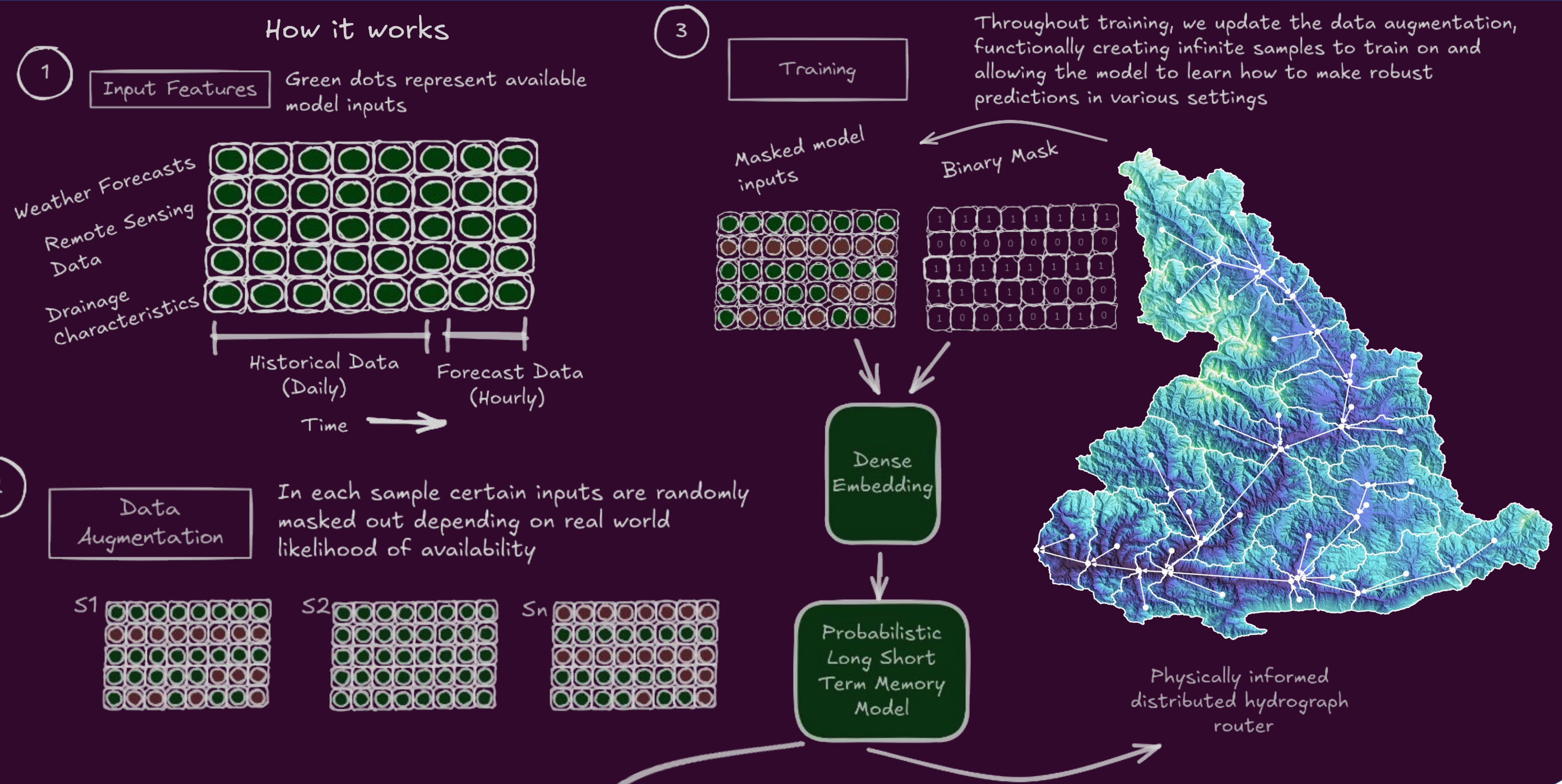


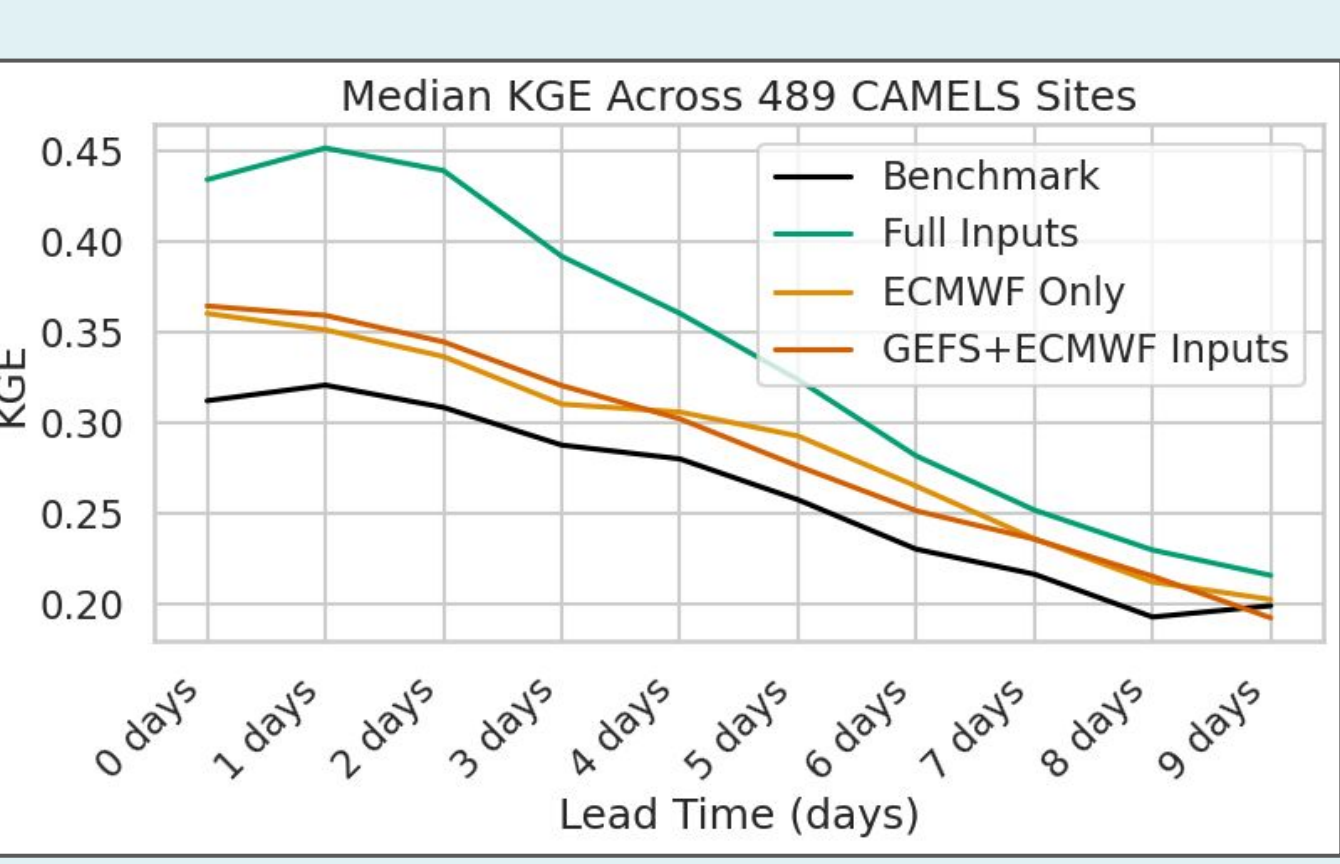
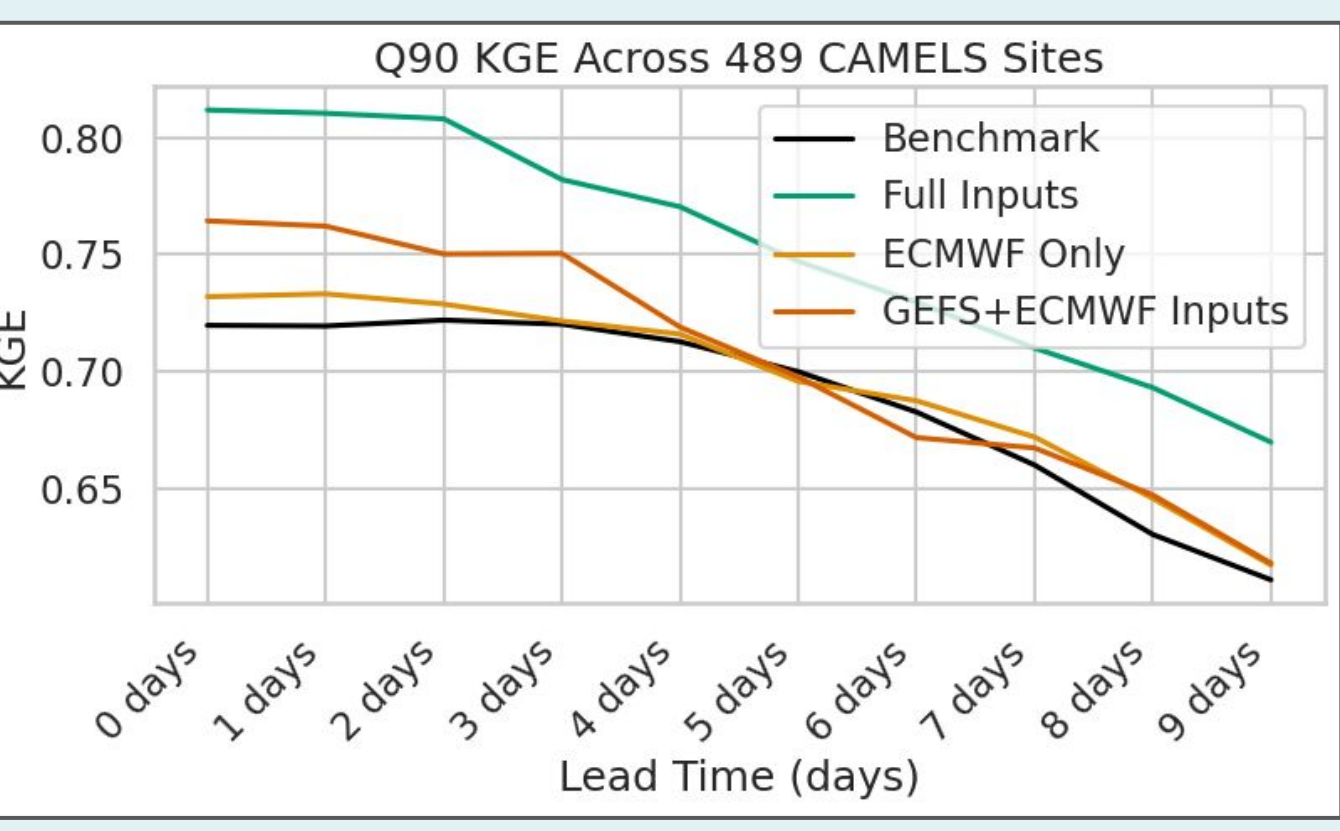
Data augmentation creates state-of-the-art hydrological forecasts using theory informed deep learning



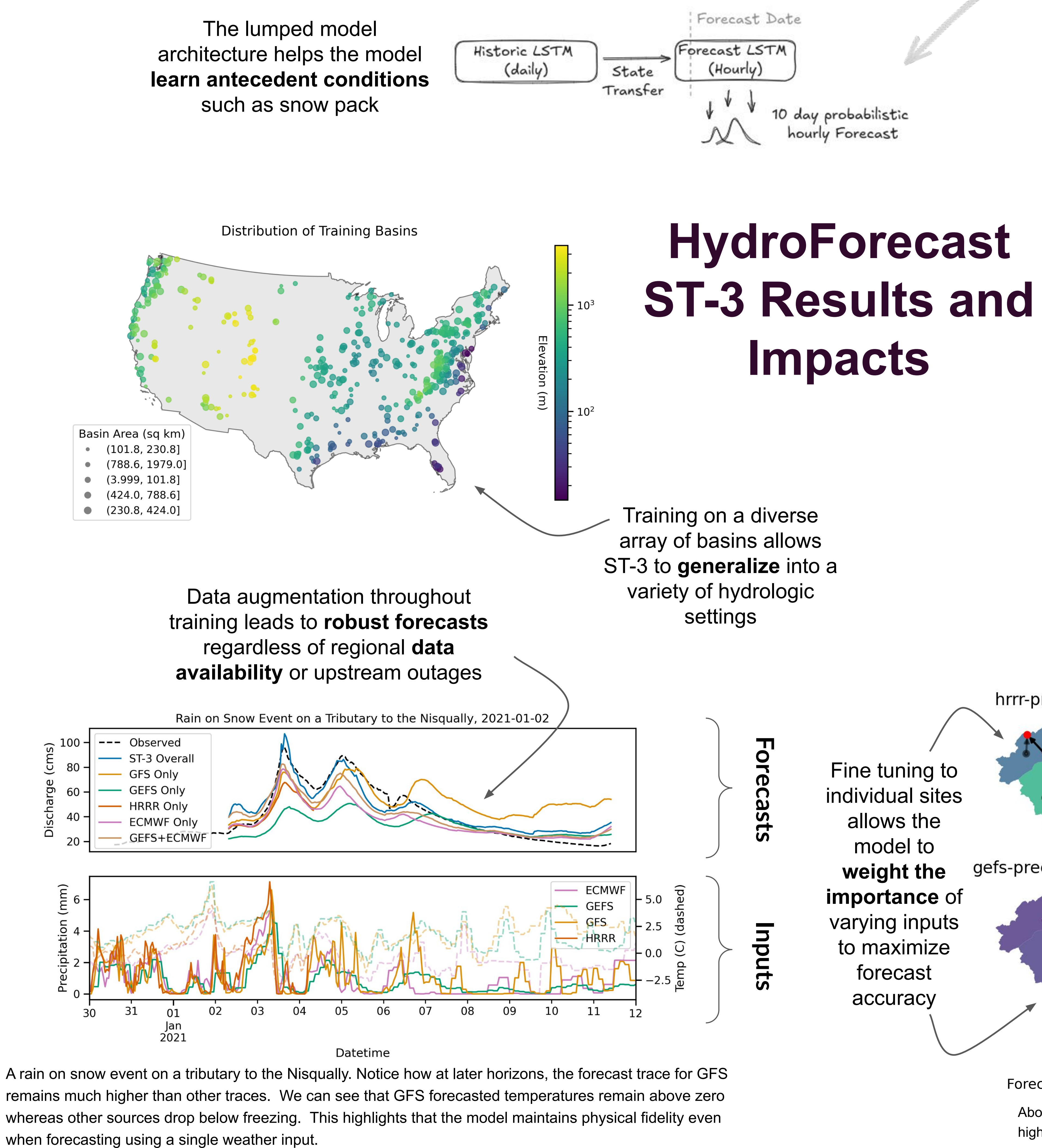
Background

