



# Flow-DB: A new large-scale dataset of stream and river flows

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## Societal Problems

- Floods result in the most lives lost of any natural disaster in the US.
- In 2011 the government declared 58 flood disasters, totaling \$8 billion dollars.
- The most common cause of floods are large-scale precipitation events
- Accurately forecasting river flows, precipitation, and adverse weather events can help government officials plan responses, warn residents, and mitigate the damage.
- In the opposite direction forecasting low flows can help plan for droughts.

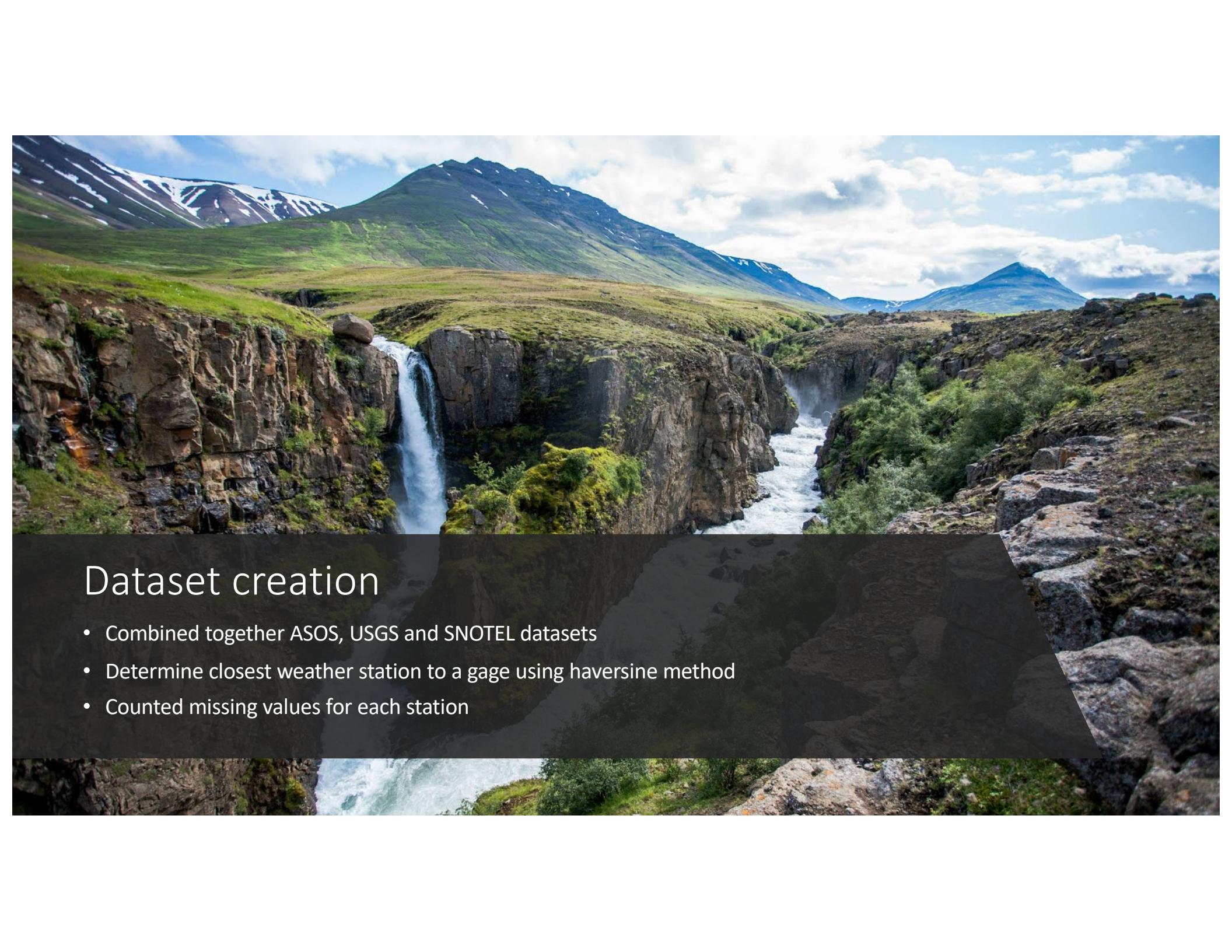


<https://www.americanrivers.org/rivers/discover-your-river/10-facts-about-flooding/>

# Prior research

- [CAMELS dataset](#)
  - Contained 671 catchments
  - Data reported daily
- Despite limited size of CAMELS several papers found ML useful at predicting river flows.
  - [F Kratzert et al 2019 \(LSTMs\)](#)
  - Gauch et al Aug 2020
- Other research has studied flash flood and natural disaster damage estimates





## Dataset creation

- Combined together ASOS, USGS and SNOTEL datasets
- Determine closest weather station to a gage using haversine method
- Counted missing values for each station



## Core dataset

- Contains hourly flow, temperature and precipitation data.
- Collected for 2014-2019 with goal to automate ingestion of new data.
- Data for more than 9,000+ streams and rivers around U.S.
- Gage meta-data (i.e. lat/lon, mean snow fall, slope, soil depth, etc)
- Working on incorporating snow-pack, soil moisture data, and aerial imagery

The background image shows a wide-angle aerial view of a residential neighborhood completely inundated by floodwaters. Numerous houses, streets, and surrounding greenery are submerged in muddy brown water. The scene extends to a distant horizon where more flooded areas are visible under a hazy sky.

# Flash Flood Subset

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Small subset of ~10,000 floods across USA

# Evaluation Methods

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$$MSE = \frac{1}{N} \sum_{i=1}^N (f_i - y_i)^2$$

where  $N$  is the number of data points,  
 $f_i$  the value returned by the model and  
 $y_i$  the actual value for data point  $i$ .

$$MASE = \frac{MAE}{MAE_{in-sample, naive}}$$

## Key ML Challenges

- What deep learning architectures can effectively incorporate static river basin meta-data with dynamic (hourly) time series data?
- Is transfer learning effective and to what extent?
- What ways can we most effectively impute missing data?
- How can we effectively incorporate seasonality into model forecasts?
- How can we ensure models will perform well in the face of out of distribution events (e.g. 1000-year flood)?



# Models and methods

- Information is saved to Weights and Biases
- We have tried many models: LSTM, DA-RNN, and GRUs.
- Difficult for models to fully learn seasonal patterns on some gages.
- Particularly hard for models to generalize to out of distribution events





## Using dataset for pre-training

- We found success in using river flow data to pre-train large transformer models for time series follow by fine-tuning to a target task:
  - COVID-19 forecasting
  - Solar forecasting
- We believe there could be even more positive transfer for other climate and/or agriculture tasks

# Can your model do better?

Visit to find out how to test your model on our dataset.

- [pytorchforecasting.com/flow](http://pytorchforecasting.com/flow)
  - <http://github.com/AIStream-Peelout/flow-forecast>
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