3e). The deterministic forecast showed good agreement with the backcalculated inflows with a NSE of 0.85 and PBIAS of 0% (Fig. 3d, e).

For the forecast issued on 28th August 2011, 24h prior to the event, the spread of the ensemble members was significantly reduced in terms of the peak magnitude and timing (Fig. 3c). The deterministic forecast underestimated the peak and compared well with median of the ensemble forecast. There was reduction in the forecast spread (Fig. 3d), with the NSE having an interquartile range of 0.7 to 0.8 and median of 0.75. There was also a decrease in the interquartile range of the PBIAS (-20% to -27%) indicating decrease in the forecast spread.

3.3 Release Optimization Using Dynamic Programming Under Different Scenarios

To optimize the release decisions over a 120-h forecast horizon, inflows to the reservoirs were used as inputs to the multi-objective dynamic programming model. The forecasts were updated every 24 hours to assess the effects of forecast uncertainty at different lead times on the release decisions.

3.3.1 Hurricane Irene

Inflow forecasts with a 120-h lead time issued on 26th August 2011 at 00:00 UTC, 27th August 2011 at 00:00 UTC and 28th August 2011 at 00:00 UTC (Fig. 3a, b, c) were used as inputs to the optimization model to obtain water levels (Fig. 4a1, a2, a3) resulting from optimized releases (Fig. 4b1, b2, b3). The dotted red line in Fig. 4a1, a2 and a3 indicates the maximum elevation of the reservoir with the water levels exceeding this value indicating the spill. The water level in the reservoir was initialized using the observed water level. The target release was set to 115 m³/s which corresponded to four open sluice gates. This value was selected based on the guidelines which stated that the reservoir could be drained in less than one day for the design capacity of 197 m³/s which corresponded to seven open gates [Baker III 1978].

Results showed that 72 hours prior to the arrival of the peak, release decisions were more conservative (Fig. 4b1) with the optimized release strategy for the backcalculated inflow showing no spill (Fig. 4a1). The inflow forecasts when used in the deterministic dynamic programming model provided an ensemble of releases and the corresponding water levels in the reservoir. Results indicated that initially all the ensemble members showed releases less than 50 m³/s (Fig. 4b1). The median of the probabilistic forecasts underestimated the peak inflows to the reservoir (Fig. 3a) and the water levels obtained by using the release decisions indicated no spill (Fig. 4a1, b1). A less conservative release strategy would have resulted in a lower number of members indicating spill. This would entail increasing the weight of the minimize spill objective and decreasing the weight of the maintain water level objective.

In the forecast issued 48 hours prior to the event, the release strategy was less conservative when compared to the forecast issued 72 hours before the event (Fig. 4b2). This was due to the necessity of draining a larger volume from the reservoir in a shorter period. The optimized release strategy applied to the backcalculated inflow showed no spillage. The reduced spread in the inflow forecast (Fig. 3b) was also reflected in the releases and the water levels in the reservoir (Fig. 4a2, b2). The water levels obtained using the probabilistic forecasts as inflows to the dynamic programming model showed more members exceeding the major levels in the reservoir (Fig. 4b2).

In the final forecast issued 24 hours before the event, the release strategy as depicted in Fig. 4b3 was the least conservative with high initial releases indicating the urgency to release more