Making **accurate, operational streamflow forecasts** is essential for effectively managing water resources. However, common input weather forecasts occur at varying resolutions and are subject to data outages from their providers. This work combines a **novel LSTM architecture** with a training routine focused on **data augmentation**. The result is **HydroForecast Short-Term 3 (ST-3)** a robust, flexible model that can learn from **mixed frequency data sources**, **maintain performance** in the event of an upstream data outage, and leverage **regional data** to make state-of-the-art streamflow forecasts

Validation

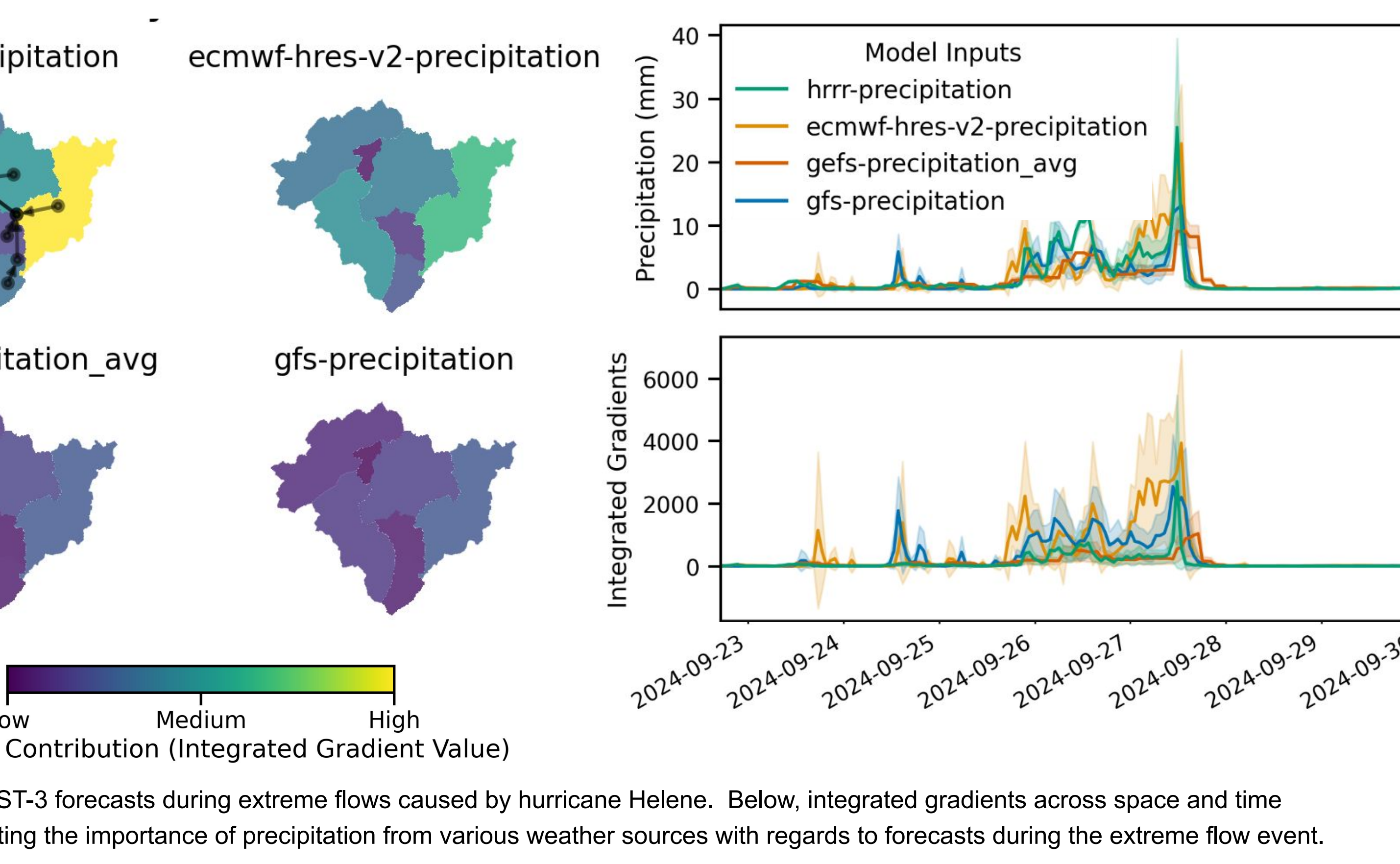
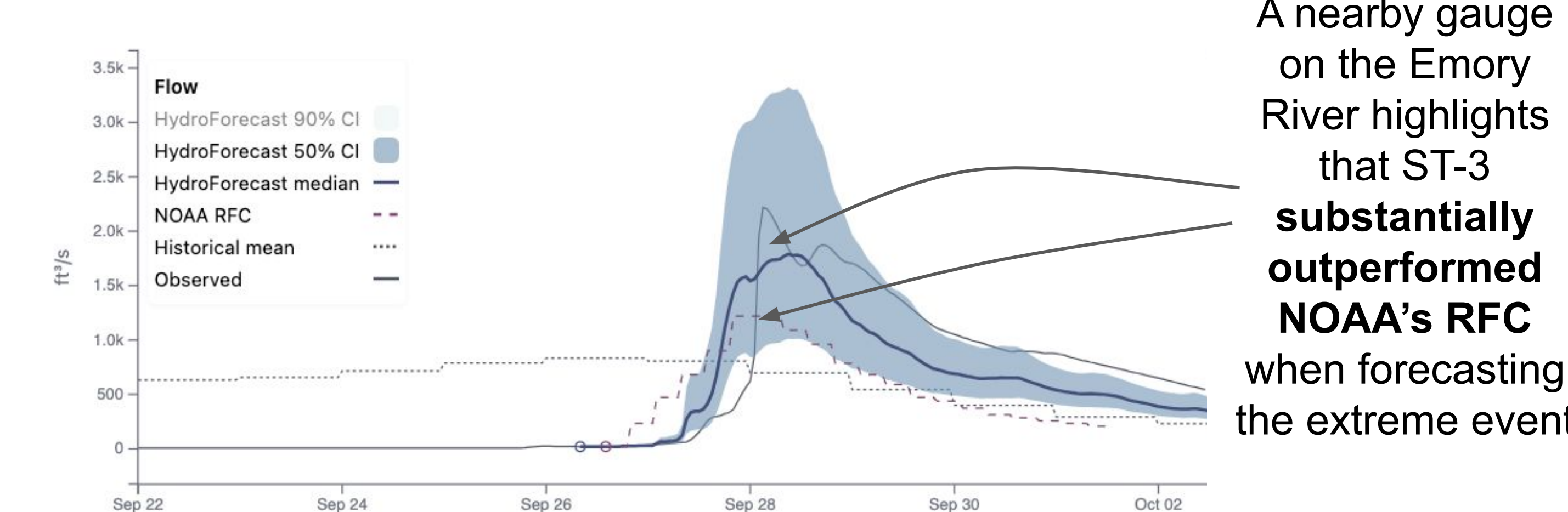
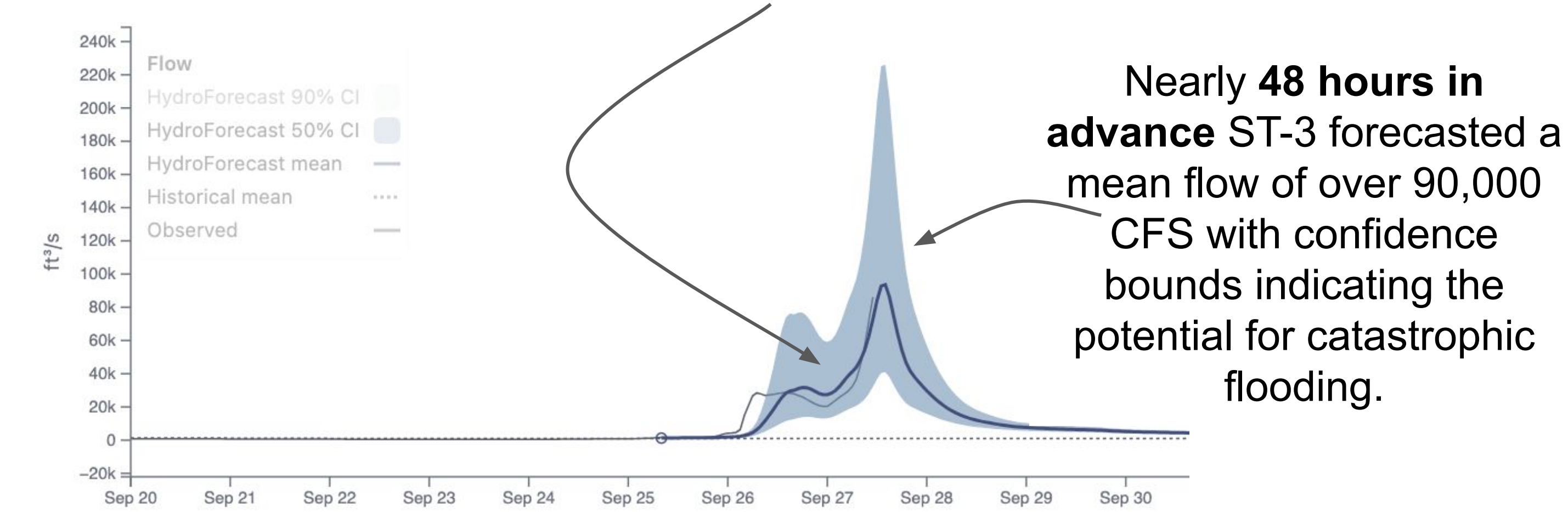


Metrics for streamflow forecasts on the test partition (WY 2020-2021) across 489 sites in the CAMELS dataset. Benchmark metrics represent a model trained without data augmentation or NOAA High Resolution Rapid Refresh weather inputs. Remaining metrics represent tuned model with varying sets of input weather sources.



A Case Study with Extreme Flows From Hurricane Helene

On Sept 27, the USGS gauge on the Nolichucky River in Tennessee **failed due to extreme flow** caused by Hurricane Helene, subsequently impeding emergency response planning



Simon Topp, Alden Keefe Sampson, Mostafa Elkurdy, Phil Butcher, David Lambl, Laura Read