# Interactive Visualization of Ensemble Data Assimilation Forecasts for Freshwater Floods


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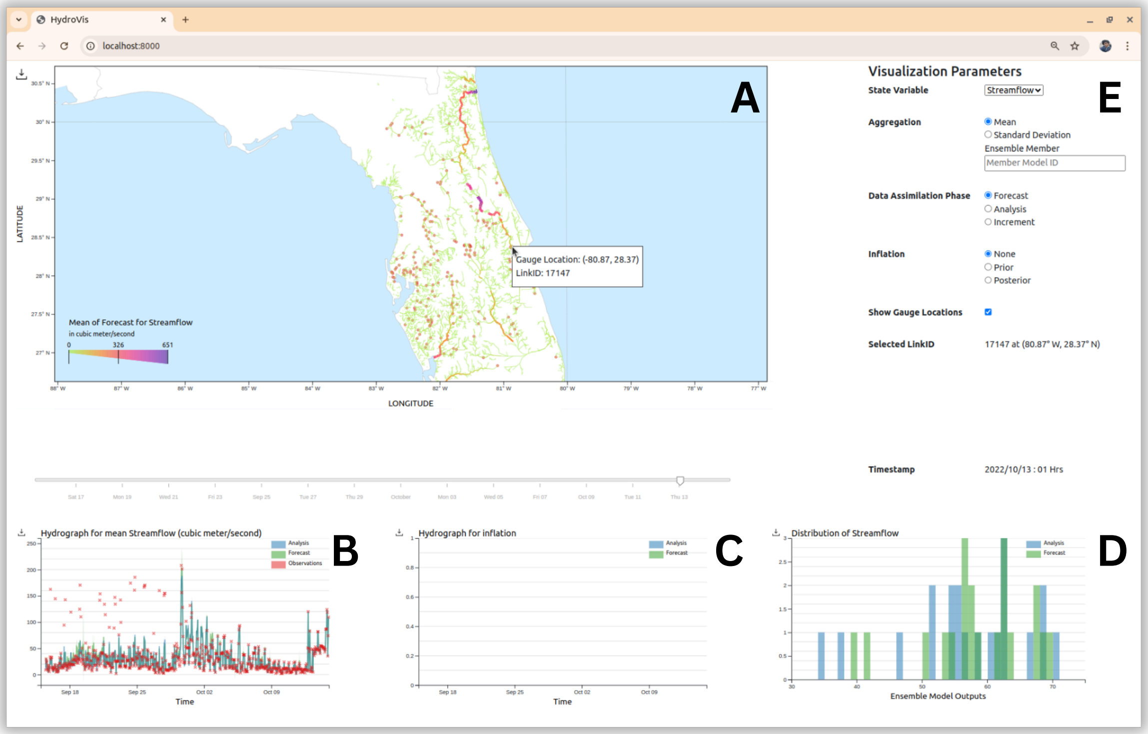


Figure 1: Snapshot of the HydroVis dashboard visualizing the forecast for Streamflow i.e., amount of water flowing per unit time, and corresponding uncertainties, in the river system of Florida during hurricane Ian, Sept-Oct 2022


## Abstract

Freshwater floods during hurricanes are known to cause significant damage to life and property. We could be better prepared to prevent these losses if flood forecasts can be made accurately and understood effectively. In addition to the technical complexities when modeling freshwater systems, forecasting freshwater floods also involves numerous uncertainties which also need to be considered to make reliable data driven decisions. In this demo, we describe the design and implementation of HydroVis–a decision support system designed to help both weather scientists to triage the flood forecasting models, and the policymakers to help them understand the forecasts effectively and make informed decisions accordingly.



**Index Terms:** Interactive dashboard, decision support system, data assimilation, wrf-hydro, hydrology forecasting.



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## 1 Introduction

Forecasts for weather events play a significant role in planning daily activities both at the personal and the community level. One such weather event is freshwater flooding due to hurricanes, which have the potential to disrupt infrastructure and damage lives [3].

Forecasting weather events is difficult because of our limitations in comprehensively modeling Earth system variables like wind speed, precipitation and temperature. This, coupled with the internal biases and approximation errors of the forecasting models, means that there are significant uncertainties associated with weather forecasts.

In this demo, we present HydroVis – a decision support system to understand freshwater flood forecasts, along with the associated uncertainties. We designed HydroVis to serve both the weather scientists, to help them triage the performance of weather models, and the policy makers, to help them understand the forecasts with the associated uncertainties and make informed decisions accordingly.

The contribution of this demo is not the actual modeling of freshwater floods, but providing an easy interface to access, understand and communicate that information. HydroVis was prototyped at the National Center for Atmospheric Research (NCAR) where the WRF-Hydro model [1] is used along with the Data Assimilation Research Testbed (DART) [2] for flood forecasting.