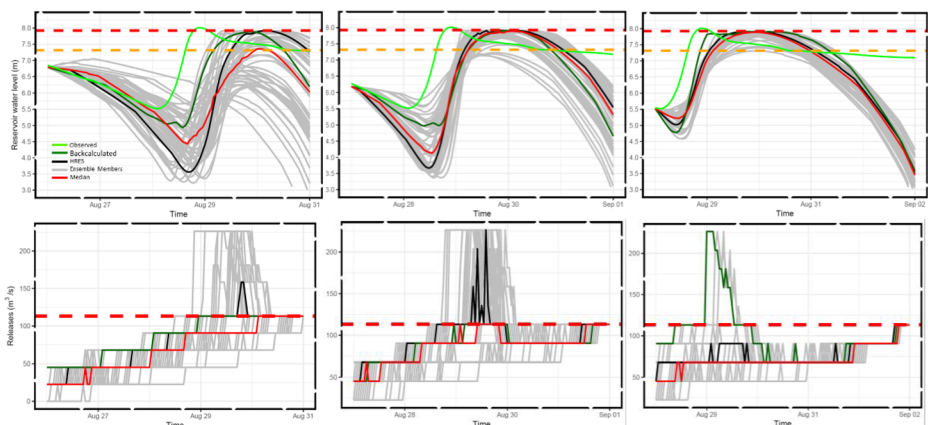


Fig. 4 Water levels in the reservoir 72, 48 and 24h before the observed peak based on the release decisions obtained using the deterministic dynamic programming approach

water as the event approaches. The water level (Fig. 4a3) corresponding to the backcalculated inflow (Fig. 4b3) exceeded the threshold value indicating spillage. It was observed that the spread in the ensemble inflows to the reservoir was reduced as the forecasts were updated. The spread of the ensemble members is a useful measure of the forecast uncertainty and higher spread hinders effective decision-making. However, forecast sharpness does not indicate reliability as evident from the forecast issued on 28th August 2011 (Fig. 4a3).

3.3.2 Hurricane Sandy

The optimized releases for Hurricane Sandy inflow forecasts were issued on 26th October 2012, 27th October 2012 and 28th October (Fig. 5a1, a2, a3).

The results showed that the conservative release decisions (Fig. 5c1) obtained for the inflow forecasts issued on 26th October 2012 (Fig. 5a1) resulted in a range of possible water levels in the reservoir (Fig. 5b1). A few members of the ensemble-based forecasts showed overtopping 72 hours prior to the peak of the forecasted event (Fig. 5b1).

The inflow forecast issued on 27th October 2012 was characterized by a wider spread in the time and magnitude of the peak inflow (Fig. 5a2). The release decisions (Fig. 5b2) and the corresponding water levels (Fig. 5c2) showed a high spread. The conservative release decisions resulted in more members exceeding the major flood threshold indicating a higher chance of overtopping if the updated forecasts are used.

The inflow forecast issued on 28th October 2012 showed more members depicting higher inflows compared to the previous forecasts (Fig. 5a1, a2, a3). The less conservative release decisions (Fig. 5c3) and the increase in the magnitude of the forecasted inflows resulted in majority of the water levels exceeding the moderate threshold of the reservoir with a few

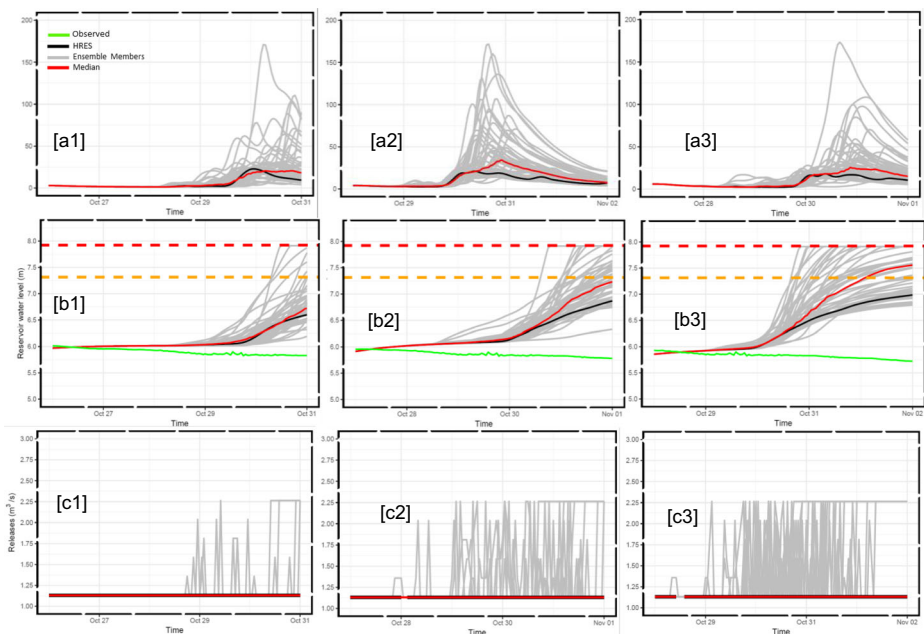


Fig. 5 Ensemble and deterministic inflow forecasts, water level in the reservoir and the corresponding release decisions at lead times of approximately 72, 48 and 24h from the forecasted peak flow

members exceeding the major threshold (Fig. 5b3). The deterministic inflow forecast was characterized by low magnitude and was similar to the forecast issued the previous day.

