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River Level Forecasting

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soundbendor lab

College of Engineering | Computer Science

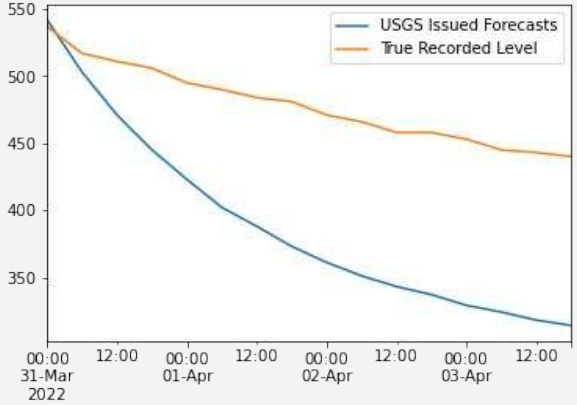
Introduction to Problem

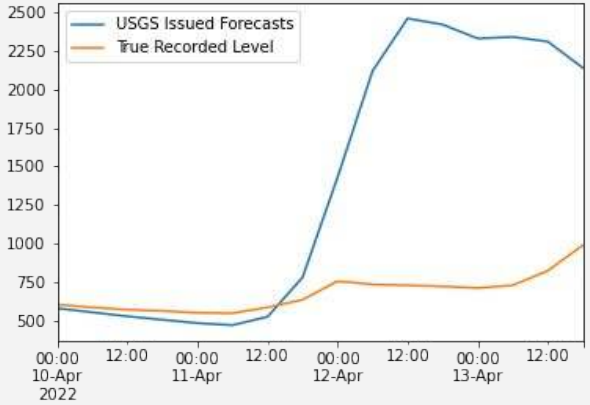
- Changes in river flow rate affect many stakeholders
  - agricultural users
  - river adjacent landowners
  - recreational users
- Flow rate is directly related to weather
  - complex relationship
  - challenging to model with traditional statistical methods

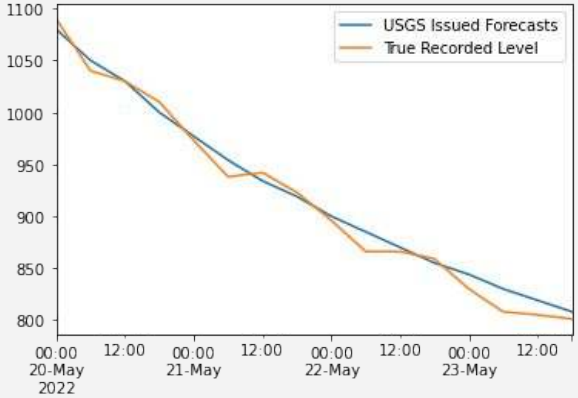
Existing Production Solutions

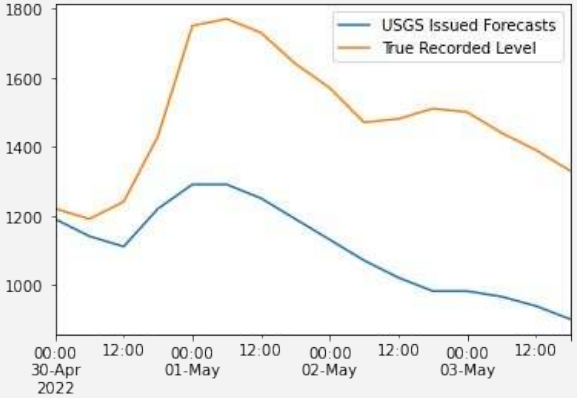
- National Oceanic and Atmospheric Administration (NOAA)
  - provides forecasts for a subset of rivers in the United States
- Leverage precipitation, temperature, and snowpack data
  - proprietary statistical algorithm
  - lacks transparency
  - lacks interpretability
  - lacks accuracy

Examination of NOAA Accuracy









Error Metrics

MAE = 192.06 (ft^3/sec)

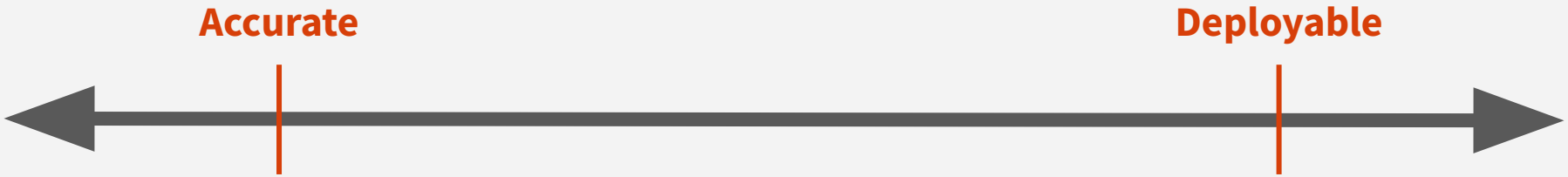
MAPE = 16.46%

Metrics computed for 24 hour advance forecasts across 110 samples

Existing Research Solutions

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- Neural networks are well suited to this task
- Prior solutions faced a trade off between **accuracy** and **deployability**



- large networks
- all available data
- extensive compute resources
- long training times
- slower inference
- **hard to deploy at scale**

- lightweight networks
- subset of available data
- hardware flexibility
- short training times
- rapid inference
- **less accurate**