## 2 BACKGROUND

We briefly cover some background details required to understand the forecasting process and the design of HydroVis.

**Chaotic Systems** are governed by deterministic laws of physics, but are difficult to model because of their highly sensitive nature towards minor variations in the initialization values of the model. The Earth weather system is one example. Even small differences in the initialization of the model, along with the internal biases of the model, can build up over time and result in estimates which are significantly different from the real-life observed state of the system.

**Ensemble Forecasts** are one way of handling chaotic systems. The idea is to use multiple models instead of a single model, to estimate the next state of the system. Each model in the ensemble is initialized differently to account for the chaotic nature of the system. If all the ensemble models reach the same state at a future time step, we can be more certain of the estimate, otherwise, we get a range of possible next states of the system, along with the corresponding uncertainties.

**Data Assimilation (DA)** combines multiple sources of information of a system, with a model of the system, to course correct the model, and improve the accuracy of the model estimates. In the context of predicting freshwater floods, we combine ensemble model *forecasts* of the water flow or water level in river systems, with corresponding real-life *observations*, to get refined forecasts known as *analysis*.

**Sources of uncertainty** In the ensemble data assimilation process, there are 4 sources of uncertainty.

- *Initial state uncertainty* because of the different initialization values for each ensemble model to account for the chaotic nature of the system,
- *Model prediction uncertainty* due to the inherent biases/errors of the model,
- *Observation uncertainty* due to the errors in the measuring instrument used to record real-life observations, and
- *Inflation uncertainty* or spread applied artificially to the variable being estimated. It helps mitigate the tendency of ensembles to underestimate uncertainty, particularly in the presence of model and sampling errors. Without the use of inflation, there is a risk of the ensemble collapsing to a single member, effectively rendering the ensemble DA process ineffective.

We extend prior work on decision support systems implemented for understanding oceanic system forecasts [4, 5], and implement it in the domain of freshwater floods.

## 3 DESIGN & IMPLEMENTATION

HydroVis [1] is designed as a web app using Python-Flask framework for the web server, and D3.js for the front-end. Figure 1 and Figure 2 show snapshots of the dashboard. It has the following 4 interactive visualizations:

**A** The map visualization shows the geographical context and has options to visualize the *streamflow* i.e., the amount of water flowing per unit time, or the *bucket* value i.e., the water level in the river system, along with the observation gauge locations (red circles). This visualization can also be configured to show the *Model prediction uncertainty*.

[1] Walkthrough video: https://youtu.be/hqkGGSkeyeI

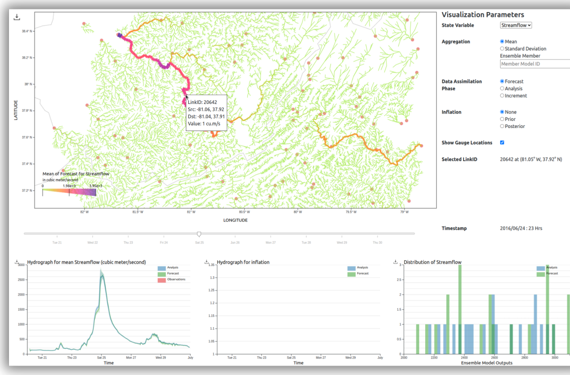


Figure 2: Snapshot of the HydroVis dashboard visualizing the forecast for Streamflow i.e., amount of water flowing per unit time, and corresponding uncertainties, in the river system of West Virginia, during the flash floods in June 2016

**B** A line chart or *hydrograph* which shows the *forecast*, *observation* and *analysis* values over time, with the corresponding uncertainties except for observation uncertainty. This chart conveys the *Model prediction uncertainty* through error bands encoding the standard deviation.

**C** A line chart or *hydrograph* which shows the inflation amount applied to both the *forecast* and *analysis* values. This plot specifically conveys the *Inflation uncertainty*.

**D** Histogram showing the distribution of *forecast* and *analysis* values of the individual models in the ensemble. This plot shows how much individual models have/have not drifted away from each other and thus convey both the *Model prediction uncertainty* and the *Initial state uncertainty* propagated over time. It also conveys the difference between the *forecast* and *analysis* value distributions thus helping users evaluate the efficacy of the data assimilation process.

The visualization controls (**E**) allow users to visualize different variables (*streamflow* or *bucket*), with different aggregations (mean, standard deviation or individual model estimates), different data assimilation phases (*forecast*, *analysis* or the difference between them i.e., *increment*), and the inflation applied to them. Observation gauge locations can also be visualized using a toggle switch, and the time slider can be used to investigate the forecasts at any timestamp of choice. All the visualizations in the dashboard are cross-linked, and the map visualization supports direct manipulation to select and investigate in detail, any river segment of choice.

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