4 Summary and Discussion

The first part of this work consisted of implementing a hydrologic modeling framework on the Hackensack River basin. The hydrologic model was calibrated and validated for the extreme rainfall event Hurricane Irene using NARR precipitation data and the observed streamflow from the USGS gauges. The second part investigated the use of ECMWF ensemble and deterministic precipitation inputs to retrospectively forecast the inflows to reservoir during Hurricane Irene and Hurricane Sandy, with a 120h forecast horizon. The uncertainty arising from the parametrization of the hydrologic model was not addressed in this study as the focus was on the importance of uncertain precipitation inputs on the inflow forecasts for extreme rainfall events.

The evolution of release decisions based on the forecasted inflows and the optimization methods were then assessed for the different lead times for the two events. For Hurricane Irene, the release decisions progressed from more conservative to less conservative releases with the change in the forecast lead time. The ensembles provided a way to visualize the uncertain release decisions and uncertainties in the corresponding water levels associated with those decisions. However, the proposed method should be used as an assistive tool and all sources of errors must be acknowledged before making operational decisions [Bourdin et al. 2012]. Using ensembles from multiple meteorological models can be used to improve the predictive capability of the modeling system [Saleh et al. 2018]. The importance of the uncertainties arising from the hydrologic modeling framework and their impact on the release decisions was highlighted in the Hurricane Sandy simulation. The conservative release strategies resulted in a broader range of release decisions that showed the reservoir overtopping as the forecasts were updated.

In terms of the optimization framework the dynamic programming approach can be updated with optimization techniques such as the stochastic dynamic programming and model predictive control [Anvari et al. 2014; Côté and Leconte 2016]. Future work would involve including the multiple reservoirs to better represent the water system and assess the potential of the system for flood control during extreme rainfall events.

Compliance with Ethical Standards

Conflict of Interest None

References

- Adamowski JF (2008) Peak Daily Water Demand Forecast Modeling Using Artificial Neural Networks. *Journal of Water Resources Planning and Management* 134(2):119–128. [https://doi.org/10.1061/\(ASCE\)0733-9496\(2008\)134:2\(119\)](https://doi.org/10.1061/(ASCE)0733-9496(2008)134:2(119))
- Akbari-Alashti H, Bozorg Haddad O, Mariño MA (2015) Application of Fixed Length Gene Genetic Programming (FLGGP) in Hydropower Reservoir Operation. *Water Resources Management* 29(9):3357–3370. <https://doi.org/10.1007/s11269-015-1003-1>
- Anderson J, Chung F, Anderson M, Brekke L, Easton D, Ejeta M, Peterson R, Snyder R (2008) Progress on incorporating climate change into management of California's water resources. *Climatic Change* 87(1):91–108. <https://doi.org/10.1007/s10584-007-9353-1>

