A Comparison of Data-Driven Models for Predicting Stream Water Temperature

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Tackling Climate Change with Machine Learning Workshop

NeurIPS 2020

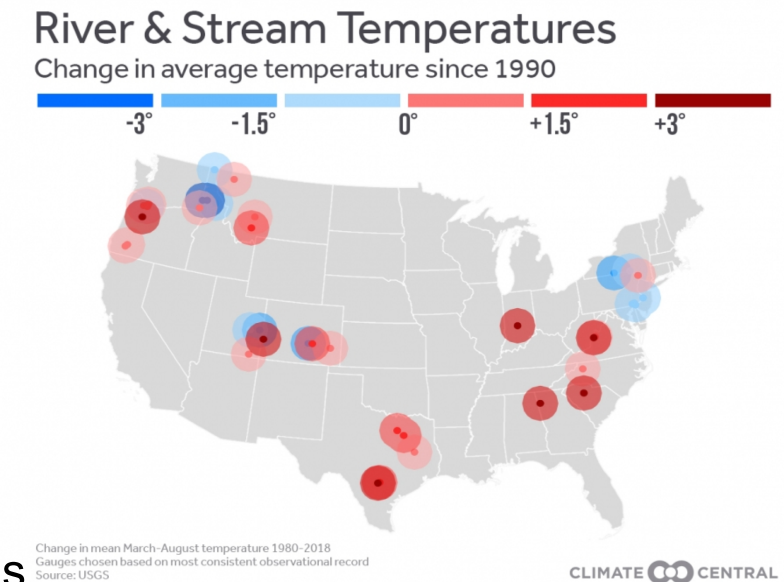
Research Objectives

- To test the viability of low-complexity ML models and understand variables for predicting stream temperature at different spatial and temporal scales.
- To predict impacts of extreme hydrological events (flood/drought) on stream temperatures

Sandy River Watershed Council

Relevance and Impact

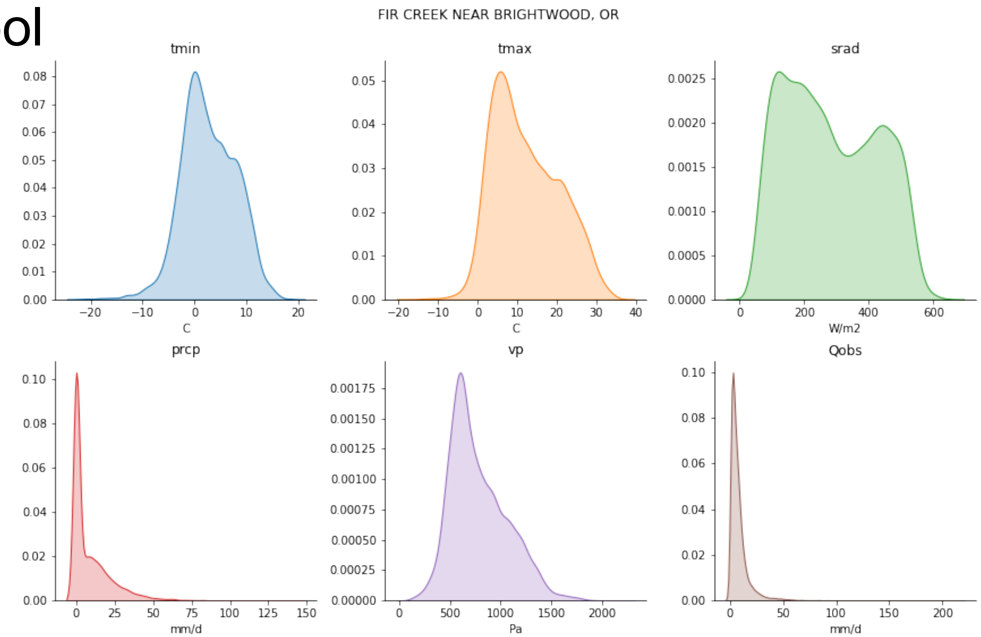
- Climate Change and Stream **Water Temperature (WT)**
  - WT drives stream physical and biogeochemical processes, important to aquatic life
  - Impacted by climate change: increased air temperature, disturbances, changing hydrological cycle
  - Water managers need **local to regional WT predictions**
- Process models and Machine Learning (ML) for WT
  - SNTEMP Process Model, ML Models (LSTMs, MLPs outlined in Zhu et al. 2020)
  - Process-Guided Deep Learning hybrid models (USGS)
  - **Test baseline approaches that can predict WT at different scales with broadly available measurements**



