



# A dual-phase ensemble framework for enhancing reservoir inflow forecasting

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**Abstract.** Growing reliance on reservoir storage makes reservoir inflow forecasting essential to water supply across many regions. We present a dual-phase ensemble modeling framework to enhance the accuracy and timeliness of flow forecasting. The first phase of the ensemble consists of primary members developed based on calibrations of a semi-distributed hydrologic model against selected events across diverse hydroclimatic conditions. Through parameter perturbation and optimization, the primary members are further tuned to address the uncertainty in initial soil moisture conditions, resulting in a set of derived models. The primary and derived models together form a complete ensemble prediction band. The second phase involves statistical ensemble band using the quantile regression forests approach. The outputs of ensemble members are converted into a probabilistic range around the ensemble mean to better accommodate modeling uncertainties. The inflow forecast further extended by three days using linear regression, enhancing operational value in specific catchments. This ensemble approach was applied to two major reservoirs in the Nueces River Basin in Texas, USA. Ensemble members were established using the HEC-HMS model, and the ensemble was validated and tested with seven-day precipitation forecast for events in summer 2025. As measured by weighted performance metrics, the ensemble forecast outperformed the National Water Model, providing a more accurate estimation of reservoir inflows while preserving the probabilistic characteristics of the weather inputs. These results highlight the benefits of ensemble forecasts for effectively dealing with the uncertainties and complexities in watershed hydrologic responses and associated data inputs, providing an improved basis to support forecast-informed reservoir operations.

**Key words:** Hydrological modeling, Streamflow forecast, Ensemble analysis, Reservoir, Water resources management

## 1 Introduction

25 Reservoirs provide essential water for multiple purposes, particularly in water-stressed regions where storage is critical for domestic supply and environmental needs. Although the expansion of water infrastructure has slowed considerably in the US, modernization of the monitoring and management of existing water infrastructure is required to meet growing challenges related to environmental and societal objectives (Thornton et al., 2022). Storage trends in U.S reservoirs show decreasing peak storage levels and increasing prolonged and severe low storage periods (Simeone et al., 2024), indicating increased



30 vulnerability of water storage that requires advancing monitoring and optimization techniques to enhance water infrastructure operations. Adaptive reservoir management provides policies which can be valuable for climate change adaptation and yield water supply benefits while maintaining an adequate environment in the rivers (Taylor et al., 2024).

Although there is understanding in uncertainty during operational reservoir management, there is limited capacity and reliability to establish a scientific base for proactive water resources management strategies. A promising approach is the  
35 integration of medium range weather forecasts and hydrological modeling into reservoir operations (Faber & Stedinger, 2001). Streamflow forecasting relies on the skill of weather forecasts, the estimation of initial hydrologic conditions, and the hydrological model's ability to simulate streamflow (Mazrooei et al., 2015; Paiva et al., 2012). While precipitation is the primary driver of forecasted streamflow variability, multiple studies have shown that antecedent soil moisture, land-use/land-cover changes, and other catchment attributes can substantially modify the magnitude and timing of runoff, amplifying or  
40 dampening streamflow responses to the same precipitation input (Bennett et al., 2018; Gupta et al., 2015; Moges et al., 2022; Slater et al., 2017). Integration of historical and probabilistic data offers significant promise for enhancing streamflow forecast skill by improving the accuracy of initial hydrological model states (DeChant & Moradkhani, 2011; El Gharamti et al., 2024). The efficiency of rainfall-runoff modeling can be improved by explicitly incorporating historical trends into event-based hydrologic parameters.

45 Implementing ensemble-based modeling requires synthetic techniques, such as deriving members from historical events on plausible scenarios, to capture a broad range of extremes and reduce forecast uncertainty. In practice, each stage of the forecasting process introduces uncertainties which can degrade the quality and limit the operational utility of streamflow forecasts (Bogner & Kalas, 2008; Demirel et al., 2015). Several studies have evaluated the performance of multimodel ensembles within operational forecasting applications. Overall, this approach improves ensemble reliability, but it also  
50 introduces added uncertainty due to inherent and often unpredictable differences among hydrological models (Goswami & O'Connor, 2007; Sharma et al., 2019; Tang et al., 2023). Chiang et al., (2017) demonstrated that the ensemble size is not sensitive to the type of hydrological model and that the inclusion of many ensemble members does not necessarily increase the performance of the modeling. This suggests that ensemble methods with greater emphasis on members representation combined with a controlled and well-evaluated selection could sample a broad range of initial hydrologic conditions and reduce  
55 the effect of parametric uncertainty through parameter perturbation and optimization. Ensemble forecasting are potentially valuable for reservoir systems where operations might seek to balance risks to meet a desired outcome (Delaney et al., 2020). Ensemble forecast systems can remain robust across varied parameter settings when paired with distribution-based post-processing, an advantage in operational contexts where precise parameter estimates are difficult to obtain (Demargne et al., 2014). Dual-phase ensemble analysis can reduce uncertainty and provide forecast ranges based on the primary ensemble mean  
60 distribution. Consequently, post-processing of ensemble forecast systems address the temporal coverability in the generated streamflow time series while avoiding over-fitting (Hopson et al., 2019). For example, trend-based quantile methods have been employed to address the full spectrum of possible extreme forecasts and better capture trends (Li et al., 2021; Tyralis &



Papacharalampous, 2023; Weerts et al., 2011). Such post-processing methods could increase forecast accuracy with flexible adjustments and providing recurrent correction in operations to extend forecast lead time.

65 This study demonstrates the development of an ensemble model framework for enhancing reservoir inflow forecasting. The ensemble framework incorporated a range of initial and constant parameter sets through two approaches: (i) primary members based on event selection and calibration, and (ii) derived members representing extreme scenarios. High-resolution HEC-HMS used to drive medium-range quantitative precipitation forecasts. A robust dual-phase ensemble modeling system, combining the physical ensemble model output with a non-parametric post-processing distribution method, was applied to account for

70 uncertainty in the forecasts. The effective use of two phase ensemble provide reliable medium-range reservoirs inflow forecasts for decision makers to guide river-flow management and dynamically adjust storage under Forecast-Informed Reservoir Operations (FIRO).

## 2 Materials and Methods

### 2.1 Study Area

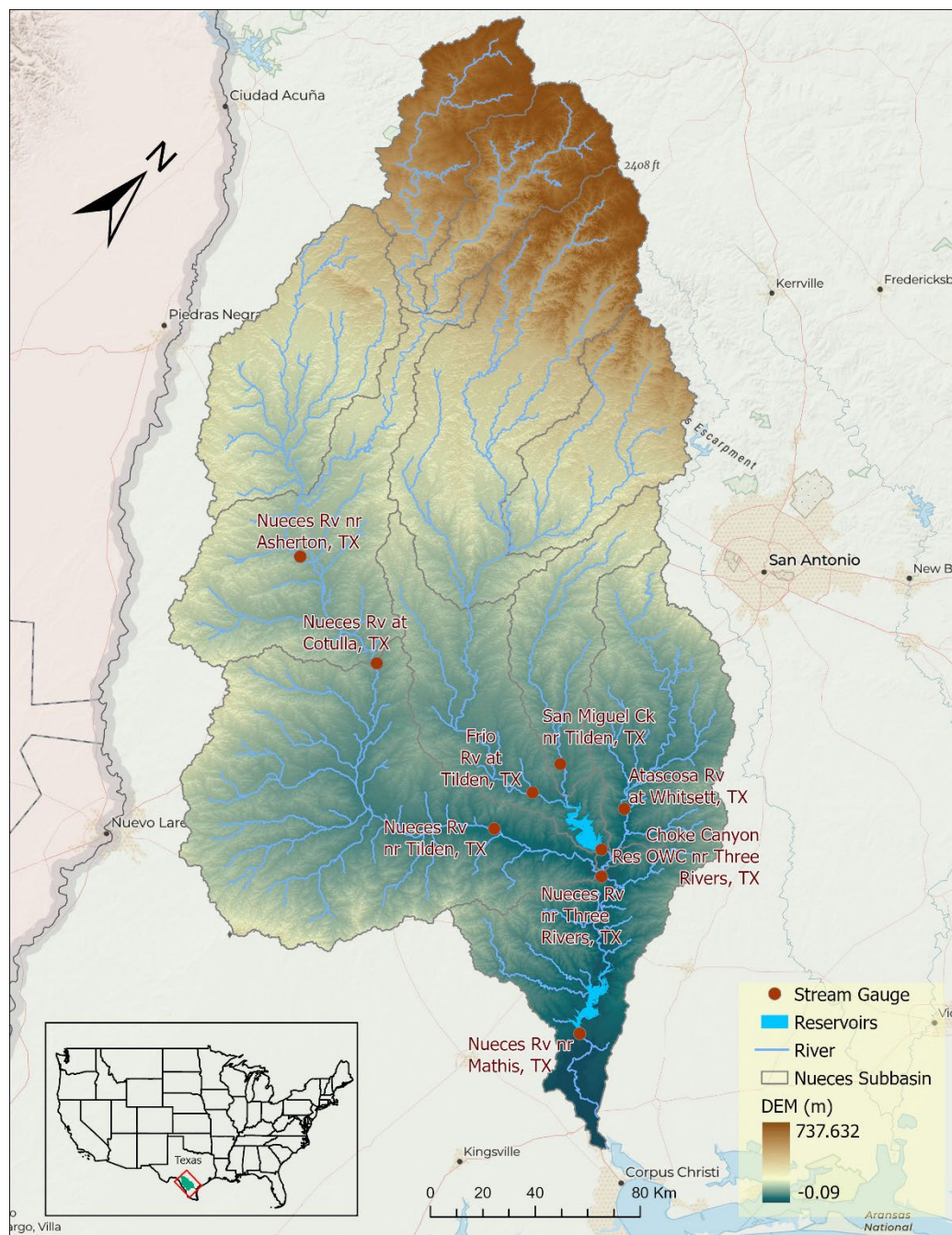
75 Nueces river basin is characterized by high rainfall variability and significant uncertainty in precipitation patterns with mean annual precipitation 760 mm/yr. Nueces River originating in Edwards and Real counties, flows southward to Nueces Bay before emptying into the Gulf of America. The basin is influenced by groundwater interactions and the widespread use of small storage systems in its upstream areas. The streamflow is controlled by a cascade major reservoir system, consisting of the upstream Choke Canyon Reservoir (CCR) with a conservation capacity of 0.818 km<sup>3</sup> and the downstream Lake Corpus

80 Christi (LCC) with a conservation capacity of 0.316 km<sup>3</sup> (Figure 1). This reservoir system provides critical water supply to the City of Corpus Christi, the booming industrial hub surrounding the Port of Corpus Christi, and the environmental flow to the Nueces estuary.

The Nueces reservoirs have been experiencing a significant decline in their storage capacity over the last decade. As of March 2025, the combined conservation storage was down with CCR at 15.3% and the LCC at 23.6% of the total capacity, reflecting

85 prolonged drought conditions (Texas Water Condition Report, 2025). The low storage levels highlight the urgent need for improved water management strategies and adaptive planning in the basin. According to the historic agreement with the Nueces River Authority (NRA) and the City of Corpus Christi, a tiered storage-based threshold is used as triggers in the drought contingency plan of the City of Corpus Christi (Corpus Christi, 2025). For example, when the combined storage is below 20% of the storage capacity, the reservoir system will not release any freshwater to the Nueces Estuary, and the city will reduce

90 residential and commercial water supply by 15%. The storage level of the CCR-LCC reservoir system plays a critical role in the water resources management in the basin and has critical impacts on environmental flow and regional water supply. Reliable reservoir inflow forecasts can help address water management challenges in the Nueces river basin by mitigating supply shortage through Forecast Informed Reservoir Operation.



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**Figure 1:** The Nueces river basin and monitoring stations in Texas, USA. The base map was designed and developed by Esri | Powered by Esri. For more information on this map, visit <https://developers.arcgis.com/documentation/esri-and-data-attribution/#esri-attribution> (last access: 14 January 2026).