- Anvari S, Mousavi SJ, Morid S (2014) Sampling/stochastic dynamic programming for optimal operation of multi-purpose reservoirs using artificial neural network-based ensemble streamflow predictions. *Journal of Hydroinformatics* 16(4):907–921. <https://doi.org/10.2166/hydro.2013.236>
- Baker, M., III (1978), Appraisal of water resources in the Hackensack River basin National Dam Safety Program. Oradell Reservoir Dam (NJ00258), Hackensack River Basin, Hackensack River, Bergen County, New Jersey. Phase I Inspection Report.
- Bartholmes J, Todini E (2005) Coupling meteorological and hydrological models for flood forecasting. *Hydrol. Earth Syst. Sci.* 9(4):333–346. <https://doi.org/10.5194/hess-9-333-2005>
- Bartholmes JC, Thielen J, Ramos MH, Gentilini S (2009) The european flood alert system EFAS – Part 2: Statistical skill assessment of probabilistic and deterministic operational forecasts. *Hydrology and Earth System Sciences* 13(2):141–153
- Boucher MA, Anctil F, Perreault L, Tremblay D (2011) A comparison between ensemble and deterministic hydrological forecasts in an operational context. *Adv. Geosci.* 29:85–94. <https://doi.org/10.5194/adgeo-29-85-2011>
- Boucher M-A, Tremblay D, Delorme L, Perreault L, Anctil F (2012) Hydro-economic assessment of hydrological forecasting systems. *Journal of Hydrology* 416:133–144
- Bourdin DR, Fleming SW, Stull RB (2012) Streamflow modelling: a primer on applications, approaches and challenges. *Atmosphere-Ocean* 50(4):507–536
- Buizza R (2008) The value of probabilistic prediction. *Atmospheric Science Letters* 9(2):36–42
- Buizza R, Hollingsworth A, Lalauette F, Ghelli A (1999) Probabilistic predictions of precipitation using the ECMWF Ensemble Prediction System. *Weather and Forecasting* 14(2):168–189
- Cannas B, Fanni A, See L, Sias G (2006) Data preprocessing for river flow forecasting using neural networks: Wavelet transforms and data partitioning. *Physics and Chemistry of the Earth. Parts A/B/C* 31(18):1164–1171. <https://doi.org/10.1016/j.pce.2006.03.020>
- Carswell, L. D. (1976), Appraisal of water resources in the Hackensack River basin, *New Jersey Rep., US Geological Survey.*
- Celeste AB, Billib M (2009) Evaluation of stochastic reservoir operation optimization models. *Advances in Water Resources* 32(9):1429–1443
- Che D, Mays LW (2015) Development of an Optimization/Simulation Model for Real-Time Flood-Control Operation of River-Reservoirs Systems. *Water Resources Management* 29(11):3987–4005. <https://doi.org/10.1007/s11269-015-1041-8>
- Choi W, Kim SJ, Rasmussen PF, Moore AR (2009) Use of the North American Regional Reanalysis for hydrological modelling in Manitoba. *Canadian Water Resources Journal* 34(1):17–36
- Cloke H, Pappenberger F (2009) Ensemble flood forecasting: a review. *Journal of Hydrology* 375(3):613–626
- Côté P, Leconte R (2016) Comparison of Stochastic Optimization Algorithms for Hydropower Reservoir Operation with Ensemble Streamflow Prediction. *Journal of Water Resources Planning and Management* 142(2):04015046. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000575](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000575)
- Coulibaly P, Anctil F, Bobée B (2000) Daily reservoir inflow forecasting using artificial neural networks with stopped training approach. *Journal of Hydrology* 230(3–4):244–257. [https://doi.org/10.1016/S0022-1694\(00\)00214-6](https://doi.org/10.1016/S0022-1694(00)00214-6)
- Cuo L, Pagano TC, Wang QJ (2011) A Review of Quantitative Precipitation Forecasts and Their Use in Short- to Medium-Range Streamflow Forecasting. *Journal of Hydrometeorology* 12(5):713–728
- D’Oria, M., P. Mignosa, and M. G. Tanda (2012) Reverse level pool routing: Comparison between a deterministic and a stochastic approach *Journal of Hydrology*, 470-471(Supplement C), 28-35, 10.1016/j.jhydrol.2012.07.045.
- DEP, S. O. N. J. D. O. E. P. (2012), Governor Christie takes action to mitigate potential impacts from Hurricane, in *Approves lowering of North Jersey reservoirs*, edited.
- EPA (2015), Lower Hackensack River Bergen and Hudson Counties New Jersey-Preliminary Assessment *Rep.*, Environmental Protection Agency.
- Eum H-I, Kim Y-O, Palmer RN (2011) Optimal Drought Management Using Sampling Stochastic Dynamic Programming with a Hedging Rule. *Journal of Water Resources Planning and Management* 137(1):113–122. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000095](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000095)
- Fan FM, Collischonn W, Meller A, Botelho LCM (2014) Ensemble streamflow forecasting experiments in a tropical basin: The São Francisco river case study. *Journal of Hydrology* 519(PD):2906–2919
- Fan FM, Schwanenberg D, Alvarado R, Assis dos Reis A, Collischonn W, Naumann S (2016) Performance of Deterministic and Probabilistic Hydrological Forecasts for the Short-Term Optimization of a Tropical Hydropower Reservoir. *Water Resources Management* 30(10):3609–3625. <https://doi.org/10.1007/s11269-016-1377-8>
- Feldman AD (2000) Hydrologic modeling system HEC-HMS: technical reference manual. US Army Corps of Engineers, Hydrologic Engineering Center