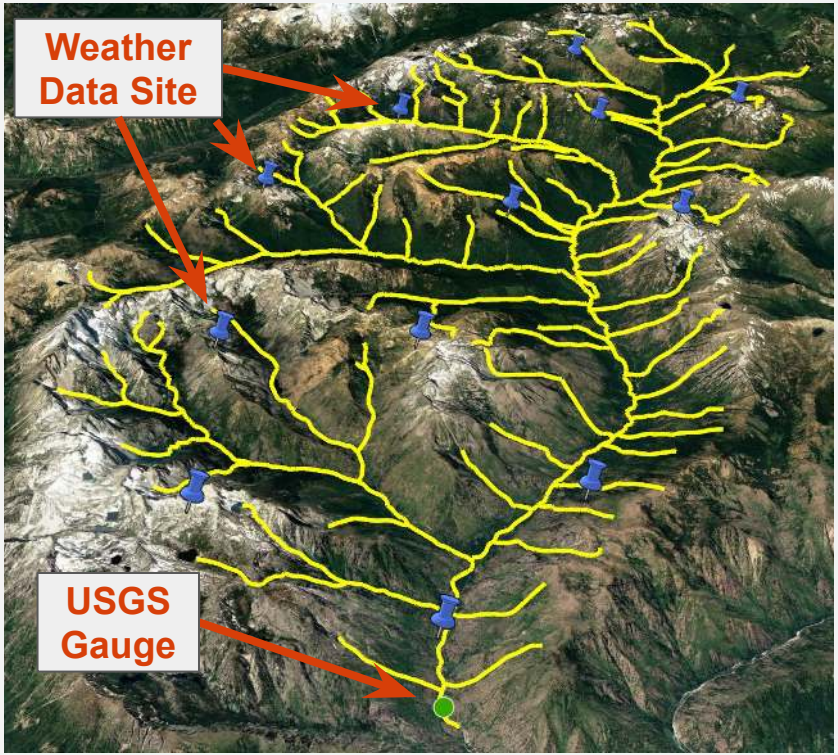
Research Goals

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1. Produce a forecasting model that achieves **high accuracy**, without sacrificing **real-world deployability**

2. Match or beat NOAA forecast accuracy with more **transparency** and **interpretability**

Data Collection



Icicle Creek Data Sources

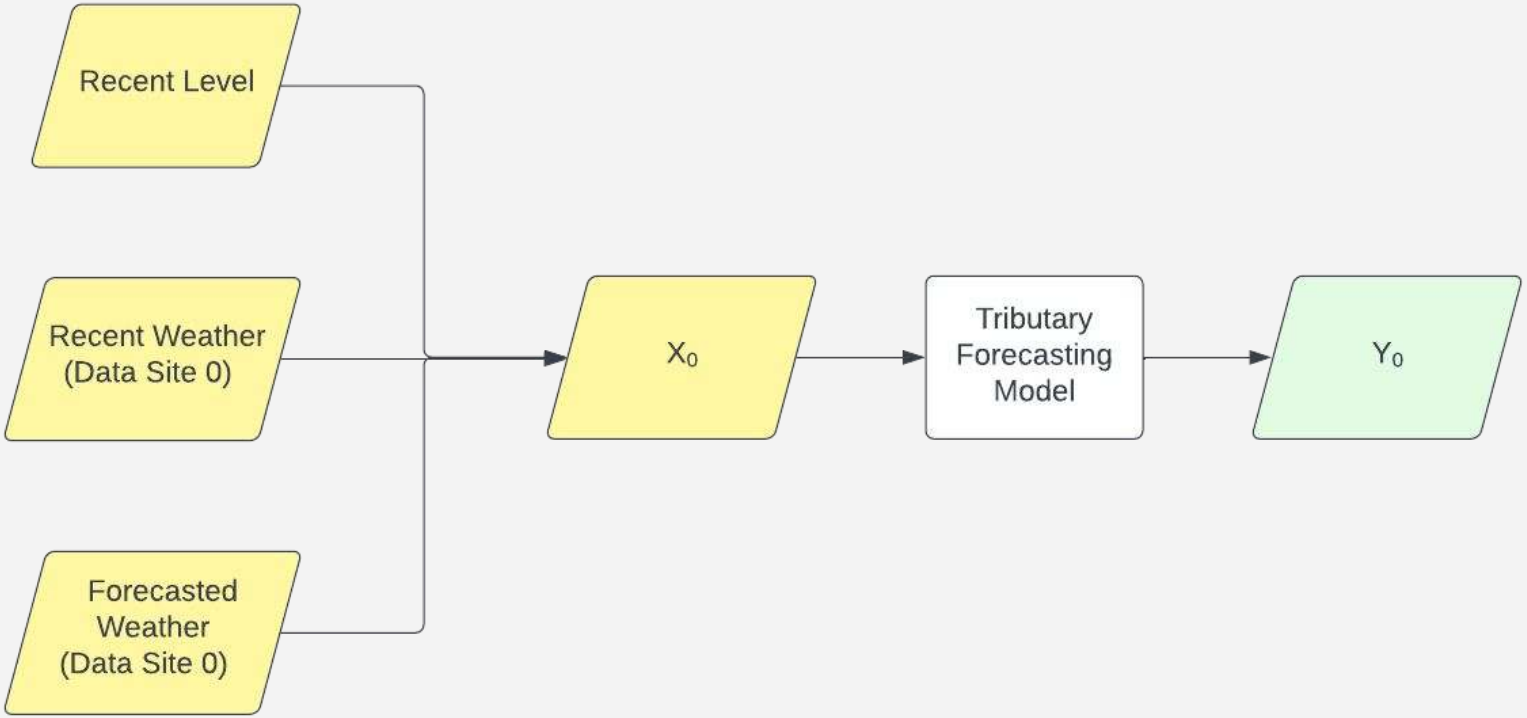
- River Level Data
  - USGS historical and current flow rate
  - specific gauge sites
- Weather Data
  - OpenWeatherMap provides historical, current and forecasted
  - any desired latitude & longitude

