Flood prediction in ungauged basins with machine learning and satellite precipitation data

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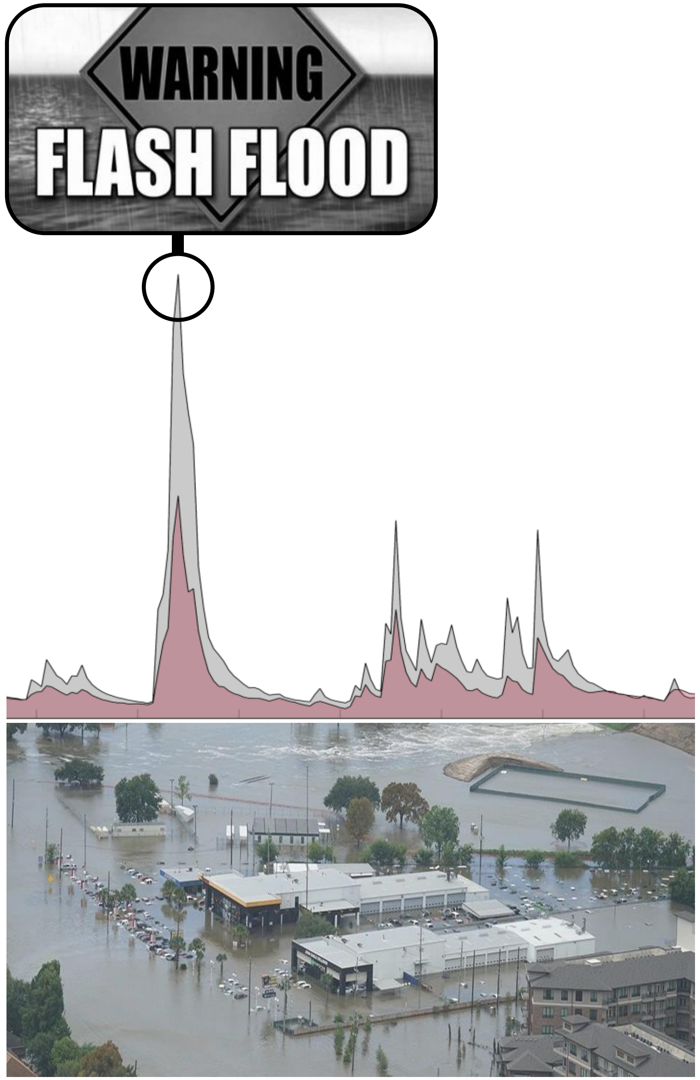
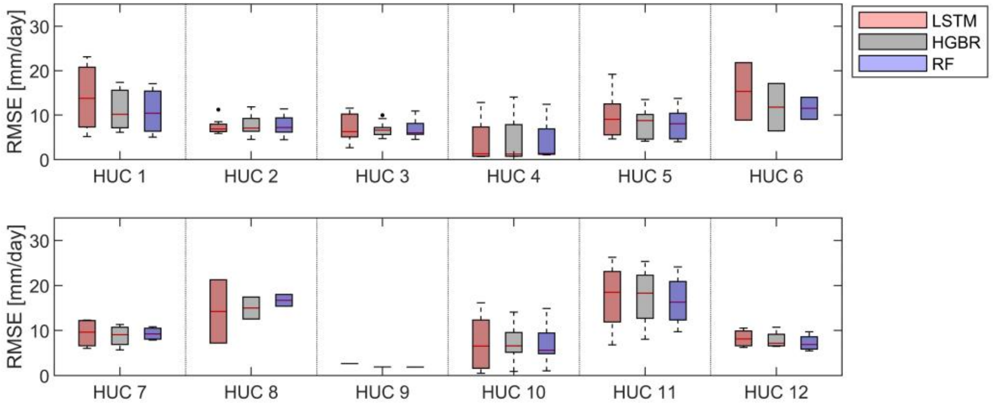
Flood Peak Prediction in Ungauged Catchments (PUCs)