## 100 2.2 Data

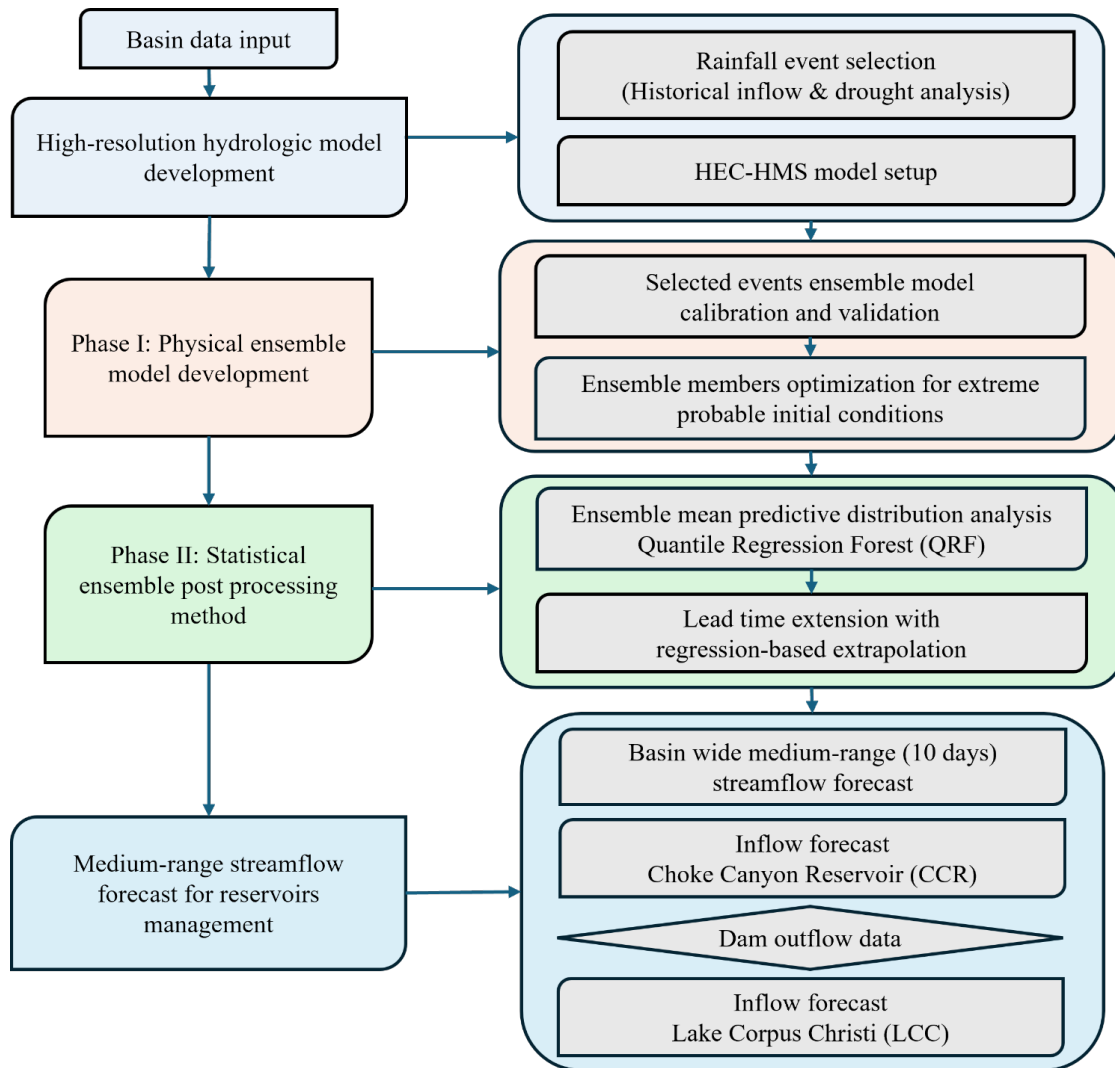
Elevation data were collected from the United States Geological Service (USGS) 10-m 3D Elevation Program of the National Elevation Dataset (NED, accessed October 2024). The watershed and subbasin delineations for the HEC-HMS model was performed using the highest resolution watershed boundary dataset obtained from the National Hydrography Dataset (USGS). We generated a detailed river network to drive a high-resolution drainage system aligned with the watershed boundaries. The streamflow data used in this study involved six stream gages, including Nueces at Asheron, Nueces at Cotulla, Nueces at Tilden, Atascosa at Whitsett, St Miguel at Tilden and Frio at Tilden stations. 15-minute stream flow data was collected from the National Water Information System of the USGS (*USGS Water Data*, 2025). The observation datasets have been used for model calibration and validation.

Reservoir storage data were collected from Water Data, Texas Water Development Board (TWDB, 2024). Historic precipitation data were acquired from the National Weather Service (NWS) 4-km gridded precipitation data and Stage IV grids from National Centre for Atmospheric Research (NCAR) (Du, 2011). For drought category identification we used data from U.S. Drought Monitor (USDM) analysed for various drought index since the year 2000 (Simeral, 2025). Several federal agencies including the U.S. Department of Agriculture (USDA), the National Oceanic and Atmospheric Administration (NOAA), and National Drought Mitigation Center (NDMC) have their input to produce the weekly maps of areal coverage of USDM drought intensity categories. USDM was developed as a comprehensive tool to depict the drought conditions across the U.S (Leelaruban et al., 2017; Svoboda et al., 2002).

For forecast simulation we used the National Weather Service medium range open-source data downloaded from NOAA (NOAA's Climate Prediction, 2025). We also used the National Water Model (NWM) medium range streamflow forecast for inflow events evaluation in comparison with this study streamflow forecast results. The NWM is produced by the National Water Prediction Service (NWPS), the (NOAA) map-based platform that provides access to river forecasts and flood maps (NOAA, 2025).

## 2.3 Methodology

Figure 2 presents the proposed methodological framework designed to enhance reservoir operational efficiency by providing reliable inflow forecast using two phase ensemble approach. The major component of this framework includes the development of high-resolution distributed models and development of an ensemble approach for wide range of representations. The primary objective of expanding the ensemble models was twofold: (1) to develop multiple individual model realizations (ensemble members) that capture different hydrologic responses, and (2) to integrate these models into a single ensemble system that reflects the full range of basin characteristics. This ensemble-based strategy enhances the model's capability to represent spatial and temporal variability across the watershed, providing a more comprehensive assessment of potential flow responses under varying conditions. The results present comparative presentations of existing established stream flow forecast products.



**Figure 2:** The framework of ensemble-based reservoir inflow forecasting.

### 2.3.1 Configuration of the base model

135 A wide range of hydrological models and software have been developed to simulate rainfall-runoff processes, each varying in complexity, data requirements, and application scope (Hamel et al., 2017; Kibii et al., 2021; Primožič et al., 2008). Compared to physically based distributed models, semi-distributed models incorporate conceptual elements to simulate complex watershed processes and are less computationally intensive. We selected the USACE’s Hydrologic Modeling System (HEC-HMS) model because of its versatility in both event-based and continuous simulations and its extensive applications in medium range and long-term water resource management (Odey & Cho, 2025; Sahu et al., 2023). It offers a flexible framework for



140 modeling hydrologic processes, including precipitation-runoff transformation, baseflow, infiltration, and channel routing, and  
can easily incorporate gridded precipitation data.

In this study, we applied the HEC-HMS model to represent the entire watershed system of the Nueces river basin. Two base  
models were established for high resolution sub basin classification to each reservoir. In each base model, drainage areas were  
discretized into multiple subbasins and computational elements to capture spatial variability in hydrologic response based on  
145 the National Hydrography Dataset (NHD). The river network and catchment connections were generated based on 10-meter  
resolution DEM from the USGS 3DEP. For event-based simulation, characteristics such as loss, transform, baseflow and  
routing were calculated from the basin characteristics. Additional channel routing and channel loss parameters were adopted  
from existing monitoring and study in the basin, which we recalculated to account for differences in geometry due to our higher  
resolution subbasins and shorter river reach. The Interagency Flood Risk Management (InFRM) model served as a baseline,  
150 particularly in channel loss and diversion parameters, providing essential guidance for estimating losses using the Modified  
Pulse method. We adopt these parameters to our models at finer details, using 431 subbasins and 361 reaches across the two  
watersheds compared to 199 subbasins and 1561 reaches in the InFRM model. The InFRM is a joint effort by Federal  
Emergency Management Agency (FEMA), the U.S. Army Corps of Engineers (USACE), the US Geological Survey (USGS),  
and the National Weather Service (NWS) (InFRM, 2025).

### 155 2.3.2 Selection of rainfall events

Hydrometeorological events were selected aimed at enhancing the model's ability to simulate a wide range of flow  
characteristics with particular attention to capture the variability of inflow amount and watershed conditions. This includes  
storage change, antecedent drought scenarios and intensity of precipitation. Historical reservoir inflow hydrographs translated  
from elevation measurements into volume using elevation rating curves were used to initially select the inflow events (*USGS*  
160 *Water Data*, 2025). These historical peak inflows, which have contributed to significant changes in reservoir storage, were  
evaluated together with the precipitation and surface conditions preceding each storm event.

The U.S. Drought Monitor index was used to assess antecedent soil moisture, allowing for the inclusion of diverse initial and  
drought severity conditions. To maintain consistency, a 12-week period drought index prior to each rainfall event was used as  
it directly influence antecedent watershed wetness. Droughts ranging from the drought intensity categories from D0 to D4  
165 were used as initial events. The events physical characteristics included all ranges, that are abnormally dry (D0), moderate  
drought (D1), severe drought (D2), extreme drought (D3), and exceptional drought (D4). As a guideline, the system uses a  
percentile approach in determining the thresholds for each severity level, and all data used in drought severity determinations  
are considered with reference to their historical frequency of occurrence for the location and time of year in question (Svoboda  
et al., 2002). This classification enabled flexible, straightforward integration of data requirements with rainfall patterns and  
170 allowed selection of representative events based on subjective assessments.

The next step involved evaluating the spatial distribution and intensity of rainfall and comparing these characteristics with the  
outcomes of the preceding analyses to identify the most representative storm events for model setup. Radar-based quantitative



precipitation estimates were processed into spatial rainfall maps using NWS 4 km gridded precipitation datasets due to their high temporal resolution and broad spatial coverage (Lin & Mitchell, 2005). The rainfall exhibited substantial variability in both intensity and spatial extent, creating a meaningful link between the selected drought indices and the corresponding inflow responses observed in the reservoirs. Accordingly, rainfall event selection was guided by historical hydrographs that showed substantial inflow responses, combined with a systematic assessment of 12 week drought index conditions preceding each event. This approach ensured that each selected event represented both the hydrometeorological extremes and the antecedent moisture dynamics essential for accurate model calibration and scenario analysis.

### 2.3.3 Physical ensemble model development

#### 2.3.3.1 Development of primary ensemble members

The primary ensemble model members were developed by calibrating the base model with selected rainfall events. The calibration was generally performed from upstream to downstream by systematically adjusting parameters within each subbasin and comparing the simulated results at gauging stations. Key parameters adjusted included initial and constant loss parameters and baseflow parameters. Subsequently, the Snyder lag and peaking coefficients were fine-tuned to better represent the timing and magnitude of runoff. Routing parameters, specifically the Muskingum  $X$  and  $K$  values, were refined in the final calibration stage.

The calibration of the CCR model used two stream gages (Frio at Tilden and San Miguel at Tilden), and the calibration of the LCC model used involved four gauging sites, including three on the mainstream of the Nueces river (Asherton, Cotulla, and Tilden) and on Atascosa at Whitsett. The locations of these gages are shown in Fig. 1. Validation was also conducted on the 12 ensemble members mean flow using the 2004 event. The calibration and validation performances were evaluated using performance metrics, comparing simulated flows against observed data. The selection of statistical error metrics is guided by the specific requirements of the study on total reservoir inflow estimation for the forecast period. For evaluating the performance of our statistical models, we focused on three widely accepted indicators: PBIAS, RSR and NSE. These metrics provide reliable insights into model accuracy and efficiency. The corresponding equations are provided below.

$$PBIAS = 100 \times \frac{\sum_{i=1}^n (Q_{obs,i} - Q_{sim,i})}{\sum_{i=1}^n (Q_{obs,i})} \quad (1)$$

where  $Q_{obs,i}$  = Observed value at time step  $i$ ,  $Q_{sim,i}$  = Simulated value at time step  $i$ ,  $n$  = Number of time steps

$$RSR = \frac{\sqrt{\frac{\sum_{i=1}^n (Q_{obs,i} - Q_{sim,i})^2}{n}}}{\sqrt{\frac{\sum_{i=1}^n (Q_{obs,i} - \bar{Q}_{obs})^2}{n}}} = \frac{RMSE}{STDEV_{obs}} \quad (2)$$

where  $Q_{obs,i}$  = Observed value  $i$ ,  $Q_{sim,i}$  = Simulated value at  $i$ ,  $\bar{Q}_{obs}$  = Mean observed values,  $n$  = Number of time steps, RMSE = Root Mean Square Error,  $STDEV_{obs}$  = Standard deviation of observed values



$$NSE = 1 - \frac{\sum_{i=1}^n (Q_{obs,i} - Q_{sim,i})^2}{\sum_{i=1}^n (Q_{obs,i} - \bar{Q}_{obs})^2} \quad (3)$$

where  $Q_{obs,i}$  = Observed value at  $i$ ,  $Q_{sim,i}$  = Simulated value at  $i$ ,  $\bar{Q}_{obs}$  = Mean observed values,  $n$  = Number of time steps.