Dimensionality Reduction

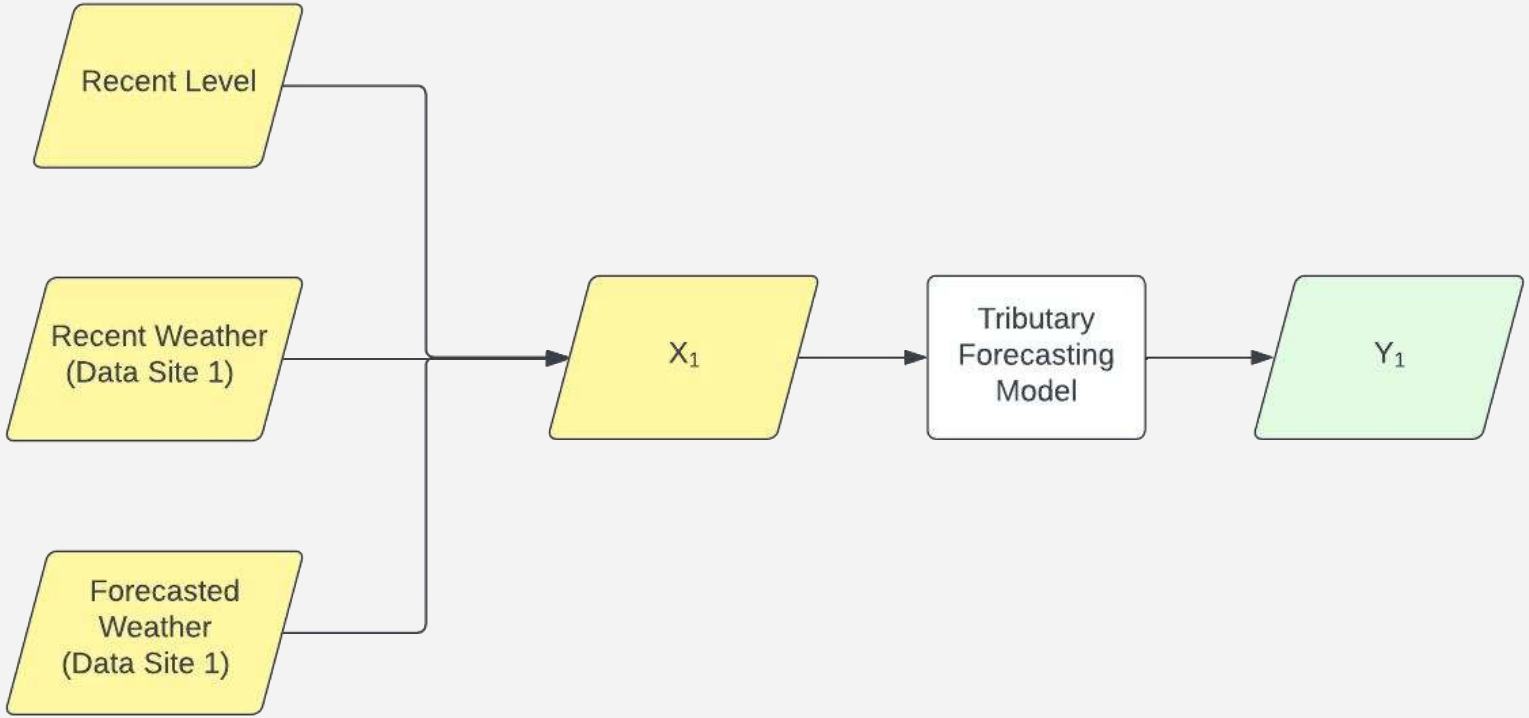
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- Multiple data sources results in high dimensionality
  - high order relationships are lost amidst noise
  - necessitates extensive compute resources/training time
- Reducing featurespace hinders accuracy
- Adopt ensemble approach
  - mitigates issues raised by high dimensionality
  - retains full featurespace to maximize accuracy