- FEMA (2014), Flood Insurance Study Bergen County, New Jersey*Rep.*
- Ficchi A, Raso L, Dorchies D, Pianosi F, Malaterre P-O, Overloop P-JV, Jay-Allemand M (2016) Optimal Operation of the Multireservoir System in the Seine River Basin Using Deterministic and Ensemble Forecasts. *Journal of Water Resources Planning and Management* 142(1):05015005. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000571](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000571)
- Fleming, M., and J. Doan (2013), HEC-GeoHMS geospatial hydrologic modelling extension: user's manual version 10.2, US Army Corps of Engineers, Institute for Water Resources, Hydrologic Engineering Centre, Davis, CA.
- Galelli S, Goedbloed A, Schwanenberg D, Overloop P-JV (2014) Optimal Real-Time Operation of Multipurpose Urban Reservoirs: Case Study in Singapore. *Journal of Water Resources Planning and Management* 140(4): 511–523. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000342](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000342)
- García-Ruiz JM, López-Moreno JI, Vicente-Serrano SM, Lasanta-Martínez T, Beguería S (2011) Mediterranean water resources in a global change scenario. *Earth-Science Reviews* 105(3-4):121–139. <https://doi.org/10.1016/j.earscirev.2011.01.006>
- Gaume E, Gosset R (2003) Over-parameterisation, a major obstacle to the use of artificial neural networks in hydrology? *Hydrology and Earth System Sciences Discussions* 7(5):693–706
- Gesch D, Oimoen M, Greenlee S, Nelson C, Steuck M, Tyler D (2002) The national elevation dataset. *Photogrammetric engineering and remote sensing* 68(1):5–32
- Graf WL, Wohl E, Sinha T, Sabo JL (2010) Sedimentation and sustainability of western American reservoirs. *Water Resources Research* 46(12). <https://doi.org/10.1029/2009WR008836>
- Gragne AS, Sharma A, Mehrotra R, Alfredsen K (2015) Improving real-time inflow forecasting into hydropower reservoirs through a complementary modelling framework. *Hydrol. Earth Syst. Sci.* 19(8):3695–3714. <https://doi.org/10.5194/hess-19-3695-2015>
- Gupta, H. V., K. J. Beven, and T. Wagener (2005), Model Calibration and uncertainty estimation, in *Encyclopedia of Hydrological Sciences.*, edited, pp. 2015-2032, John Wiley and Sons.
- Hagedorn, R. (2008), Using the ECMWF reforecast data set to calibrate EPS reforecasts, in *ECMWF Newsletter*, edited, pp. 8-13.
- Halwatura D, Najim MMM (2013) Application of the HEC-HMS model for runoff simulation in a tropical catchment. *Environmental Modelling and Software* 46:155–162
- Hanak, E., and J. R. Lund (2012), Adapting California's water management to climate change, *Climatic Change*, 111(1), 17-44. <https://doi.org/10.1007/s10584-011-0241-3>.
- HEC (2000a), Hydrologic Modeling System: Technical Reference Manual. US Army Corps of Engineers Hydrologic Engineering Center, Davis, CA.
- HEC (2000b), Hydrologic Modeling System: Technical Reference Manual. US Army Corps of Engineers Hydrologic Engineering Center, Davis, CA.*Rep.*
- Ho M, Lall U, Allaire M, Devineni N, Kwon HH, Pal I, Raff D, Wegner D (2017) The future role of dams in the United States of America. *Water Resources Research* 53(2):982–998. <https://doi.org/10.1002/2016WR019905>
- Huizinga, R. J. (2014), An initial abstraction and constant loss model, and methods for estimating unit hydrographs, peak streamflows, and flood volumes for urban basins in Missouri*Rep.* 2328-0328, US Geological Survey.
- Johnson, C., A. Yung, K. Nixon, and D. Legates (2001) The use of HEC-GeoHMS and HEC-HMS to Perform Grid-Based Hydrology Analysis of a Watershed, edited, Texas: Dodson & Associated, inc. (tidak dirujuk).
- Jothiprakash V, Magar RB (2012) Multi-time-step ahead daily and hourly intermittent reservoir inflow prediction by artificial intelligent techniques using lumped and distributed data. *Journal of Hydrology* 450–451:293–307. <https://doi.org/10.1016/j.jhydrol.2012.04.045>
- Juracek KE (2015) The Aging of America's Reservoirs: In-Reservoir and Downstream Physical Changes and Habitat Implications. *JAWRA Journal of the American Water Resources Association* 51(1):168–184. <https://doi.org/10.1111/jawr.12238>
- Krzysztofowicz R (2001) Integrator of uncertainties for probabilistic river stage forecasting: precipitation-dependent model. *Journal of Hydrology* 69-85
- Kull DW, Feldman AD (1998) Evolution of Clark's unit graph method to spatially distributed runoff. *Journal of Hydrologic engineering* 3(1):9–19
- Kumar S, Tiwari MK, Chatterjee C, Mishra A (2015) Reservoir Inflow Forecasting Using Ensemble Models Based on Neural Networks, Wavelet Analysis and Bootstrap Method. *Water Resources Management* 29(13): 4863–4883. <https://doi.org/10.1007/s11269-015-1095-7>
- Labadie JW (2004) Optimal Operation of Multireservoir Systems: State-of-the-Art Review. *Journal of Water Resources Planning and Management* 130(2):93–111. [https://doi.org/10.1061/\(ASCE\)0733-9496\(2004\)130:2\(93\)](https://doi.org/10.1061/(ASCE)0733-9496(2004)130:2(93))
- Lane, N. (2008), Aging infrastructure: Dam safety*Rep.*