To combine the best performing model results, we assigned weighted percentages to the three-evaluation metrics, giving greater weight to parameters that represent total flow volume. Accordingly, we developed a composite performance index by normalizing each metric. This gives values that provides a comparable and consistent range. This normalization allows us to combine the metrics and evaluate overall model performance. The normalized error metrics are presented as follows:

$$PBIAS_{norm} = 1 - \left( \frac{|PBIAS|}{100} \right) \quad (4)$$

$$RSR_{norm} = 1 - RSR \quad (5)$$

$$NSE_{norm} = NSE \quad (6)$$

The calculation of the weighted composite performance index (CPI) is shown below:

$$CPI_{weighted} = \frac{A * PBIAS_{norm} + B * RSR_{norm} + C * NSE_{norm}}{n} \quad (7)$$

where  $A$ ,  $B$  and  $C$  are weights of error metrics and  $n = A + B + C$ .

In this study, since the primary objective is to estimate reservoir storage based on the total volume of inflow, greater weighting values were placed on parameters that best represent the overall flow volume, specifically, PBIAS and RSR. The two parameters capture the total inflow conditions most effectively, so the weights of PBIAS, RSR and NSE were assigned as 3, 2 and 1, respectively, to establish the CPI.

### 2.3.3.2 Development of derived ensemble members

For each primary ensemble member, two additional derived ensemble members were established by modifying the initial watershed conditions to span a wider range of maximum and minimum inflow scenarios. The derived models based on the originally calibrated configuration were developed to better represent anticipated extreme hydrologic conditions in the basin. This approach enabled the modeling framework to incorporate both upper-bound and lower-bound hydrologic responses that may occur under extreme wet or dry antecedent conditions. Such adjustments follow established ensemble-forecasting practices in hydrologic modeling, where initial conditions exert a dominant influence on peak flow magnitude and timing (Ajami et al., 2004; Clark et al., 2015).

To achieve this, we systematically modified the initial loss parameters in the loss methods for each scenario, deviating from the four calibrated baseline models. The parameter adjustments targeted the upper and lower plausible limits of soil moisture and surface storage. The wet scenario was represented by assuming fully saturated antecedent conditions, consistent with standard procedures. Conversely, the dry-condition scenario was modelled by increasing the initial loss parameter to twice that of the calibrated model, simulating significantly drier soils and reduced runoff efficiency. These two contrasting configurations



230 provide meaningful insight into the sensitivity of inflow hydrographs to antecedent moisture conditions and allow the reservoir-  
routing model to account for hydrologic behaviours beyond the historical calibration events. The model then optimized  
specifically for constant loss and groundwater parameters to minimize the objective function error at key observation flow  
stations.

Together, the three-member structure of each event, (i.e. calibrated baseline, wet-condition derived model, and dry-condition  
235 derived model) reflects hydrologic expectations under statistically credible extremes. This ensemble strategy enhances the  
robustness of the simulation framework and improves evaluation of reservoir response under a full spectrum of inflow  
conditions, including those outside the historical record but relevant for planning, operations, and risk assessment (Moradkhani  
et al., 2005; Todini, 2008). This adjustment ensures that each ensemble member reflects unique soil moisture and infiltration  
characteristics, representing definite hydrologic states of the watershed. The most direct approach to ensemble combination  
240 is the equal-weighting method, in which all ensembles are averaged into one composite (Barnston et al., 2003; Hagedorn et  
al., 2005). In total, twelve models with distinct parameter sets were used to generate the ensemble forecasting. This approach  
allowed us to account for variability in antecedent watershed conditions, thereby improving the robustness of the ensemble  
framework.

### 2.3.4 Statistical ensemble post-processing

245 The second phase of ensemble forecast modeling builds on the output of the flow generated from the first phase. This post  
processing of ensemble forecasting is particularly valuable for hydrologic applications, as it allows decision-makers to assess  
risk and confidence levels when interpreting forecast results. Nonparametric ensemble forecast demonstrate that forest-based  
methods yield calibrated predictive distributions often improving forecast quality and generate full predictive distributions,  
even when the raw ensemble exhibits limited spread, or structural deficiencies (Taillardat & Mestre, 2020). Quantile  
250 Regression Forest (QRF) has gained wide spread adoption as a post-processing tool because it does not assume a specific  
parametric distribution and can incorporate a large number of predictors, offering greater flexibility and improved probabilistic  
calibration compared to traditional methods (Evin et al., 2021; Kim et al., 2025).

Recent comparative research demonstrates that QRF can perform competitively with, and sometimes outperform, advanced  
deep-learning architectures, particularly in tasks requiring reliable uncertainty quantification. For instance, Zhang et al. (2023)  
255 compared QRF with a suit of deep-learning model for hydrologic prediction and found that QRF offered more stable and  
computationally efficient estimation of prediction intervals. Deep learning models may achieve lower point-prediction error,  
but QRF frequently provides superior coverage and calibration of forecast uncertainty, making it a robust choice for ensemble  
post-processing and hazard-oriented hydrologic applications. In addition, the application of quantile-based regression for  
ensemble post-processing enables the expansion and refinement of predictive uncertainty ranges derived from physical  
260 ensemble model forecast.

In this study the QRF was effectively utilized on the ensemble mean values generated from the 12-member ensemble forecasts  
by estimating the 5<sup>th</sup>, 50<sup>th</sup> and 90<sup>th</sup> percentiles. This approach provides a probabilistic forecast envelope that captures the range



of possible outcomes and quantifies the uncertainty associated with the forecast model. The QRF method is especially useful when the model inputs or the catchment characteristics are uncertain and provide the distributional characteristics to preserve flow forecast outputs. We used a comprehensive python-based QRF package for conditional quantile accuracy and uncertainty estimate developed by Johnson (2024). This study is expected to represent a new modeling effort in reservoirs inflow forecasting in the Nueces river basin and beyond by implementing a standardized and repeatable forecasting approach. Furthermore, the lead time of the ensemble forecast was extended by three days while maintaining a reasonable level of accuracy. The three days were selected based on the stable time of concentration needed for the flow to be routed to the reservoirs. To achieve this, a linear regression technique was applied using data from the most recent days to project streamflow conditions. By extrapolating short-term flow behaviours based on recent trends and the catchment characteristics, it effectively bridges the gap in forecasted data and provide additional three days inflows. The method is adaptive as the regression parameters and lead-time extension can be modified based on the prevailing hydrometeorological conditions or observed deviations during operational forecasting. This flexibility enhances the robustness of the ensemble system, making it suitable for real-time applications in river basin management and reservoir operation.

### 2.3.5 Forecast Simulation

For accurate simulation of the streamflow forecast, we used the medium range forecast from the NOAA gridded precipitation. This source utilizes state-of-the-art forecasting techniques to generate the precipitation forecasts retrieved from an FTP server for larger files. The medium range data, which is up to 7 days at 6 hour accumulation, is available from 00 hours to 18:00 four times a day. The 00 hour and 12-hour original forecast data while the other two are derived from the original. These datasets are configured to generate a cumulative flow at 6-hour intervals. Historical forecast data are available upon request for a specified period. For this study, we obtain 168 hours of real-time forecast data for each simulation day. In addition, three days of hindcast data prior to the forecast date were used to capture the full streamflow hydrograph. Observed inflows at the two reservoirs locations indicate delayed accumulation due to river routing, small storage, and abstractions, with peak inflow typically occurring after three days. Therefore, incorporating a 3 day hindcast period strengthens the representation of inflow patterns during forecasted rainfall events. The inflow is further extended using linear regression, consistent with the basin's three-day time of concentration and associated confidence in the inflow trend.

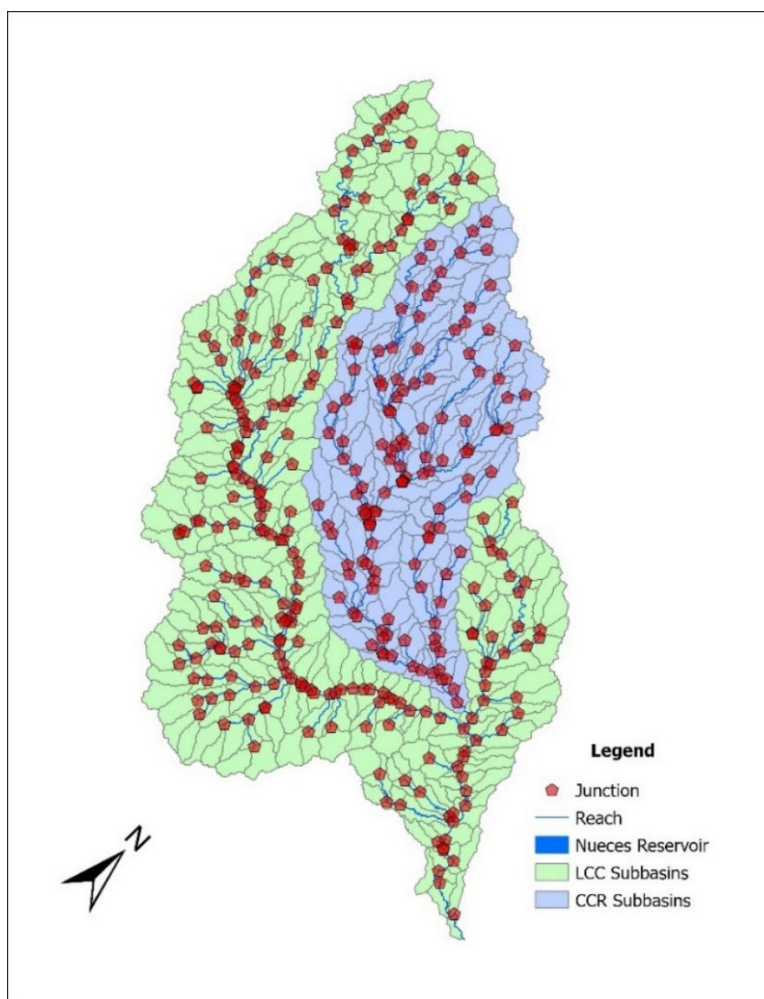
Further, the National Water Model (NWM) flow forecast was also presented along with this study model outputs to account for uncertainty and improve forecast reliability. The NWM offers continuous forecast products across the United States, making it a valuable tool for analysing river inflows at key locations (NOAA, 2025). These forecasts are particularly useful for understanding flow behaviours in major river systems. By aligning the NWM hydrographs with those generated from our high-resolution HEC-HMS model, we will provide a more robust and comprehensive forecast product for decision makers.



### 3 Results

#### 3.1 HEC-HMS model setup

295 The study presents a high-resolution distributed hydrologic model developed for the two major reservoirs in the Nueces river  
basin for assessing the efficiency of inflow forecast simulation. The first model covered the drainage area of the upstream  
Choke Canyon Reservoir (i.e., the CCR model), and the second model covered the rest of the basin drainage area flowing to  
Lake Corpus Christi (i.e., the LCC model). This resulted in 153 subbasins and 127 reaches for the CCR model and 278  
subbasins and 234 reaches for LCC model. Parameter values for the model such as the flow path length and slope were derived  
300 based on elevation and the subbasin boundaries. The increased number of subbasins allow for a more detailed calibration of  
the model to enhance accuracy at multiple gauging stations across the basin. Fig. 3 shows the HEC-HMS model configuration  
with subbasins, junctions and river reach networks.