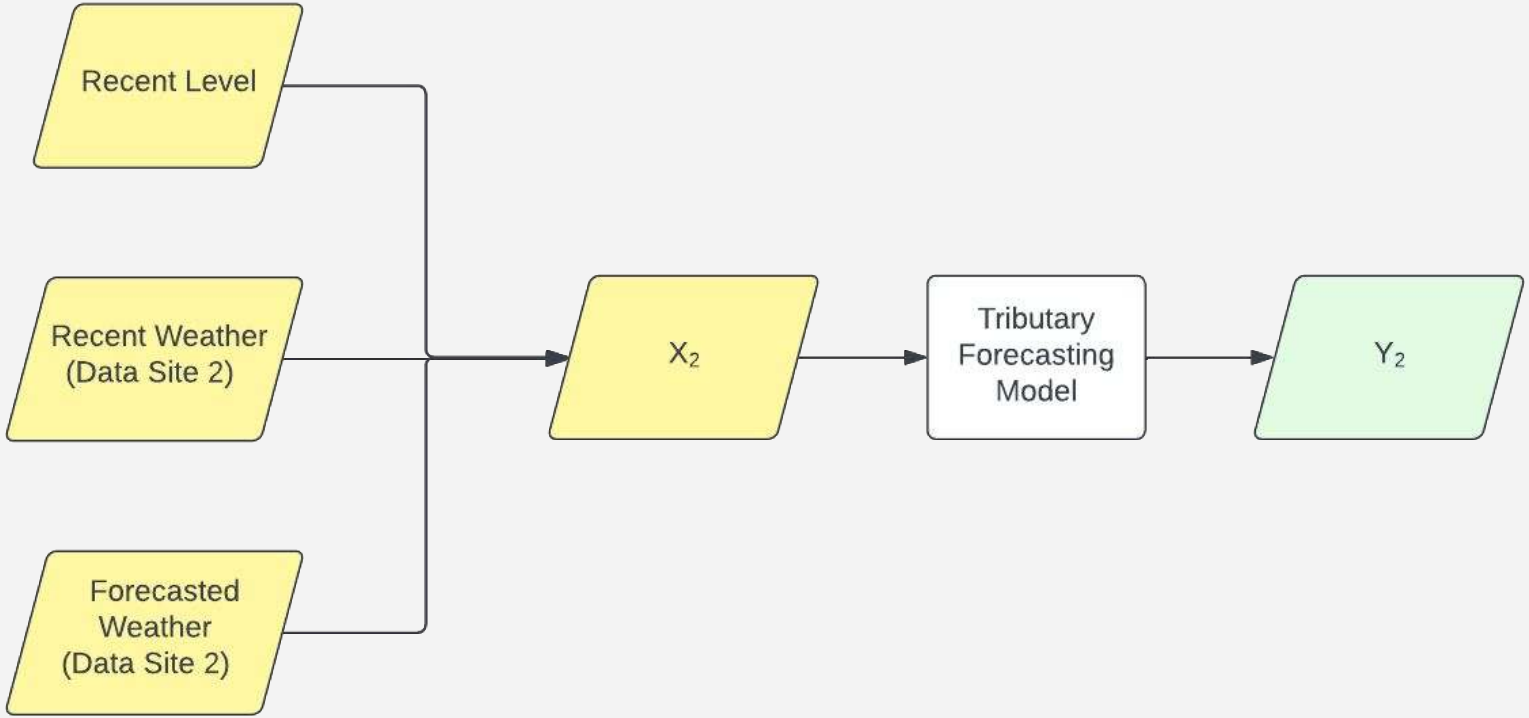
Tributary Forecasting Model



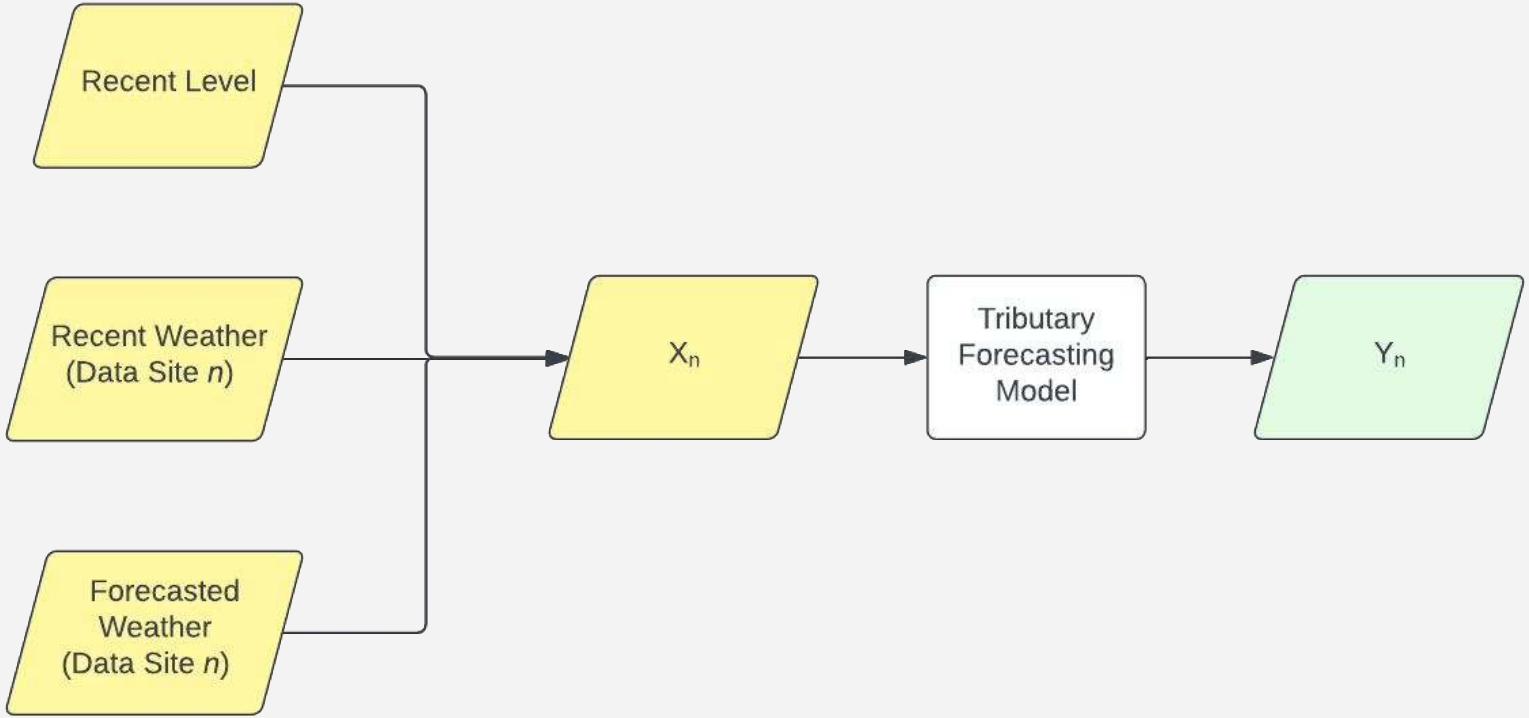
Tributary Forecasting Model



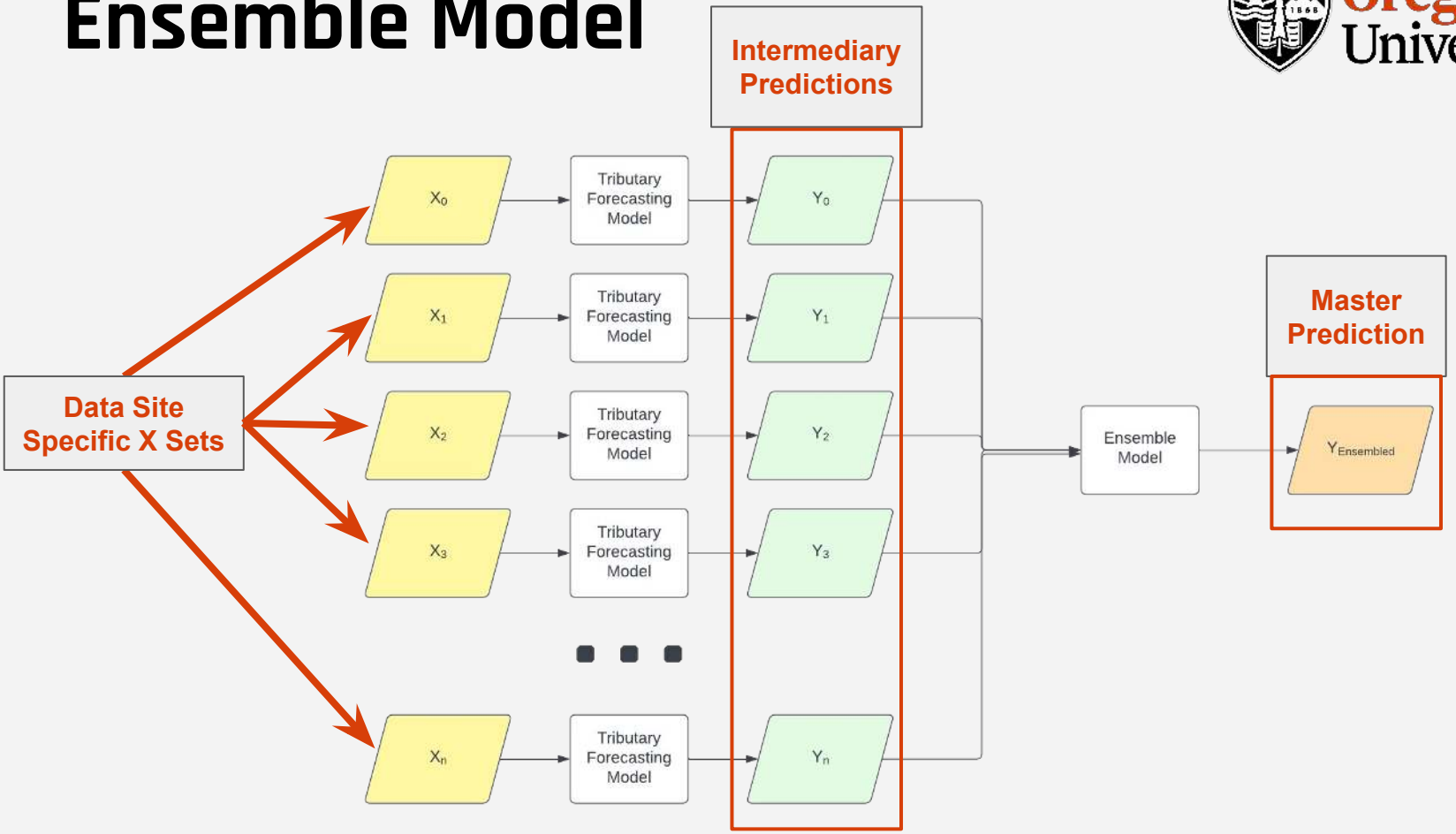
Tributary Forecasting Model



Tributary Forecasting Model



Ensemble Model



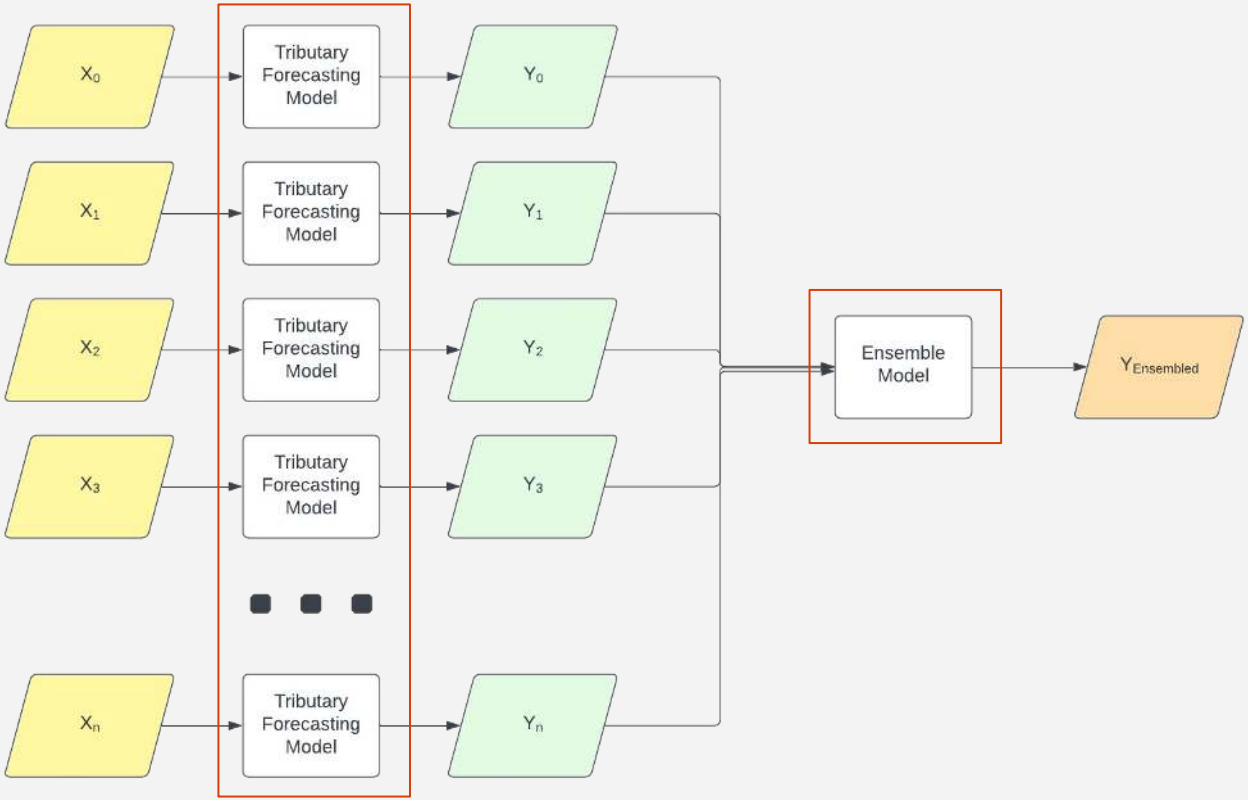
Advantages of Approach

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- Leverage all available data