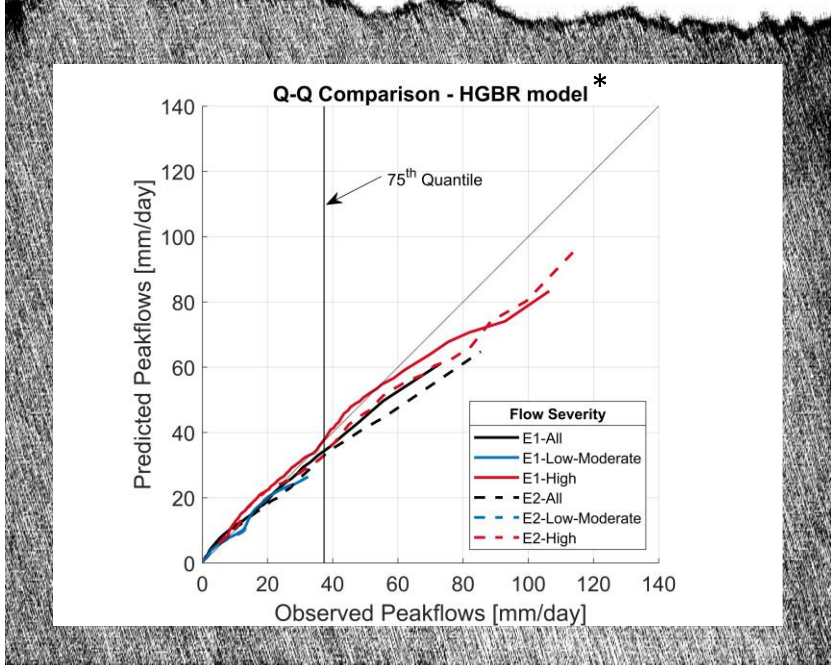
Source: (Top) Field Walsh, TXK Today | (Bottom) NOAA (News and Features); September 2018