- Laugesen, R., N. Tuteja, D. Shin, T. Chia, and U. Khan (2011), Seasonal Streamflow Forecasting with a workflow-based dynamic hydrologic modelling approach, paper presented at Paper accepted for oral presentation at Modelling and Simulation Society of Australia and New Zealand Conference.
- Lettenmaier DP, Wood AW, Palmer RN, Wood EF, Stakhiv EZ (1999) Water Resources Implications of Global Warming: A U.S. Regional Perspective, *Climatic Change* 43(3):537–579. <https://doi.org/10.1023/a:1005448007910>
- Loucks DP, Van Beek E, Stedinger JR, Dijkman JP, Villars MT (2005) Water resources systems planning and management: an introduction to methods, models and applications. Unesco, Paris
- Maidment, D. R. (1992), *Handbook of hydrology*, McGraw-Hill Inc.
- Maidment DR, Djokic D (2000) Hydrologic and hydraulic modeling support: With geographic information systems. ESRI, Inc
- McCullor D, Stull R (2008) Hydrometeorological short-range ensemble forecasts in complex terrain. Part II: Economic evaluation, *Weather and Forecasting* 23(4):557–574
- Mehta R, Jain SK (2009) Optimal Operation of a Multi-Purpose Reservoir Using Neuro-Fuzzy Technique. *Water Resources Management* 23(3):509–529. <https://doi.org/10.1007/s11269-008-9286-0>
- Mesinger F et al (2006) North American Regional Reanalysis. *Bulletin of the American Meteorological Society* 87(3):343–360
- Molteni F, Buizza R, Palmer TN, Petroliagis T (1996) The ECMWF ensemble prediction system: Methodology and validation. *Quarterly journal of the royal meteorological society* 122(529):73–119
- Mukerji A, Chatterjee C, Raghuvanshi NS (2009) Flood Forecasting Using ANN, Neuro-Fuzzy, and Neuro-GA Models. *Journal of Hydrologic Engineering* 14(6):647–652. [https://doi.org/10.1061/\(ASCE\)HE.1943-5584.0000040](https://doi.org/10.1061/(ASCE)HE.1943-5584.0000040)
- Munsell EB, Zhang F (2014) Prediction and uncertainty of Hurricane Sandy (2012) explored through a real-time cloud-permitting ensemble analysis and forecast system assimilating airborne Doppler radar observations. *Journal of Advances in Modeling Earth Systems* 6(1):38–58. <https://doi.org/10.1002/2013MS000297>
- Partal T (2009) Modelling evapotranspiration using discrete wavelet transform and neural networks. *Hydrological Processes* 23(25):3545–3555. <https://doi.org/10.1002/hyp.7448>
- Rabuffetti D, Barbero S (2005) Operational hydro-meteorological warning and real-time flood forecasting: the Piemonte Region case study. *Hydrology and Earth System Sciences* 9(4):457–466