- Minimize training time/compute resources needed
  - each individual model is lightweight
  - training is highly parallelizable
- Interpretability
- Modularity

Ensemble Model

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Results - Simulated Historical

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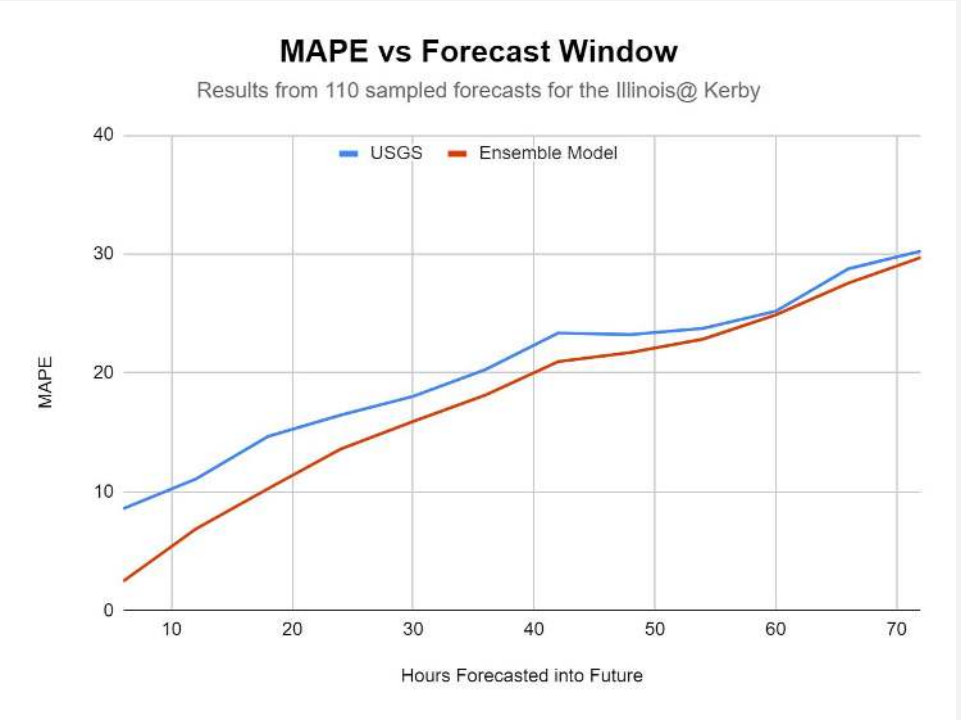
- 24 hour advance forecasts of the Illinois at Kerby
  - **MAPE of 8.57%**
  - 10.02% better than the best performing tributary model
  - demonstrates the efficacy of ensemble approach
- <12 hour train time, <30 second inference time (Nvidia 3070)
  - demonstrates viability of training/inference without HPC cluster
  - parallelization across a cluster can improve this substantially