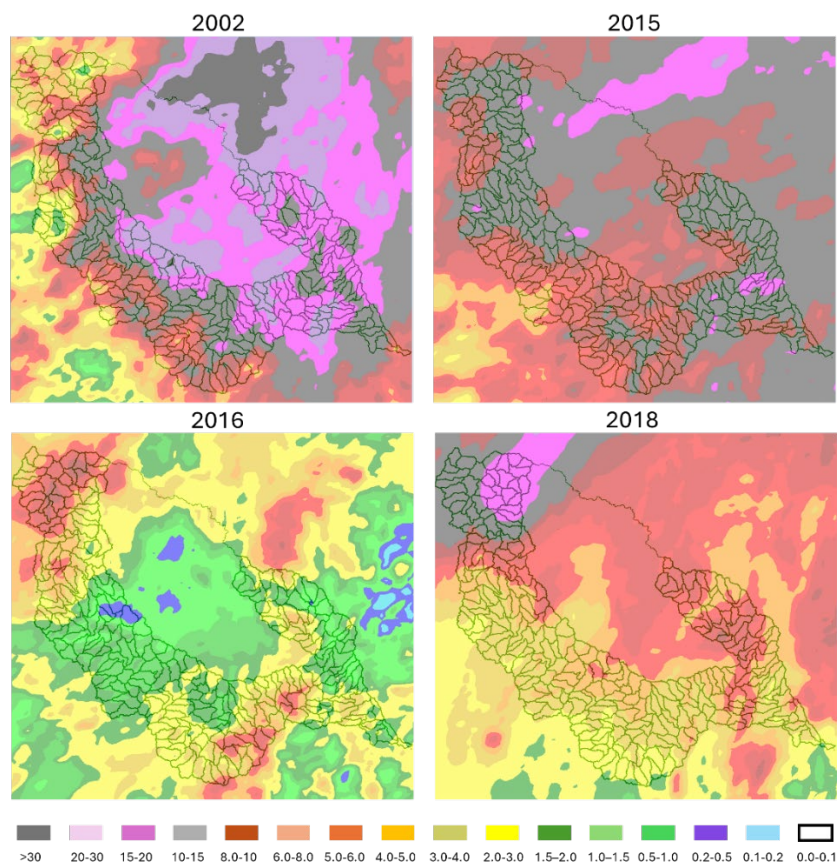


**Figure 3:** HEC-HMS model framework for Choke Canyon Reservoir and Lake Corpus Christi



### 305 3.2 Events selection

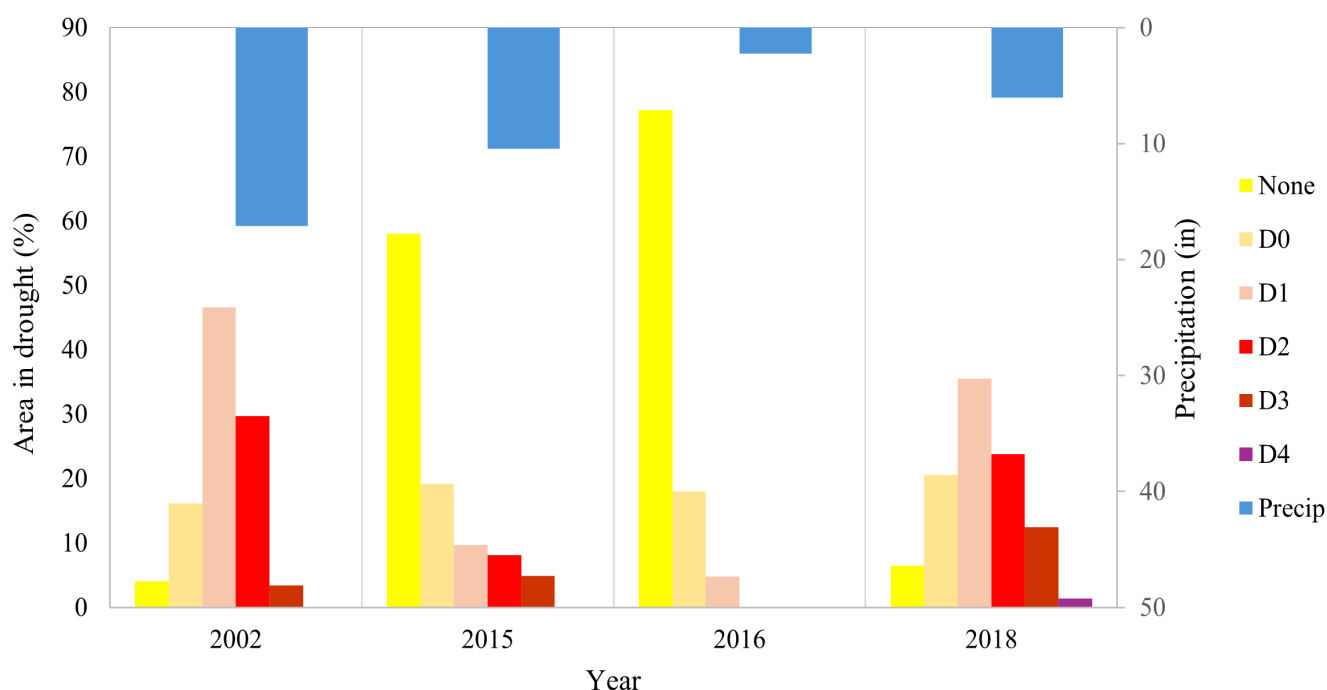
The first step in defining ensemble member events involved identifying historical storage variations in the CCR and LCC reservoirs. Reservoir storage records and associated inflow hydrographs from 1990 and 2025 were systematically analysed to characterize a range of storage change conditions. Based on the magnitude and variability of these changes, ten representative events for CCR and twelve for LCC were selected. These events were further evaluated to ensure they adequately represent catchment conditions using corresponding rainfall and drought datasets. Subsequently, distinct storm events spatial distribution was selected to reflect the basin's response to differences in rainfall intensity combining with the antecedent moisture conditions. The rainfall totals for the selected events ranging from low to high intensity, had significant inflow contribution to the two dams. The selected rainfall events for Choke Canyon model are 1997 (June 20 – July 6), 2002 (June 29 – July 29), 2015 (May 11 – June 7), and 2018 (October 7 – October 30). Similarly, for the Lake Corpus Christi inflow model, the selected events are 2002 (June 29 – July 29), 2015 (May 11 – June 17), 2016 (September 24 – October 30), and 2018 (October 7 – November 25). The average rainfall intensity distribution for event displays a higher intensity of the precipitation in the northern part of the Nueces river basin as shown in fig. 4.



**Figure 4:** Total rainfall depth and spatial distribution of selected events



320 The rainfall patterns of high to low intensity rainfall were combined with drought index representing a range of soil moisture  
 scenario from saturated to dry conditions, Fig 5. The drought condition in the preceding 12 weeks was used to select a variety  
 of initial soil moisture conditions, see the supplement figure 1 for further information. This enables the model to capture the  
 full range of soil moisture conditions, including potential extreme scenarios. Consequently, four distinct events were selected  
 to reflect the basin’s response to differences in rainfall intensity and antecedent moisture conditions. These events encompassed  
 325 the full hydrologic spectrum extending from probable maximum to probable minimum conditions. The average rainfall  
 intensity distribution for each event shows a higher intensity of 17.13 (2002), 10.86 (2015) and 6.34 (2018). The average  
 rainfall intensity for LCC is 11.7 (2002) 9.99 (2015), 2.23 (2016) and 6.69 (2018). This also indicates the drought condition  
 probability matching with the rainfall observed to enable a wider range of rainfall and drought initial condition combination.



330 **Figure 5:** Initial drought index for 12 weeks prior to the events onset and cumulative precipitation of the events.

### 3.3 Ensemble members development

Each base model was calibrated for the selected rainfall events, resulting in four primary members for the ensemble model. The calibration was performed manually to achieve acceptable error indices using a Composite Performance Index (CPI). Tables 1 and 2 presents the calibration performances of CCR and LCC models, respectively. Model calibration details and hydrographs are provided in Fig S2 and S3 of the supplement. Overall, the results demonstrate that the models are capable of  
 335 accurately simulating streamflow compared with the gauged data.

Table 1: Calibration performance of the primary members of the CCR ensemble.



Station	Parameter	Events			
		1997	2002	2015	2018
San-Miguel at Tilden	PBIAS (%)	1.85	-1.37	40.96	-4.81
	RSR	0.4	0.4	0.6	0.7
	NSE	0.824	0.811	0.635	0.511
	CPI Weighted	<b>0.83</b>	<b>0.83</b>	<b>0.54</b>	<b>0.66</b>
Frio near Tilden	PBIAS (%)	-7.03	-8.05	27.35	-16.74
	RSR	0.3	0.4	0.8	0.7
	NSE	0.92	0.807	0.41	0.55
	CPI Weighted	<b>0.85</b>	<b>0.79</b>	<b>0.49</b>	<b>0.61</b>

Table 2: Calibration performance of the primary members of the LCC model.

Station	Parameter	Events			
		2002	2015	2016	2018
Nueces at Asherton	PBIAS (%)	-3.67	40.89	-38.78	-41.47
	RSR	0.3	0.8	0.4	0.6
	NSE	0.913	0.436	0.868	0.581
	CPI Weighted	<b>0.87</b>	<b>0.44</b>	<b>0.65</b>	<b>0.52</b>
Nueces at Cotulla	PBIAS (%)	-6.3	34.66	-28.03	-27.68
	RSR	0.5	0.6	0.5	0.6
	NSE	0.763	0.632	0.784	0.646
	CPI Weighted	<b>0.76</b>	<b>0.57</b>	<b>0.66</b>	<b>0.60</b>
Nueces at Tilden	PBIAS (%)	-0.31	21.76	-20.22	-19.77
	RSR	0.5	0.7	0.7	0.6
	NSE	0.793	0.54	0.503	0.621
	CPI Weighted	<b>0.80</b>	<b>0.59</b>	<b>0.58</b>	<b>0.64</b>
Atascosa near Whitset	PBIAS (%)	-7.12	-9.95	-23.35	-32.74
	RSR	0.6	0.7	0.6	0.6
	NSE	0.684	0.517	0.586	0.598
	CPI Weighted	<b>0.71</b>	<b>0.64</b>	<b>0.61</b>	<b>0.57</b>

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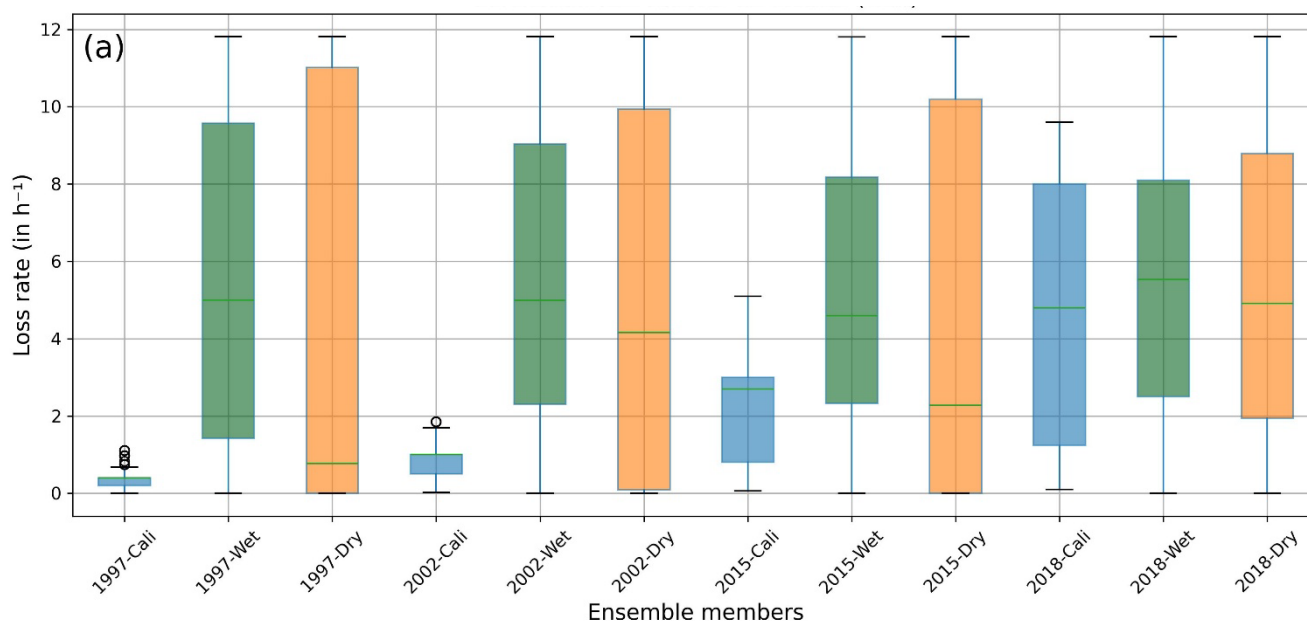
During calibration, a distinctive hydrologic feature of the Nueces river basin was observed in some river reaches, which is peak flows decrease sharply from upstream to downstream. Significant losses were observed between Asherton and Cotulla in the LCC model, and between the Frio–Derby and Frio–Tilden stations in the CCR model. This reduction occurs where streams transition from steep hill-country channels to wide, irrigated floodplains. The decline is also attributed to aquifer recharge, irrigation withdrawals, and floodplain attenuation. Several major aquifers within the watershed divert surface water to