- Rajagopalan B, Nowak K, Prairie J, Hoerling M, Harding B, Barsugli J, Ray A, Udall B (2009) Water supply risk on the Colorado River: Can management mitigate? *Water Resources Research* 45(8):n/a–n/a. <https://doi.org/10.1029/2008WR007652>
- Ramos MH, Bartholmes J, Thielen-del Pozo J (2007) Development of decision support products based on ensemble forecasts in the European flood alert system. *Atmospheric Science Letters* 8(4):113–119
- Saleh F, Ramaswamy V, Georgas N, Blumberg AF, Pullen J (2016) A retrospective streamflow ensemble forecast for an extreme hydrologic event: a case study of Hurricane Irene and on the Hudson River basin. *Hydrol. Earth Syst. Sci.* 20(7):2649–2667. <https://doi.org/10.5194/hess-20-2649-2016>
- Saleh F, Ramaswamy V, Georgas N, Blumberg AF, Pullen J (2018) Inter-comparison between retrospective ensemble streamflow forecasts using meteorological inputs from ECMWF and NOAA/ESRL in the hudson river sub-basins during hurricane irene (2011). *Hydrology Research*:nh2018182–nh2018182. <https://doi.org/10.2166/nh.2018.182>
- Schwanenberg D, Fan FM, Naumann S, Kuwajima JI, Montero RA, dos Reis AA (2015) Short-term reservoir optimization for flood mitigation under meteorological and hydrological forecast uncertainty. *Water Resources Management* 29(5):1635–1651
- Seo DJ, Herr HD, Schaake JC (2006) A statistical post-processor for accounting of hydrologic uncertainty in short-range ensemble streamflow prediction. *Hydrol. Earth Syst. Sci. Discuss.* 2006:1987–2035. <https://doi.org/10.5194/hessd-3-1987-2006>
- Shoghli, B., Y. H. Lim, and J. Alikhani (2016), Evaluating the Effect of Climate Change on the Design Parameters of Embankment Dams: Case Studies Using Remote Sensing Data, paper presented at World Environmental And Water Resources Congress 2016: Hydraulics and Waterways and Hydro-Climate/Climate Change - Papers from Sessions of the Proceedings of the 2016 World Environmental and Water Resources Congress.
- Singh H, Sinha T, Sankarasubramanian A (2014) Impacts of Near-Term Climate Change and Population Growth on Within-Year Reservoir Systems. *Journal of Water Resources Planning and Management* 141(6): 04014078. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000474](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000474)
- Solaiman TA, Simonovic SP (2010) National Centers for Environmental Prediction-National Center for Atmospheric Research (NCEP-NCAR) reanalyses data for hydrologic modelling on a basin scale. *Canadian Journal of Civil Engineering* 37(4):611–623
- Thiemig V, Bisselink B, Pappenberger F, Thielen J (2015) A pan-African medium-range ensemble flood forecast system. *Hydrology and Earth System Sciences* 19(8):3365–3385