Results - Real World Evaluation

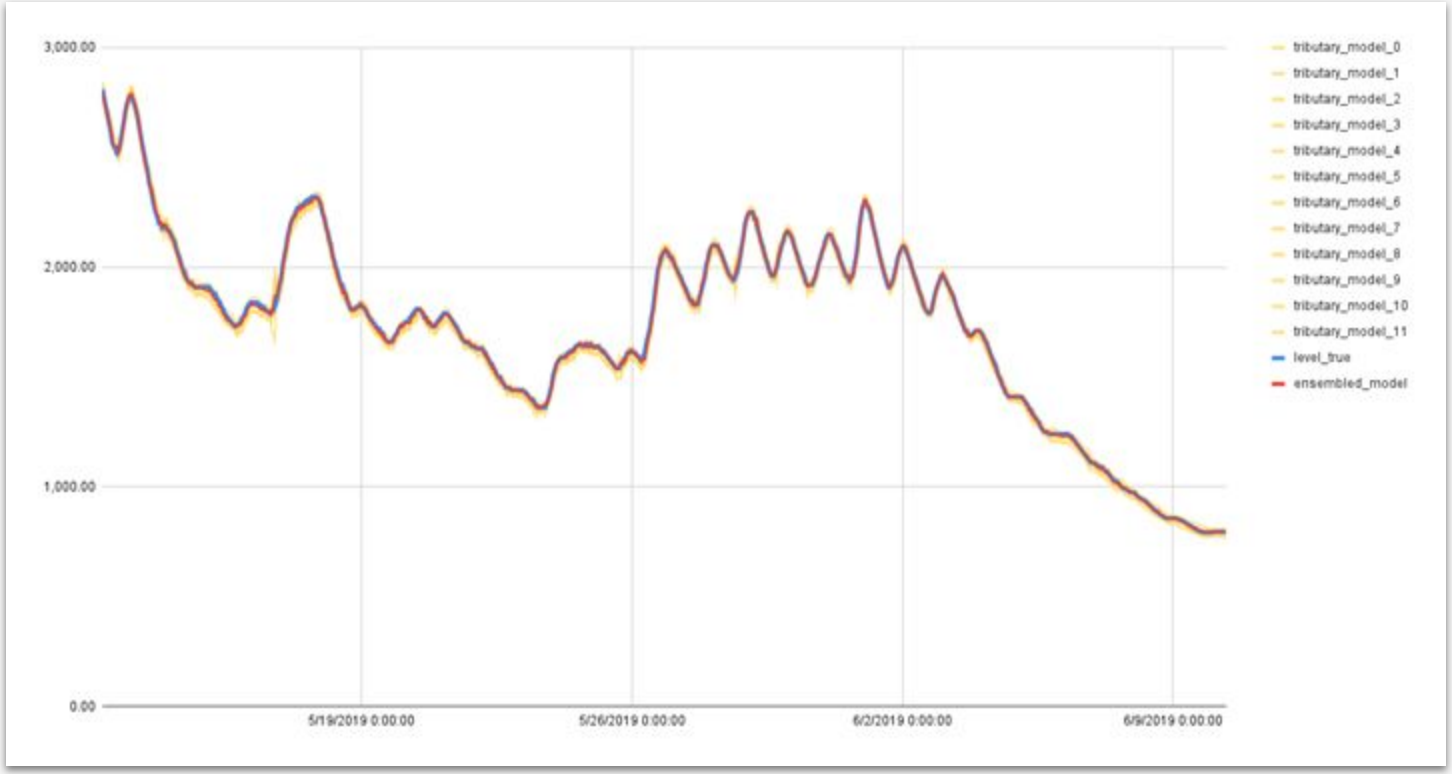
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24 hour advance forecasts of Illinois @ Kerby over 110 days

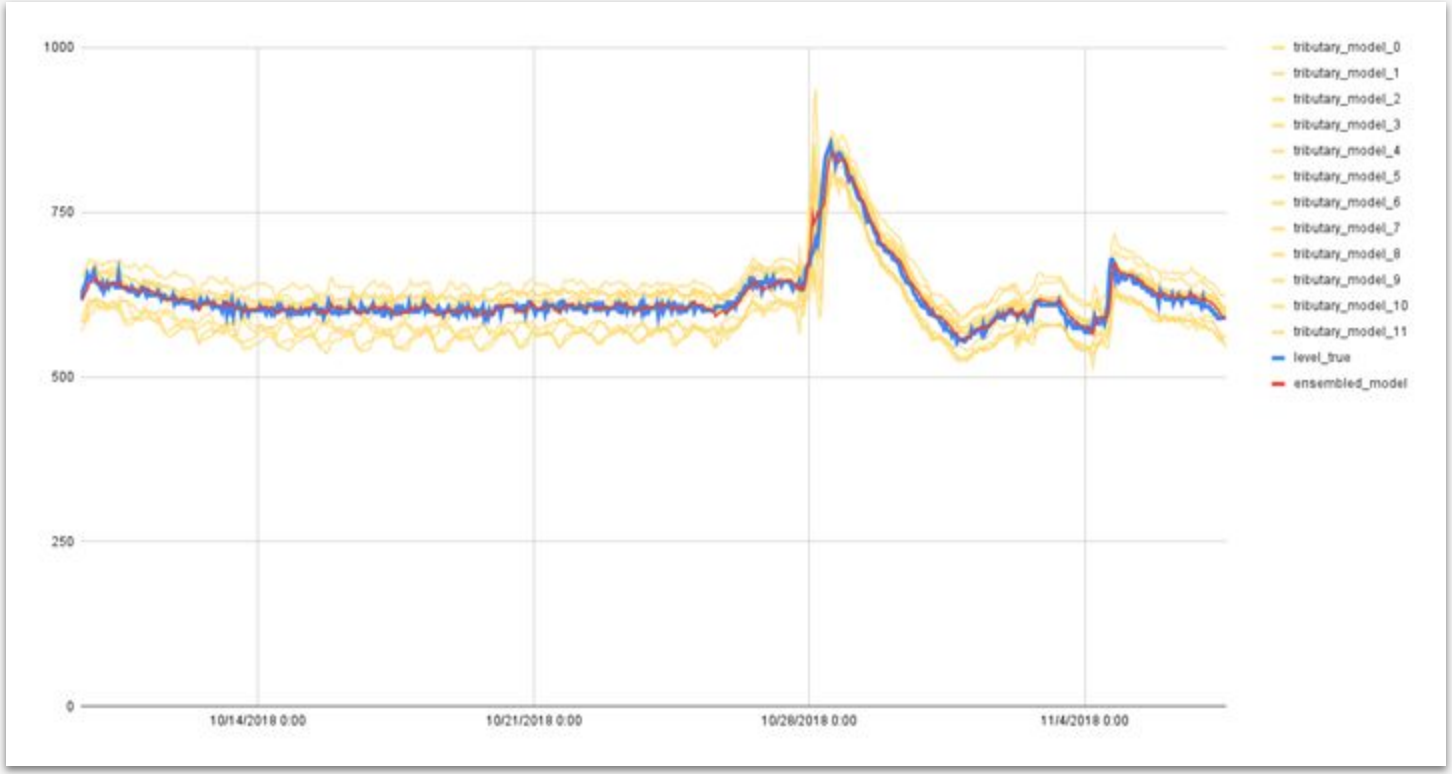
- MAPE of **13.62%**
- **2.85%** better than forecasts issued by NOAA