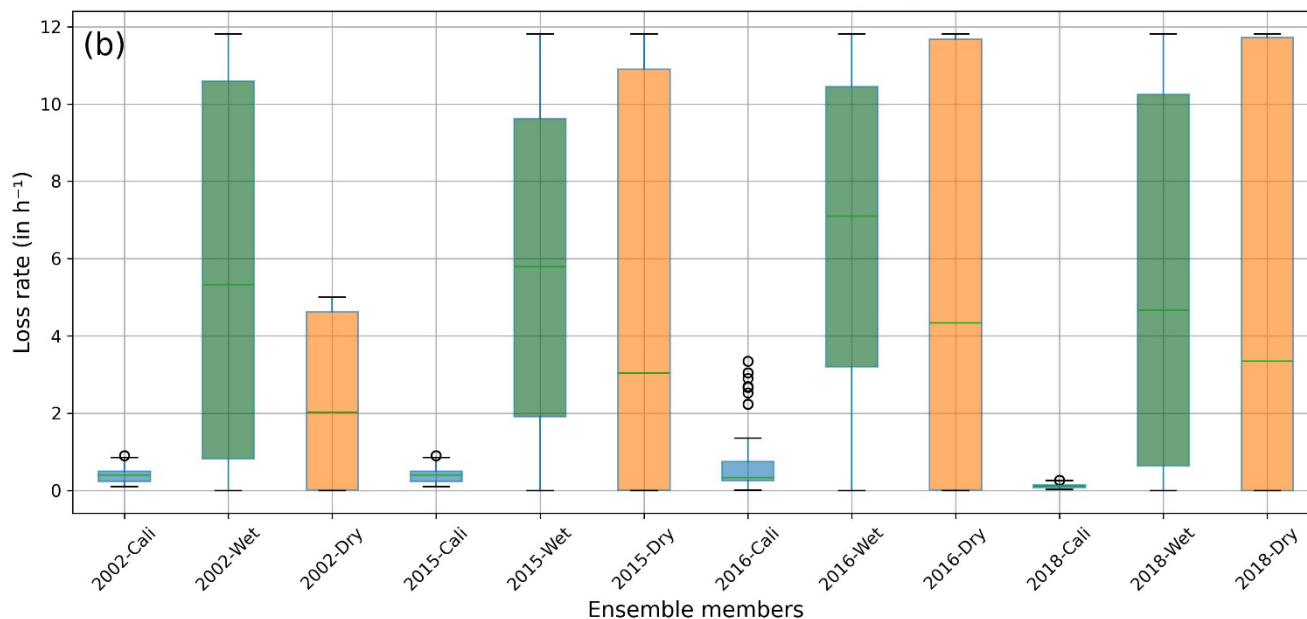
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groundwater. Portions of the Nueces river and its headwater tributaries recharge the Carrizo and Edwards aquifers within the Balcones Fault Zone, where water moves slowly downgradient before discharging through springs, seepage to streams, or groundwater withdrawals. To account for this, channel loss parameters along these losing reaches were calibrated, resulting in close agreement between modeled and observed downstream flows at stations like Asherton and Cotulla as shown in the calibration tables. Details of the river reach with channel loss, and the ground water aquifers are provided in Fig S3 of the supplement.

After rigorous calibration of the primary ensemble members, derived ensemble members were established through adjusting initial loss parameters and optimizing the constant and ground water parameters. These additional models are prepared considering a worst-case scenario beyond the selected diverse conditions of the catchment characteristics, the full list of ensemble members is given in Table S1 and S2. The parameterization technique used here has generated a range of results to increase the performance of the ensemble members which involved rigorous optimization simulations to ensure consistency and physical realism in the model response. Although smaller catchments and upstream subbasins exhibited limited variability under different initial conditions, larger basins demonstrated pronounced differences in hydrologic response. The box-and-whisker chart in Fig. 6 presents the optimized constant loss for the derived ensemble and primary models, showing values under wet and dry conditions. Finally, the established ensemble consisted of 12 individual models, i.e., four primary members and eight derived members are set up for forecast simulation.

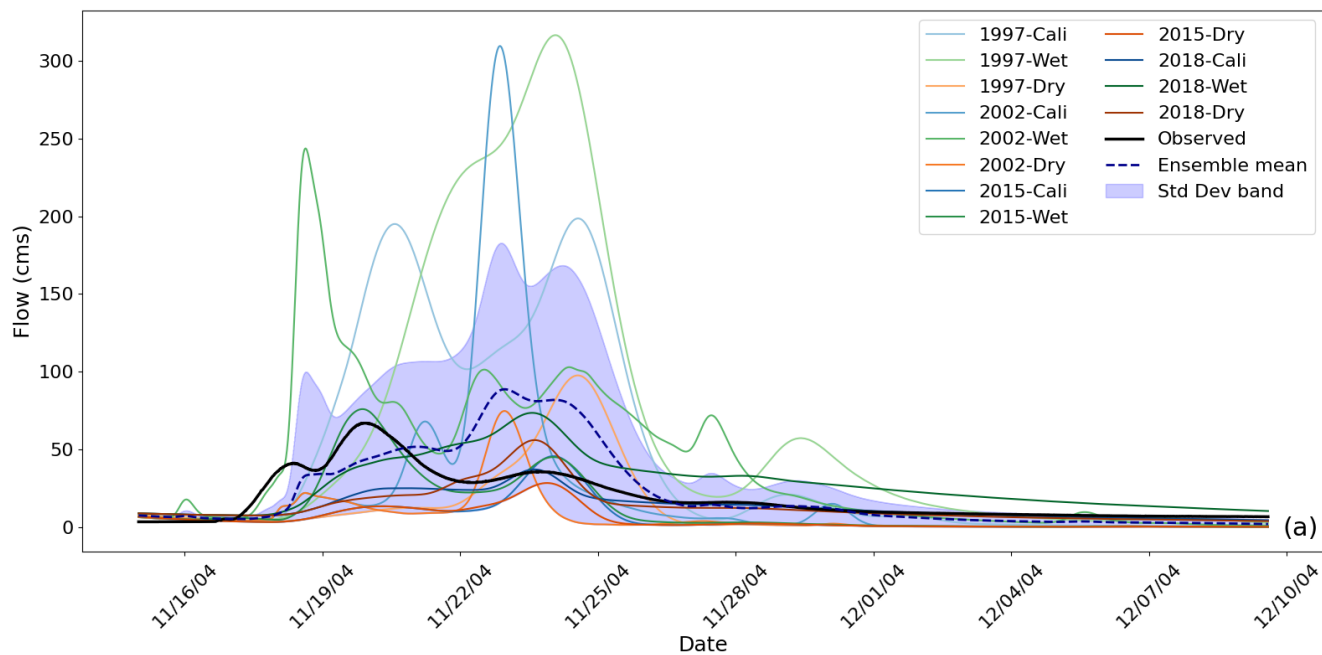




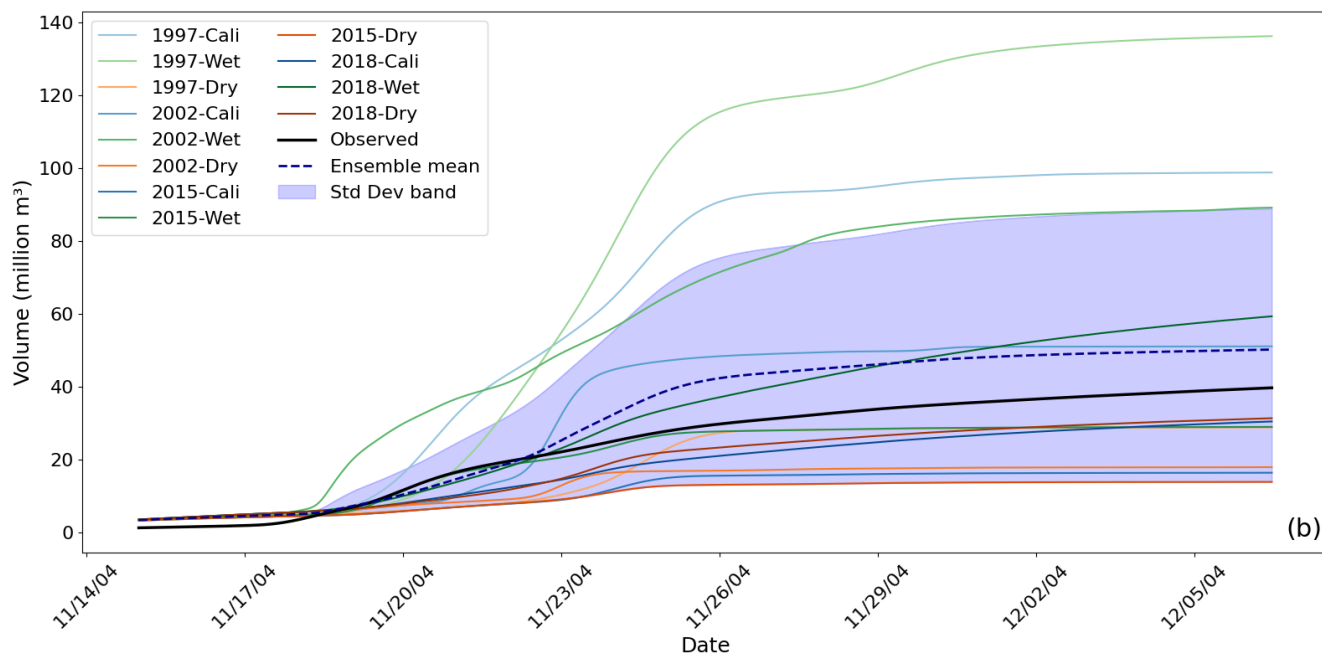
**Figure 6:** Box-and-whisker plots illustrating the distribution of optimized model parameters for the derived models, based on initial event conditions from the primary ensemble models. The plots summarize the median, interquartile range, and variability of the calibrated parameters, highlighting differences in parameter behaviour across event conditions. (a) Constant loss rate for 12 models Choke Canyon Reservoir and (b) constant loss rate for 12 models Lake Corpus Christi

### 3.4 Physical ensemble model validation

The full range model ensemble mean was validated using an independent historical storm event. Statistical calculation of CPI between the ensemble means and the observed inflow volume shows acceptable ranges. Fig 7 & Fig 8 presents the inflow volume graph for the validation simulation for the two reservoirs. It is noted that high peak values were observed at the wet scenario initial condition models in both models. While the dry condition models tend to forecast dry streamflow patterns for the same validation event. The higher and lower values under wet and dry scenarios provide a broader range of the simulation patterns as seen from the time series and the volume hydrographs. The total volume ensemble means for both stations demonstrated strong agreement with the observed inflow volume for the 2004 validation period. The statistical evaluation at the Frio near Tilden station achieved good performance for CCR reservoir, with a CPI index of 0.82. The LCC at the Nueces at Tilden station yields a CPI value of 0.56. The shaded band represents standard deviation range from the mean value, providing an estimate of model uncertainty prior to post-processing.

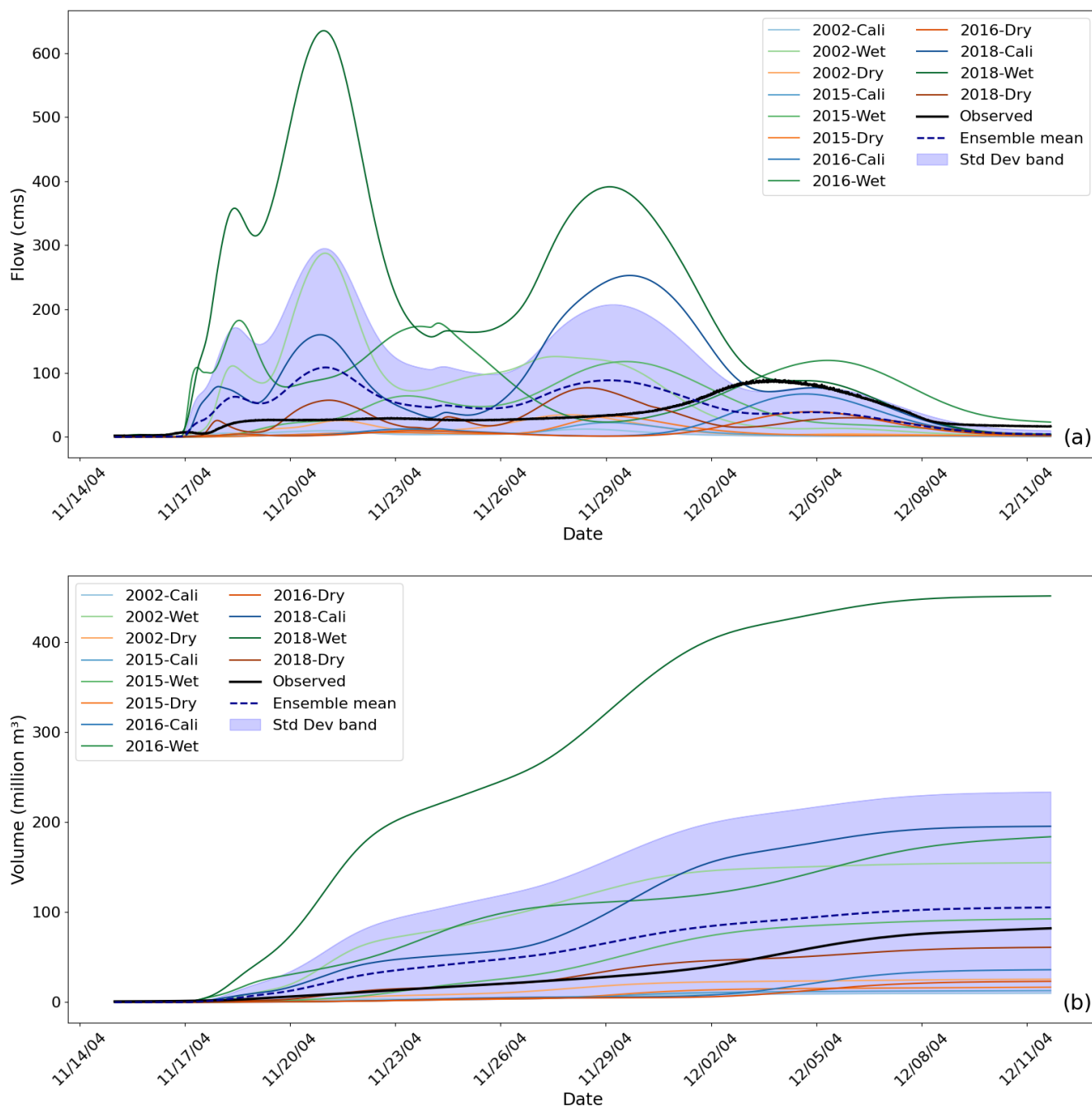


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**Figure 7:** Validation of the CCR ensemble results for the 2004 event: a) time series hydrograph; b) total volume of inflow into the CCR.