Rainfall-Runoff

ML for Peak PUCs



Rasheed et al. 2022

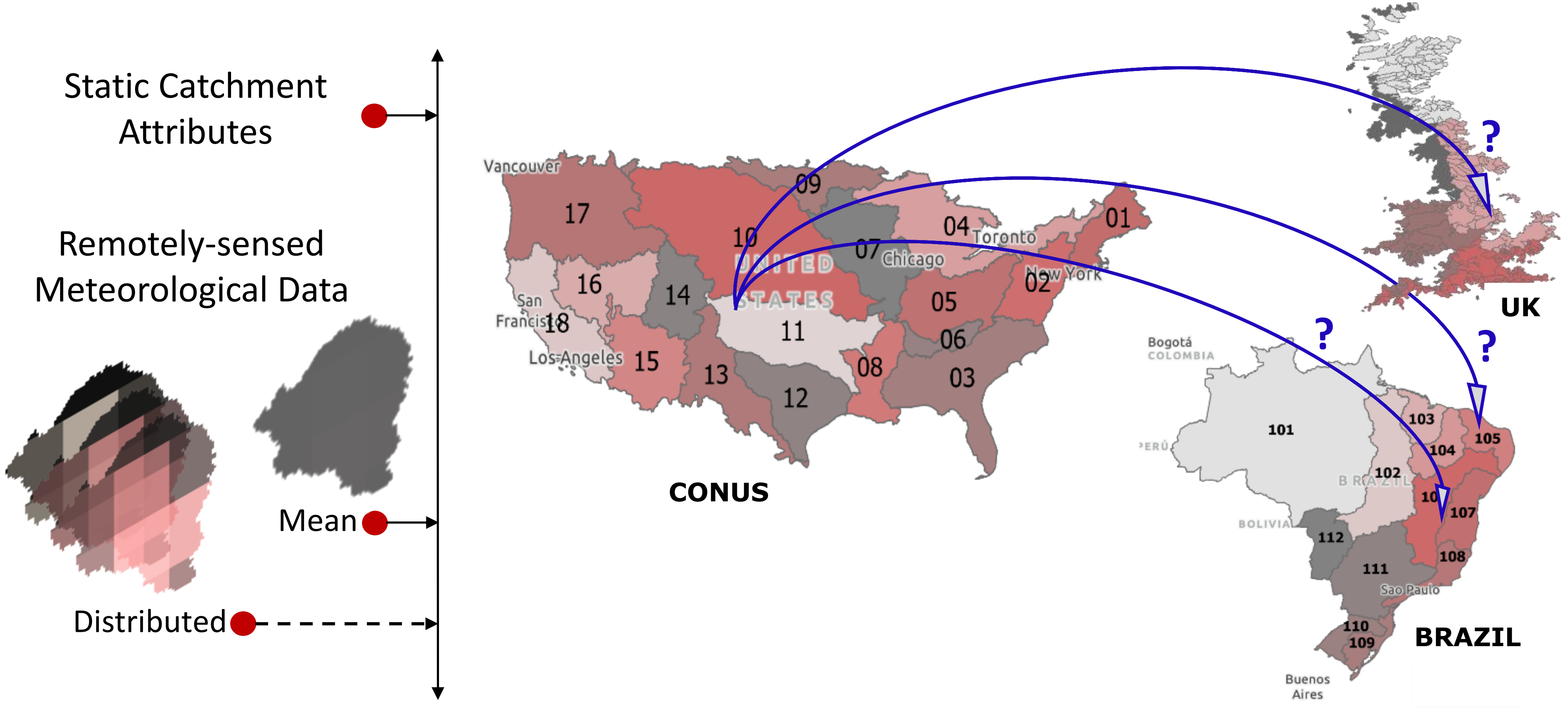


Histogram Gradient Boost Regressor (HGBR) model

ML models
(applied globally)
+
Remote Sensing

Applying ML models with satellite input

INPUT	REGIONAL MODELING	OUTPUT
UNGAUGED CATCHMENTS	GAUGED CATCHMENTS	FLOOD PEAK PREDICTION



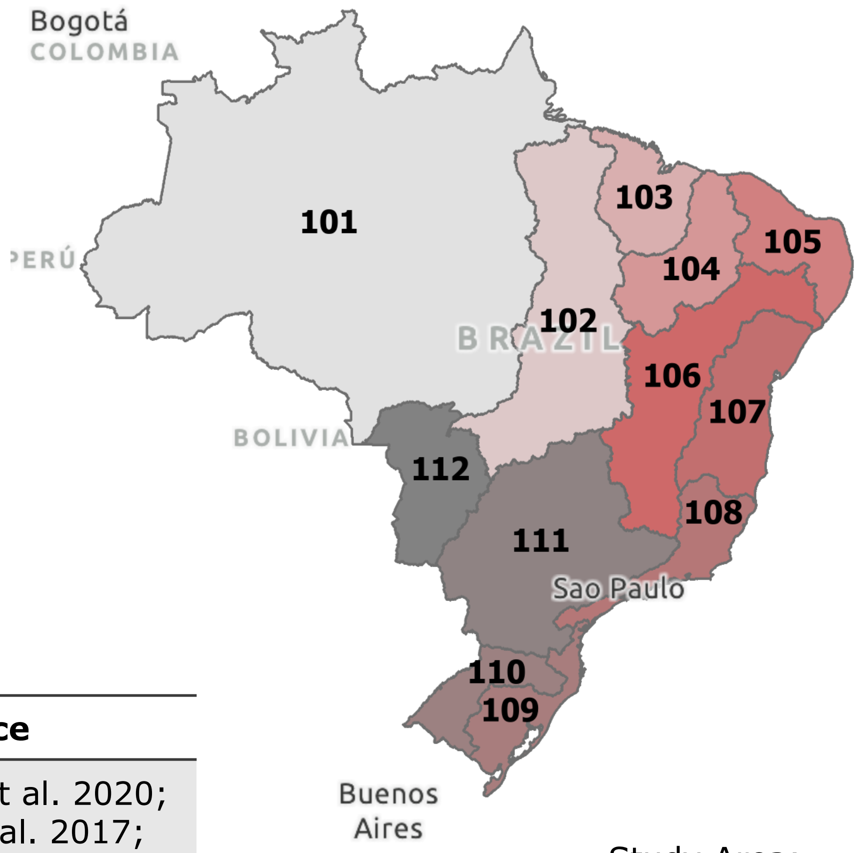
Predictors → **Trained, Regional HGBR Models** → **Prediction Accuracy; Regional Assessment**

Objectives & Application over Brazil

We investigate:

a) the performance of ML flood prediction models integrated with satellite precipitation estimates

b) the transferability/applicability of ML models trained in data rich regions for flood prediction in ungauged regions.