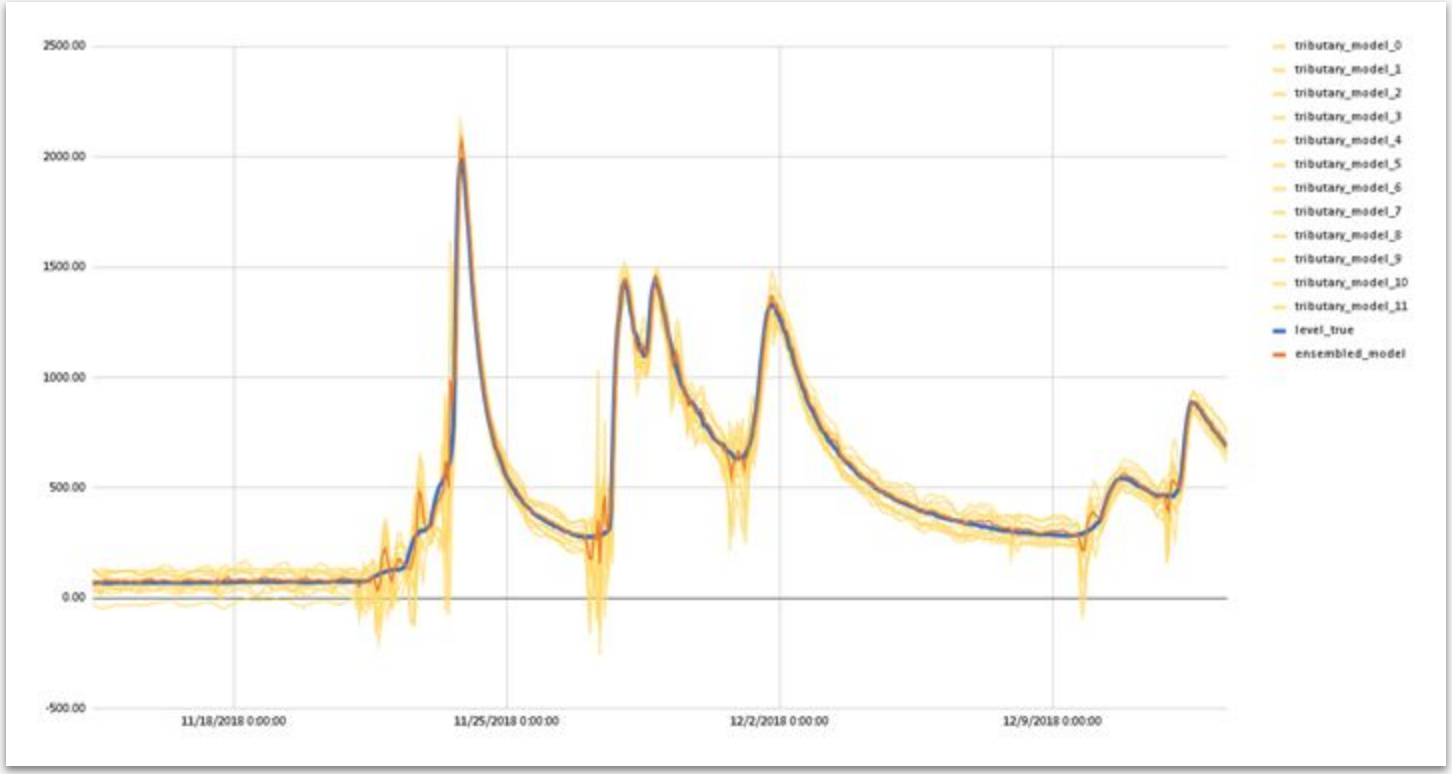
Icicle Creek



White Salmon



Illinois (Oregon)



Future Work

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- Experiment with more advanced model architectures
- Evaluate the efficacy of this approach on a more diverse set of rivers
  - larger river systems in particular
- Extrapolate a model from one river to another with transfer learning
- Explore domain generalizability of this approach
  - potentially effective for other weather related forecasting tasks
  - forest fire prediction and avalanche risk forecasting

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