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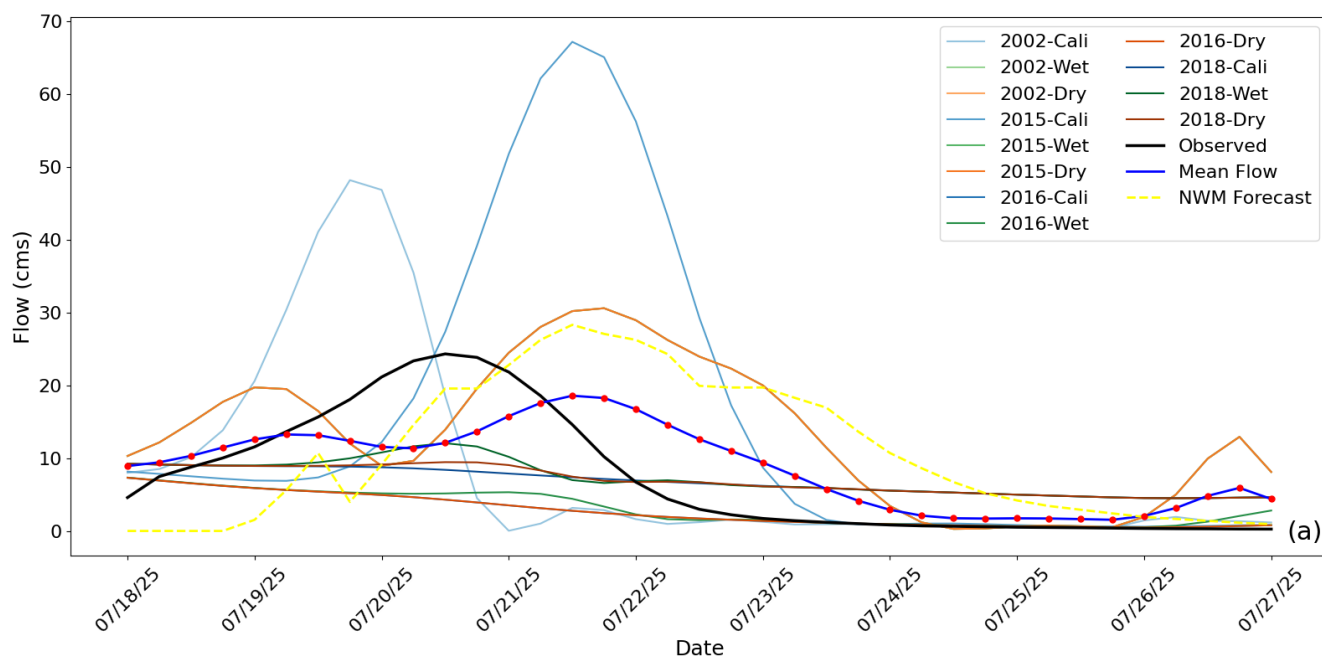


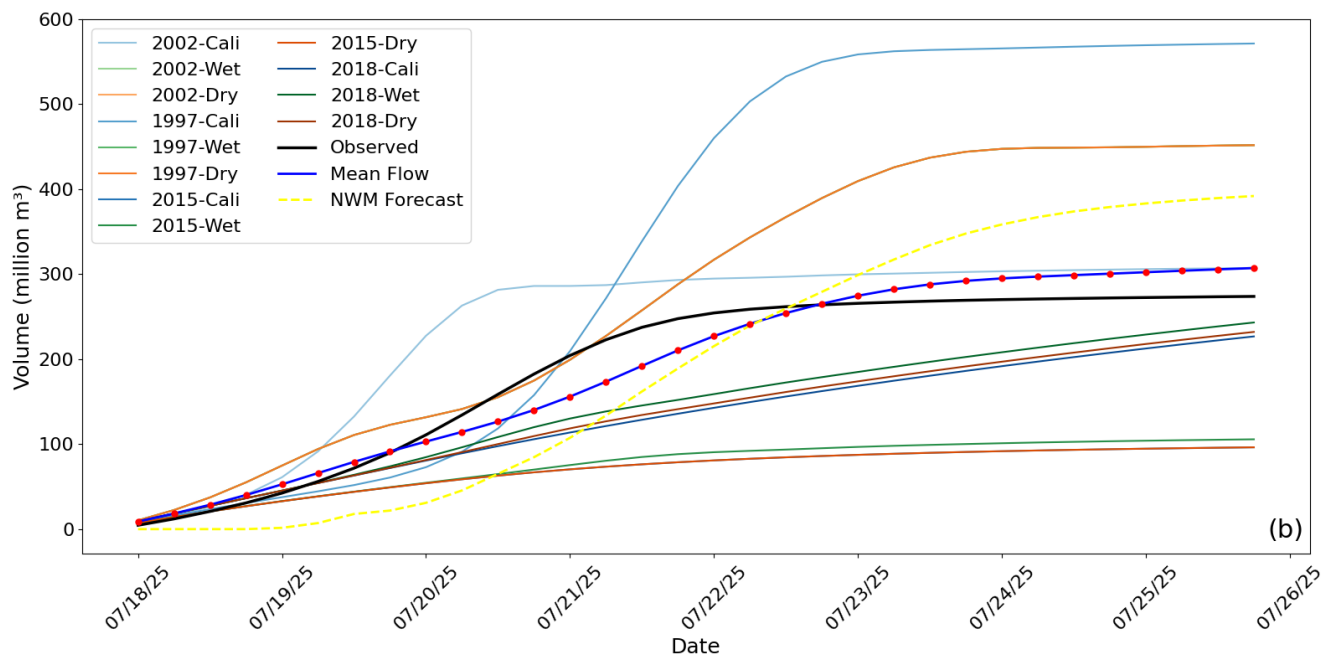
**Figure 8:** Validation of the LCC ensemble for the 2004 event: a) time series ensemble simulation for the event; b) total volume of flow.



### 3.5 Forecast simulation and post-processing

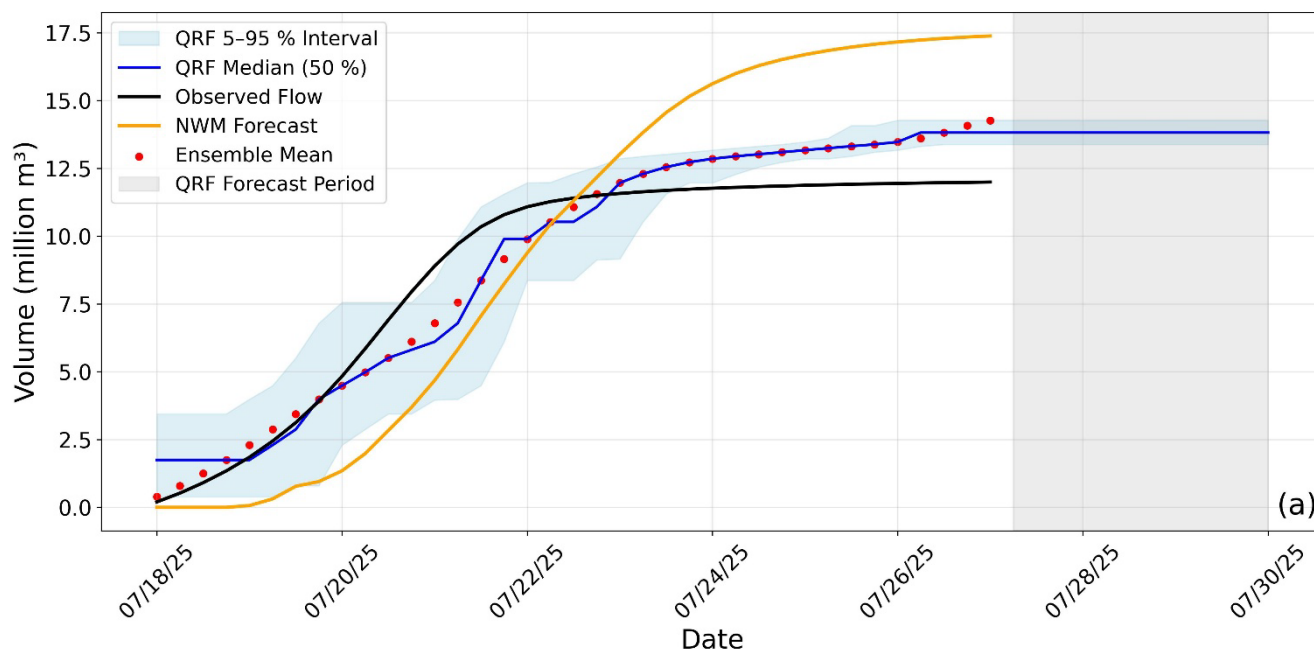
Following calibration and validation, the ensemble models were simulated using medium-range weather forecasts. The events in summer 2025, for CCR at Frio near Tilden station are presented between 18-27 July, with a total of 10 days (3 days hindcast and 7-days forecast) for capturing the full scale of inflow hydrograph based on the catchment characteristics. This events have contributed significant volume of water in the CCR reservoirs. The flow forecast results are presented in comparison with gauged data and streamflow forecast from the National Water Model (NWM). The hydrograph for CCR inflow at Frio station produced a CPI of 0.59 with the observed flow data Fig. 9. The time series graph on Fig 9b show an earlier peak in the observed data, whereas both this model and the NWM forecast a delayed peak. These differences in flow timing are particularly important for flood modeling and peak discharge identification, and forecasts can be further adjusted to better capture the timing of hydrograph peaks. Overall, the total inflow volume (Figure 9b) shows good agreement with observations, indicating that the current model provides a reliable estimate of reservoir inflow.



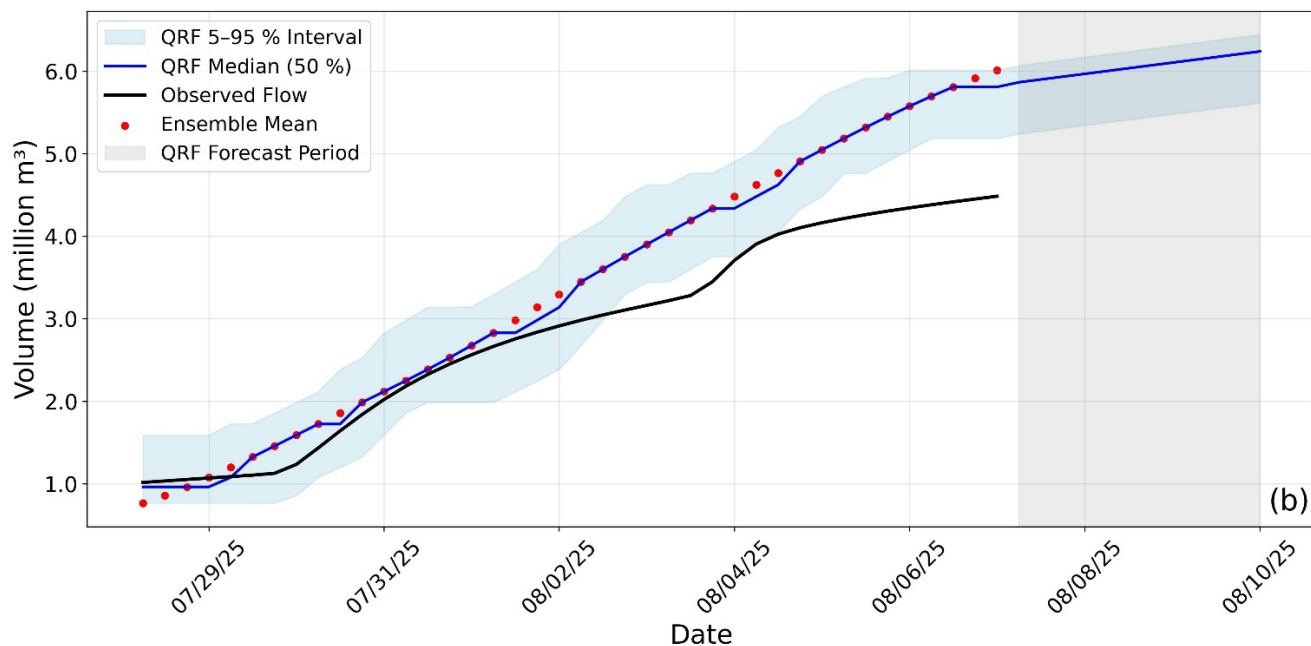


405 **Figure 9:** Validation of the CCR ensemble for a recent event in 2025: (a) time series flow; (b) total volume of flow.