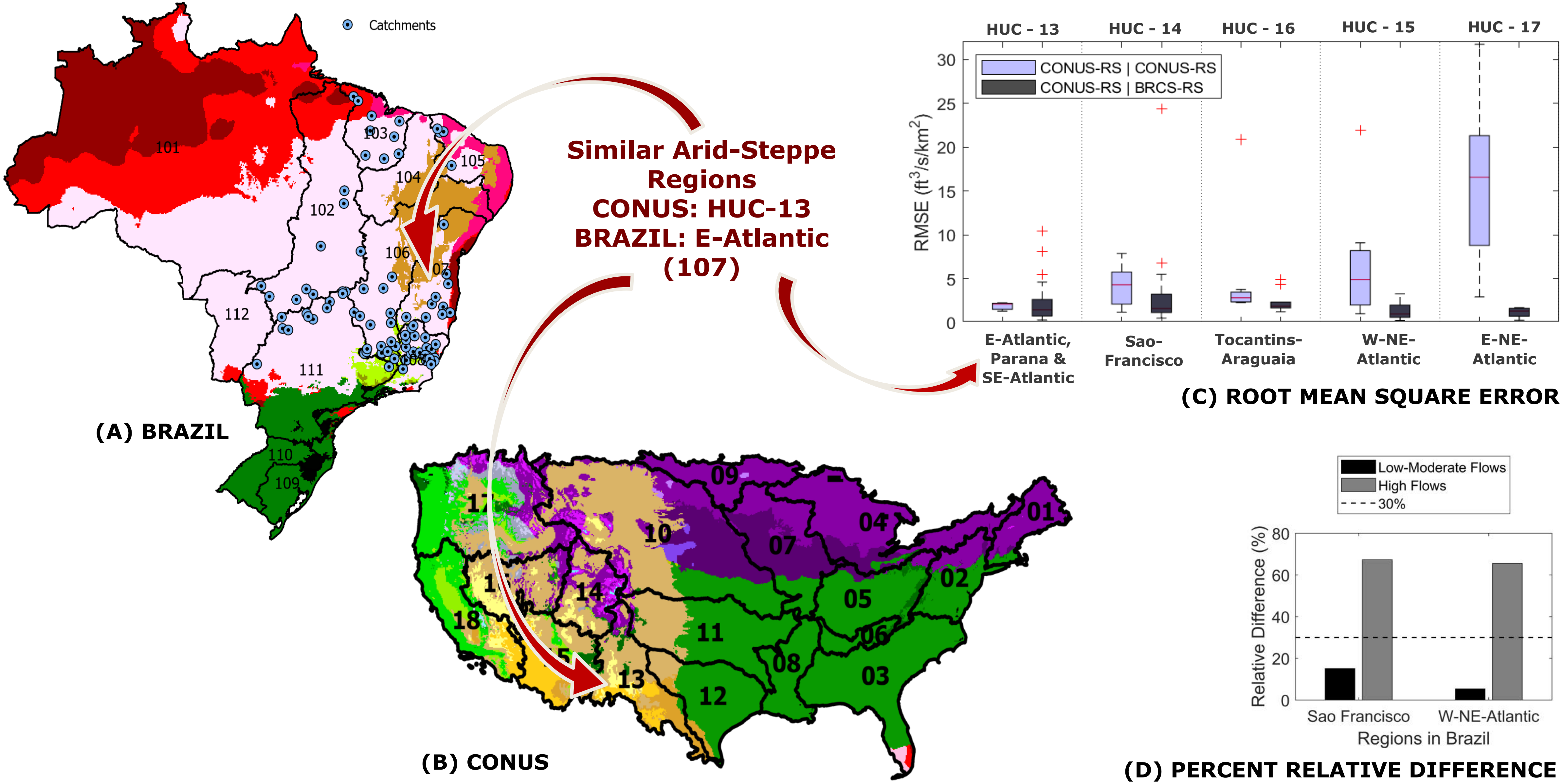


Study Area:
Regions in Brazil

Table: Datasets employed noting resolution and sources

Variables	Dataset	Resolution	Reference
Streamflow; static catchment attributes	CAMELS-US (~670); CAMELS-BR (~100)	Spatial: Catchment-averaged; Temporal: 2000 – 2014, daily	Chagas et al. 2020; Addor et al. 2017; Newman et al. 2015
Precipitation	IMERG Early Run v6	Spatial: 10km x 10km Temporal: 2000 – 2014, daily	Huffman et al. 2019
Temperature	ERA5	Spatial: 25km x 25km Temporal: 2000 – 2014, daily	Hersbach et al. 2018

Globally-applied ML models perform based on hydro-climatic similarities



ML models with satellite input useful for Flood Peak PUCs

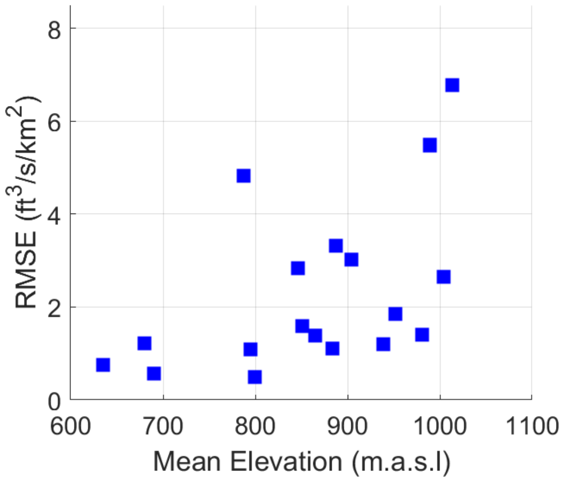
- ❑ Potential for the integration of global satellite precipitation and temperature estimates with ML models for flood prediction in ungauged basins

- ❑ The application of the CONUS-trained ML models (HGBR) indicate acceptable flood prediction performance based on hydro-climatic similarities at global scale

WORK-IN-PROGRESS

- ❑ Additional catchment-specific predictors may lead to improved performance

Sao Francisco Region, Brazil



- ❑ Incorporating distributed meteorological data into ML-models

Acknowledgement & References

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