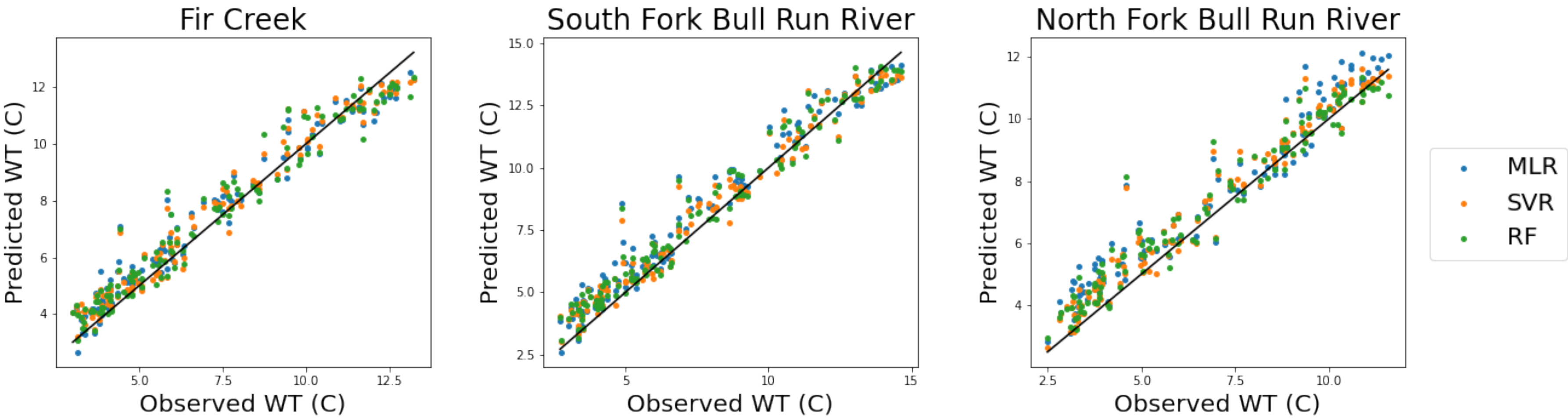
Methods- Monthly Predictions

- Limited/ sparse available data with extremes
  - **Input features:** Meteorological data from CAMELS Daymet
  - **WT:** data from USGS NWIS using BASIN-3D integration tool (Varadharajan et al. 2019)
- ML Regression Models:
  - MLR, RF, SVR (persistence, historical)
  - 70/30 train-test split, random search cross validation hyperparameter optimization

**only 3 CAMELS stations have near complete 30 year WT records = station selection*



Preliminary Results



- Simple models predict WT well **using only air temperature and solar radiation**
  - SVR, RF out-perform baseline historical and persistence models (RMSE 0.63-0.82 ℃)
- Model error is high for extremes in WT

Future Work

- **Expand spatial and temporal scales**
  - More locations is US, test limits of meteorological data
  - Train models at daily frequency
    - Incorporate lags, exploratory data analysis, new input variables, increase model complexity
  - Sensitivity analysis, UQ
    - How do predictions change with different meteorological data sources, input features etc.

Delaware River Basin Commission

US Geological Survey

Acknowledgements

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*CCAI mentor

Charu Varadharajan

Aranildo R. Lima*

Boris Faybishenko

Danielle Christianson

Val Hendrix

Funding

U.S. DEPARTMENT OF ENERGY | Office of Science