Post-processing consisted of encompassing the ensemble mean simulation were performed to represent forecast uncertainty using a probabilistic regression forest framework. The Quantile Regression Forest (QRF) ensemble approach generated a 5–95% probabilistic flow envelope, effectively characterizing uncertainty in the forecasted watershed response as shown in Fig 10. This approach provides a balanced trade-off between uncertainty representation and forecasts reliability, supporting  
 410 informed operational decision-making. Figure 10a presents the ensemble forecasts after post-processing for CCR in comparison to the observation and NWM forecasts. The simulated forecast result achieved a CPI value of 0.87 at Frio–Tilden station whereas the NWM produced a CPI of 0.53 compared to the gauged flow, indicating that the proposed model performs substantially better and exhibits lower overestimation compared to the NWM forecast.



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**Figure 10:** Ensemble forecasts after post-processing for July 2025 Event: (a) CCR inflow at Frio nr Tilden; (b) LCC inflow at the Three river station.



Figure 10b presents the LCC model result on the Nueces river at Three River gauging station for the same summer 2025  
420 rainfall event, 10 days between July 29 and August 7, 2025. The result achieved a CPI value of 0.77. The generated flow  
volume from the current ensemble model shows a strong agreement with the observed total inflow, indicating good  
representation of cumulative flow dynamics. Forecast data from the NWM were not available for this station and therefore are  
not included in the comparison. It is noted that the NWM does not consistently provide medium range forecast hydrographs  
for all streams, as availability depends on several factors, including the hydrologic significance of the event, such as flood risk.  
425 This study local model also provides flow forecast in small streams flowing into reservoirs. In addition, the forecast lead time  
in this study extended by three days using a linear regression-based extrapolation, thereby enhancing forecast usability in the  
two reservoirs. This extension is supported by previously observed flow trends within the forecast window and is consistent  
with the basins maximum time of concentration. The three-day extension demonstrated reliability in regression-based  
extrapolation potentially inform operational reservoir management. The overall performance of the established dual-phase  
430 ensemble modeling framework highlights the robustness of the methods and their operational implementation.

#### 4 Discussions

A dual phase ensemble streamflow forecast developed in this study systematically combines independent ensemble techniques  
for high accuracy forecasting. Adequate ensemble members were selected through rigorous event selection which enabled a  
precise method to substitute probabilistic methods. Chieng et al. (2017) demonstrated that the ensemble size is not sensitive to  
435 the type of hydrological model in terms of streamflow modeling and the more ensemble members does not necessarily increase  
the performance of the forecast. Moreover, previous studies employed multiple model ensemble simulations approach to  
enhances ensemble reliability; however, multi-model ensembles also introduce an additional layer of uncertainty stemming  
from the inherent, and often unpredictable, differences among hydrological models (Duan et al., 2007; Goswami & O'Connor,  
2007; Sharma et al., 2019; Tang et al., 2023). The result of this study demonstrates that a relatively small number of ensemble  
440 members can produce robust and reliable forecasting performance. It is also noted that using a consistent model parameter  
approach in a high-resolution distributed model improved flow forecast accuracy.

The second phase, statistical ensemble post-processing steps alleviates possible limitations related to specific attributes in  
calibrating the hydrological model parametric assumptions about the probability distribution of inputs. While several quantile  
based approaches exist Quantile Regression Forests (QRF) approach outperforms other quantile-based models, such as quantile  
445 regression and quantile neural networks (Tyrallis et al., 2019). This approach is particularly effective when the number of  
ensemble members is limited, as it does not rely on a large ensemble size to represent uncertainty. The QRF directly estimate  
conditional quantiles of streamflow, allowing robust and well-calibrated probabilistic ranges to be constructed even from  
sparse or under-dispersed ensembles. As a result, quantile based post processing improves uncertainty characterization and  
enhances the reliability of probabilistic forecast when ensemble generation is computationally constrained or operationally  
450 simplified (Tyrallis et al., 2019; Zhang et al., 2023). Moreover, regression-based forecast extension enhances flexibility by



accounting for catchment characteristics and prevailing hydrometeorological conditions, providing indicative lead time extension. The nonparametric post processing techniques used in this study significantly improved forecast reliability and sharpen the ensemble spread. The approach emphasizes that the dual phase ensemble framework can deliver efficient, flexible and reliable forecasting outcomes, which is critical for supporting decision makers in reservoirs operation and planning.

455 The methodology developed in this study aimed at supporting Forecast Informed Reservoir Operation (FIRO), particularly in semi-arid regions. The Nueces River Basin is one of the regions affected by water scarcity, and its two major reservoirs, Choke Canyon Reservoir (CCR) and Lake Corpus Christi (LCC), have struggled to meet the basin's water supply demand. Although FIRO seems to be effective for flood risk management (FRM), it can also be used to increase reservoir storage capacities (Jasperse et al., 2020). In addition, the National Inventory of Dams (NID) reports that the Nueces river basin contains more  
460 than 400 dams, the majority of which are natural resources conservation structures, irrigation dams, or other small-scale dams (NID, 2025). Although these small dams are upstream and detailed information on water demand and losses from these reservoirs are essential for effective operational planning, the detailed flow model generated in each catchment along the river network provides valuable insights for assessing water demand and extraction in storage structures at both upstream and downstream segments of the Nueces river. Subsequently, the inflow forecast at the CCR and LCC provides essential inputs  
465 for cascaded operation of the two major reservoirs, including strategies for releasing water to the downstream while accounting for long-term demand and loss patterns.

## 5 Conclusions

This study presents a standalone inflow model that has demonstrated high efficiency on stream flow forecasting with medium range weather forecast. The study focused on leveraging hydro-meteorological forecasts to provide reliable information for  
470 reservoir operations decision making. The dual phase ensemble models provide a practical tool for managing streamflow forecasting more effectively. The results of the study present demonstrated a better agreement with the observation data in recent inflow events. Also, a comparative analysis of instant forecast with the National Water Model (NWM) official forecast shows a better performance the developed modelling framework. Therefore, the methodology developed in this study allows for more flexible and dynamic reservoir management using the principles of Forecast Informed Reservoir Opera (FIRO). The  
475 key conclusions of the study are outlined below.

- Precise selection of well-defined historical inflow events provides suitable flow regimes and catchment characteristics offering an effective alternative to probabilistic forecasting approach.
- Integration of primary ensemble members with maximum and minimum derived members effectively represent the flow conditions, demonstrating strong performance even with a relatively small number of members.
- 480 • Ensemble modelling framework enables the generation of accurate simulations across a wide range of initial conditions and precipitation patterns in regulated hydrological system., making it a reliable source for reservoirs inflow forecasting.



- Dual phase ensemble approach provided enhanced results to expand and refine the forecast range, further strengthening the reliability and robustness of ensemble forecast frameworks.

485 The future direction of this study is to develop an integrated water-availability system that explicitly incorporates reservoir dynamics and climate-driven forecast inputs. Integrating reservoir-simulation components, supported by rule-based water allocation models, will further enhance the reservoirs system's ability to evaluate storage, release decisions, and downstream water supply impacts. Such a coupled hydrology–reservoir modeling approach will ultimately support operational water management and strengthen planning for variable climate and hydrologic conditions. This work is designed to deliver reliable  
490 streamflow forecasts, ultimately supporting improved water storage management and informed operational water resource planning in the Nueces river basin and water scarce basins globally.

#### **Author contributions**

MGT and HZ designed the study. MGT developed the model, performed the simulations, analysed results, and prepared the original draft. SD participated in data processing and visualization. All authors contributed to the review and editing of the  
495 manuscript. HZ acquired the funding and supervised the project.

#### **Competing interests**

The authors declare that they have no conflict of interest.

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## 505 References

- Ajami, N. K., Gupta, H., Wagener, T., and Sorooshian, S.: Calibration of a semi-distributed hydrologic model for streamflow estimation along a river system, *Journal of Hydrology*, 298, 112–135, <https://doi.org/10.1016/j.jhydrol.2004.03.033>, 2004.
- Barnston, A. G., Mason, S. J., Goddard, L., DeWitt, D. G., and Zebiak, S. E.: Multimodel ensembling in seasonal climate forecasting at IRI, *Bulletin of the American Meteorological Society*, 84, 1783–1796, <https://doi.org/10.1175/BAMS-84-12-1783>, 2003.
- 510 Bennett, B., Leonard, M., Deng, Y., and Westra, S.: An empirical investigation into the effect of antecedent precipitation on flood volume, *Journal of Hydrology*, 567, 435–445, <https://doi.org/10.1016/j.jhydrol.2018.10.025>, 2018.
- Bogner, K. and Kalas, M.: Error-correction methods and evaluation of an ensemble-based hydrological forecasting system for the Upper Danube catchment, *Atmospheric Science Letters*, 9, 95–102, <https://doi.org/10.1002/asl.180>, 2008.
- 515 Chiang, Y.-M., Hao, R.-N., Ho, H.-C., Chang, T.-J., and Xu, Y.-P.: Evaluating the contribution of multi-model combination to streamflow hindcasting by empirical and conceptual models, *Hydrological Sciences Journal*, 62, 1456–1468, <https://doi.org/10.1080/02626667.2017.1330543>, 2017.
- Clark, M. P., Nijssen, B., Lundquist, J. D., Kavetski, D., Rupp, D. E., Woods, R. A., Freer, J. E., Gutmann, E. D., Wood, A. W., Brekke, L. D., Arnold, J. R., Gochis, D. J., and Rasmussen, R. M.: A unified approach for process-based hydrologic modeling: 1. Modeling concept, *Water Resources Research*, 51, 2498–2514, <https://doi.org/10.1002/2015WR017198>, 2015.
- 520 Corpus Christi: Drought contingency plan, <https://www.corpuschristitx.gov/media/rovbmnx5/wat-drought-contingency-plan.pdf>, 2025.
- DeChant, C. M. and Moradkhani, H.: Improving the characterization of initial condition for ensemble streamflow prediction using data assimilation, *Hydrology and Earth System Sciences*, 15, 3399–3410, <https://doi.org/10.5194/hess-15-3399-2011>, 2011.
- 525 Delaney, C. J., Hartman, R. K., Mendoza, J., Dettinger, M., Delle Monache, L., Jasperse, J., Ralph, F. M., Talbot, C., Brown, J., Reynolds, D., and Evett, S.: Forecast-informed reservoir operations using ensemble streamflow predictions for a



- 530 multipurpose reservoir in northern California, *Water Resources Research*, 56, e2019WR026604, <https://doi.org/10.1029/2019WR026604>, 2020.
- Demargne, J., Wu, L., Regonda, S. K., Brown, J. D., Lee, H., He, M., Seo, D.-J., Hartman, R., Herr, H. D., Fresch, M., Schaake, J., and Zhu, Y.: The science of NOAA's operational hydrologic ensemble forecast service, *Bulletin of the American Meteorological Society*, 95, 79–96, <https://doi.org/10.1175/BAMS-D-12-00081.1>, 2014.
- 535 Demirel, M. C., Booij, M. J., and Hoekstra, A. Y.: The skill of seasonal ensemble low-flow forecasts in the Moselle River for three different hydrological models, *Hydrology and Earth System Sciences*, 19, 275–291, <https://doi.org/10.5194/hess-19-275-2015>, 2015.
- Du, J.: NCEP/EMC 4 km gridded data (GRIB) Stage IV data, version 1.0, NSF NCAR Earth Observing Laboratory, <https://doi.org/10.5065/D6PG1QDD>, 2011.
- 540 Duan, Q., Ajami, N. K., Gao, X., and Sorooshian, S.: Multi-model ensemble hydrologic prediction using Bayesian model averaging, *Advances in Water Resources*, 30, 1371–1386, <https://doi.org/10.1016/j.advwatres.2006.11.014>, 2007.
- El Gharamti, M., Rafieeiniasab, A., and McCreight, J. L.: Leveraging a novel hybrid ensemble and optimal interpolation approach for enhanced streamflow and flood prediction, *Hydrology and Earth System Sciences*, 28, 3133–3159, <https://doi.org/10.5194/hess-28-3133-2024>, 2024.
- 545 Evin, G., Lafaysse, M., Taillardat, M., and Zamo, M.: Calibrated ensemble forecasts of the height of new snow using quantile regression forests and ensemble model output statistics, *Nonlinear Processes in Geophysics*, 28, 467–480, <https://doi.org/10.5194/npg-28-467-2021>, 2021.
- Faber, B. A. and Stedinger, J. R.: Reservoir optimization using sampling stochastic dynamic programming with ensemble streamflow prediction forecasts, *Journal of Hydrology*, 249, 113–133, [https://doi.org/10.1016/S0022-1694\(01\)00419-X](https://doi.org/10.1016/S0022-1694(01)00419-X), 2001.
- 550 Goswami, M. and O'Connor, K. M.: Real-time flow forecasting in the absence of quantitative precipitation forecasts: a multi-model approach, *Journal of Hydrology*, 334, 125–140, <https://doi.org/10.1016/j.jhydrol.2006.10.002>, 2007.