- Todini E (2007) Hydrological catchment modelling: past, present and future. *Hydrol. Earth Syst. Sci.* 11(1):468–482. <https://doi.org/10.5194/hess-11-468-2007>
- Trubilowicz JW, Shea J, Jost G, Moore R (2016) Suitability of North American Regional Reanalysis (NARR) output for hydrologic modelling and analysis in mountainous terrain. *Processes, Hydrological*
- Turner SWD, Galelli S (2016) Water supply sensitivity to climate change: An R package for implementing reservoir storage analysis in global and regional impact studies. *Environmental Modelling & Software* 76: 13–19. <https://doi.org/10.1016/j.envsoft.2015.11.007>
- USACE (2016), Hydrologic Modeling System: User's Manual Version 4.2, US Army Corps of Engineers, Hydrologic Engineering Center, Davis, CA, USA.
- Uysal G, Şensoy A, Şorman AA, Akgün T, Gezgin T (2016) Basin/Reservoir System Integration for Real Time Reservoir Operation. *Water Resources Management* 30(5):1653–1668. <https://doi.org/10.1007/s11269-016-1242-9>
- Valipour M (2012) Number of required observation data for rainfall forecasting according to the climate conditions. *American Journal of Scientific Research* 74:79–86
- Valipour M, Banihabib ME, Behbahani SMR (2013) Comparison of the ARMA, ARIMA, and the autoregressive artificial neural network models in forecasting the monthly inflow of Dez dam reservoir, *Journal of Hydrology* 476:433–441. <https://doi.org/10.1016/j.jhydrol.2012.11.017>
- Verkade JS, Werner MGF (2011) Estimating the benefits of single value and probability forecasting for flood warning. *Hydrol. Earth Syst. Sci.* 15(12):3751–3765. <https://doi.org/10.5194/hess-15-3751-2011>
- Vicuna S, Dracup JA, Lund JR, Dale LL, Maurer EP (2010) Basin-scale water system operations with uncertain future climate conditions: Methodology and case studies. *Water Resources Research* 46(4):n/a–n/a. <https://doi.org/10.1029/2009WR007838>
- Watson, K. M., J. V. Collenburgh, and R. G. Reiser (2013), Hurricane Irene and associated floods of August 27–30, 2011, in *New Jersey Rep.* 2328-0328, US Geological Survey.
- Wisser D, Frolking S, Hagen S, Bierkens MFP (2013) Beyond peak reservoir storage? A global estimate of declining water storage capacity in large reservoirs. *Water Resources Research* 49(9):5732–5739. <https://doi.org/10.1002/wrcr.20452>
- Yakowitz S (1982) Dynamic programming applications in water resources. *Water Resources Research* 18(4): 673–696. <https://doi.org/10.1029/WR018i004p00673>
- Yang S-C, Yang T-H (2014) Uncertainty assessment: reservoir inflow forecasting with ensemble precipitation forecasts and HEC-HMS. *Advances in Meteorology* 2014
- Zalachori I, Ramos MH, Garçon R, Mathevet T, Gailhard J (2012) Statistical processing of forecasts for hydrological ensemble prediction: a comparative study of different bias correction strategies. *Adv. Sci. Res.* 8(1):135–141. <https://doi.org/10.5194/asr-8-135-2012>
- Zavala VM, Constantinescu EM, Krause T, Anitescu M (2009) On-line economic optimization of energy systems using weather forecast information. *Journal of Process Control* 19(10):1725–1736
- Zhang H, Wang Y, Wang Y, Li D, Wang X (2013) The effect of watershed scale on HEC-HMS calibrated parameters: a case study in the Clear Creek watershed in Iowa, US. *Hydrology and Earth System Sciences* 17(7):2735–2745
- Zhao T, Cai X, Yang D (2011) Effect of streamflow forecast uncertainty on real-time reservoir operation. *Advances in Water Resources* 34(4):495–504. <https://doi.org/10.1016/j.advwatres.2011.01.004>
- Zoppou C (1999) Reverse Routing of Flood Hydrographs Using Level Pool Routing. *Journal of Hydrologic Engineering* 4(2):184–188. [https://doi.org/10.1061/\(ASCE\)1084-0699\(1999\)4:2\(184\)](https://doi.org/10.1061/(ASCE)1084-0699(1999)4:2(184))

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