- Gupta, S. C., Kessler, A. C., Brown, M. K., and Zvomuya, F.: Climate and agricultural land use change impacts on streamflow in the upper midwestern United States, *Water Resources Research*, 51, 5301–5317, <https://doi.org/10.1002/2015WR017323>, 2015.
- Hagedorn, R., Doblas-Reyes, F. J., and Palmer, T. N.: The rationale behind the success of multi-model ensembles in seasonal forecasting – I. Basic concept, *Tellus A*, 57, 219–233, <https://doi.org/10.1111/j.1600-0870.2005.00103.x>, 2005.
- Hamel, P., Guswa, A., Sahl, J., and Zhang, L.: Predicting dry-season flows with a monthly rainfall–runoff model: performance for gauged and ungauged catchments, *Hydrological Processes*, 31, 3844–3858, 2017.
- Hopson, T. M., Wood, A., and Weerts, A. H.: Motivation and overview of hydrological ensemble post-processing, in: *Handbook of Hydrometeorological Ensemble Forecasting*, edited by: Duan, Q., Pappenberger, F., Wood, A., Cloke, H. L., and Schaake, J., Springer, Berlin, Heidelberg, 1–11, [https://doi.org/10.1007/978-3-642-40457-3\\_36-3](https://doi.org/10.1007/978-3-642-40457-3_36-3), 2019.
- InFRM: Interagency Flood Risk Management (InFRM), <https://webapps.usgs.gov/infrm/>, 2025.
- Jasperse, J., Ralph, F. M., Anderson, M., Brekke, L., Malasavage, N., Dettinger, M. D., Forbis, J., Fuller, J., Talbot, C., Webb, R., and Haynes, A.: Lake Mendocino forecast-informed reservoir operations final viability assessment, <https://escholarship.org/uc/item/3b63q04n>, 2020.
- Johnson, R. A.: quantile-forest: A Python package for quantile regression forests, *Journal of Open Source Software*, 9, 5976, <https://doi.org/10.21105/joss.05976>, 2024.
- Kharin, V. V. and Zwiers, F. W.: Climate predictions with multimodel ensembles, *Journal of Climate*, 15, 793–799, [https://journals.ametsoc.org/view/journals/clim/15/7/1520-0442\\_2002\\_015\\_0793\\_cpwme\\_2.0.co\\_2.xml](https://journals.ametsoc.org/view/journals/clim/15/7/1520-0442_2002_015_0793_cpwme_2.0.co_2.xml), 2002.
- Kibii, J. K., Kipkorir, E. C., and Kosgei, J. R.: Application of the soil and water assessment tool (SWAT) to evaluate the impact of land use and climate variability on the Kaptagat catchment river discharge, *Sustainability*, 13, 1802, <https://doi.org/10.3390/su13041802>, 2021.
- Kim, K.-H., Andreadis, K. M., and O’Loughlin, F.: Predicting annual peak daily streamflow in natural basins using quantile regression forests, *Journal of Hydrology*, 660, 133233, <https://doi.org/10.1016/j.jhydrol.2025.133233>, 2025.
- Leelaruban, N. and Padmanabhan, G.: Drought occurrences and their characteristics across selected spatial scales in the contiguous United States, *Geosciences*, 7, 59, <https://doi.org/10.3390/geosciences7030059>, 2017.



- Li, H., Huang, G., Li, Y., Sun, J., and Gao, P.: A C-vine copula-based quantile regression method for streamflow forecasting in the Xiangxi River Basin, China, *Sustainability*, 13, 4627, <https://doi.org/10.3390/su13094627>, 2021.
- 580 Lin, Y. and Mitchell, K. E.: The NCEP Stage II/IV hourly precipitation analyses: development and applications, <https://www.scirp.org/reference/referencespapers?referenceid=2051539>, 2005.
- Mazrooei, A., Sinha, T., Sankarasubramanian, A., Kumar, S., and Peters-Lidard, C. D.: Decomposition of sources of errors in seasonal streamflow forecasting over the U.S. Sunbelt, *Journal of Geophysical Research: Atmospheres*, 120, 11809–11825, <https://doi.org/10.1002/2015JD023687>, 2015.
- 585 Moges, E., Ruddell, B. L., Zhang, L., Driscoll, J. M., and Larsen, L.: Strength and memory of precipitation’s control over streamflow across the conterminous United States, *Water Resources Research*, 58, e2021WR030186, <https://doi.org/10.1029/2021WR030186>, 2022.
- NID: National Inventory of Dams, <https://nid.sec.usace.army.mil/>, 2025.
- NOAA: National Water Model, <https://water.noaa.gov/assets/styles/public/images/wrn-national-water-model.pdf>, 2025.
- 590 NOAA Climate Prediction Center: NOAA Climate Prediction Center, <https://www.cpc.ncep.noaa.gov/products/predictions/610day/>, 2025.
- Odey, G. and Cho, Y.: Event-based vs. continuous hydrological modeling with HEC-HMS: a review of use cases, methodologies, and performance metrics, *Hydrology*, 12, 39, <https://doi.org/10.3390/hydrology12020039>, 2025.
- Paiva, R. C. D., Collischonn, W., Bonnet, M. P., and de Gonçalves, L. G. G.: On the sources of hydrological prediction uncertainty in the Amazon, *Hydrology and Earth System Sciences*, 16, 3127–3137, <https://doi.org/10.5194/hess-16-3127-2012>, 2012.
- Primožič, M., Kobold, M., and Brilly, M.: The implementation of the HBV model on the Sava River Basin, *IOP Conference Series: Earth and Environmental Science*, 4, 012004, <https://doi.org/10.1088/1755-1307/4/1/012004>, 2008.
- Sahu, M. K., Shwetha, H. R., and Dwarakish, G. S.: State-of-the-art hydrological models and application of the HEC-HMS model: a review, *Modeling Earth Systems and Environment*, 9, 3029–3051, <https://doi.org/10.1007/s40808-023-01704-7>, 2023.
- 600



- Sharma, S., Siddique, R., Reed, S., Ahnert, P., and Mejia, A.: Hydrological model diversity enhances streamflow forecast skill at short- to medium-range timescales, *Water Resources Research*, 55, 1513–1529, <https://doi.org/10.1029/2018WR023197>, 2019.
- 605 Simeone, C. E., Hammond, J. C., Archfield, S. A., Broman, D., Condon, L. E., Eldardiry, H., Olson, C. G., and Steyaert, J. C.: Declining reservoir reliability and increasing reservoir vulnerability: long-term observations reveal longer and more severe periods of low reservoir storage for major United States reservoirs, *Geophysical Research Letters*, 51, e2024GL109476, <https://doi.org/10.1029/2024GL109476>, 2024.
- Simeral, D.: U.S. states and Puerto Rico | U.S. Drought Monitor, <https://droughtmonitor.unl.edu/CurrentMap/StateDroughtMonitor.aspx?total>, 2025.
- 610 Slater, L. J. and Villarini, G.: Evaluating the drivers of seasonal streamflow in the U.S. Midwest, *Water*, 9, 695, <https://doi.org/10.3390/w9090695>, 2017.
- Svoboda, M., LeComte, D., Hayes, M., Heim, R., Gleason, K., Angel, J., Rippey, B., Tinker, R., Palecki, M., Stooksbury, D., Miskus, D., and Stephens, S.: The drought monitor, *Bulletin of the American Meteorological Society*, 83, 1181–1190, <https://doi.org/10.1175/1520-0477-83.8.1181>, 2002.
- 615 Taillardat, M. and Mestre, O.: From research to applications – examples of operational ensemble post-processing in France using machine learning, *Nonlinear Processes in Geophysics*, 27, 329–347, <https://doi.org/10.5194/npg-27-329-2020>, 2020.
- Tang, G., Clark, M. P., Knoben, W. J. M., Liu, H., Gharari, S., Arnal, L., Beck, H. E., Wood, A. W., Newman, A. J., and Papalexiou, S. M.: The impact of meteorological forcing uncertainty on hydrological modeling: a global analysis of cryosphere basins, *Water Resources Research*, 59, e2022WR033767, <https://doi.org/10.1029/2022WR033767>, 2023.
- 620 Taylor, W., Brodeur, Z. P., Steinschneider, S., Kucharski, J., and Herman, J. D.: Variability, attributes, and drivers of optimal forecast-informed reservoir operating policies for water supply and flood control in California, *Journal of Water Resources Planning and Management*, 150, 05024010, <https://doi.org/10.1061/JWRMD5.WRENG-6471>, 2024.
- 625 exas Water Development Board (TWDB): *Texas Water Condition Report, March 2025*, [https://www.twdb.texas.gov/publications/reports/waterconditions/twc\\_pdf\\_archives/2025/TWCMar2025.pdf](https://www.twdb.texas.gov/publications/reports/waterconditions/twc_pdf_archives/2025/TWCMar2025.pdf), 2025.



- Thornton, J. A., Harding, W. R., Slawski, T. M., and Lin, H.: Monitoring and evaluation: the foundation for lake and reservoir management, *Earth*, **3**, 115–124, <https://doi.org/10.3390/earth3010008>, 2022.
- 630 Todini, E.: A model conditional processor to assess predictive uncertainty in flood forecasting, *International Journal of River Basin Management*, **6**, 123–137, <https://doi.org/10.1080/15715124.2008.9635342>, 2008.
- Texas Water Development Board (TWDB): River basins—Nueces River Basin, [https://www.twdb.texas.gov/surfacewater/rivers/river\\_basins/nueces/index.asp](https://www.twdb.texas.gov/surfacewater/rivers/river_basins/nueces/index.asp), 2024.
- Tyralis, H. and Papacharalampous, G.: Hydrological post-processing for predicting extreme quantiles, *Journal of Hydrology*, **617**, 129082, <https://doi.org/10.1016/j.jhydrol.2023.129082>, 2023.
- 635 Tyralis, H., Papacharalampous, G., Burnetas, A., and Langousis, A.: Hydrological post-processing using stacked generalization of quantile regression algorithms: large-scale application over CONUS, *Journal of Hydrology*, **577**, 123957, <https://doi.org/10.1016/j.jhydrol.2019.123957>, 2019.
- Tyralis, H. and Papacharalampous, G.: Quantile-based hydrological modelling, *Water*, **13**, 3420, <https://doi.org/10.3390/w13233420>, 2021.
- 640 U.S. Geological Survey (USGS): USGS water data for the nation, <https://waterdata.usgs.gov/nwis>, 2025.
- Weerts, A. H., Winsemius, H. C., and Verkade, J. S.: Estimation of predictive hydrological uncertainty using quantile regression: examples from the National Flood Forecasting System (England and Wales), *Hydrology and Earth System Sciences*, **15**, 255–265, <https://doi.org/10.5194/hess-15-255-2011>, 2011.
- Zhang, Y., Ye, A., Analui, B., Nguyen, P., Sorooshian, S., Hsu, K., and Wang, Y.: Comparing quantile regression forest and mixture density long short-term memory models for probabilistic post-processing of satellite precipitation-driven streamflow simulations, *Hydrology and Earth System Sciences*, **27**, 4529–4550, <https://doi.org/10.5194/hess-27-4529-2023>, 2023.