Modeling and Forecasting Human Modified Streamflow Using a Recurrent Neural Network

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Abstract

Providing accurate forecasts of human modified streamflow is critical for applications ranging from natural resource management to hydropower generation. In this study we evaluate the performance of Long Short Term Memory (LSTM) based neural networks, which maintain an internal set of states and are therefore well-suited to modeling dynamical processes. This research builds on previous work demonstrating that an LSTM model can predict streamflow in out of sample basins with similar or greater accuracy than traditional forecast models specifically calibrated on those basins [1]. Using meteorological data from NOAA's Global Forecasting System (GFS) and North American Land Data Assimilation System (NLDAS), remote sensing data including snow cover, vegetation and surface temperature from NASA's MODIS sensors and streamflow data from USGS, we first train an LSTM model on 100 unmodified river basins, and evaluate its predictions on previously unseen human-altered basins. We then train models on a combination of natural and human modified basins and experiment with the effects of new data sources and additional model architecture in predicting human altered streamflow. By training on multiple basins with dynamic climate, land surface and human inputs, we can test the model's understanding of general hydrologic relationships and human use patterns. We evaluate our models on "out of sample" rivers (previously unseen by the model) that have been altered by dam operations and agricultural withdrawals in northern California. We find that the models trained on natural and modified basins capture human modified flows better than our baseline model trained on natural basins. [1] Kratzert, F., Klotz D., Shalev, G., Klambauer, G., Hochreiter, S. & Nearing, G. Benchmarking a Catchment-Aware Long Short-Term Memory Network (LSTM) for Large-Scale Hydrological Modeling. Preprint at https://arxiv.org/abs/1907.08456 (2019)

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Background

Long Short Term Memory (LSTM) neural networks trained on regional hydrology datasets produce better predictions at previously unseen basins than commonly used hydrology models individually calibrated at the same basins[1,2]. Previous experiments have focused on unmodified or "natural" river basins.

In this research, we evaluate the performance of LSTMs in predicting streamflow modified by dams and agriculture.

An LSTM neural network trained on a regional hydrology dataset can predict streamflow accurately at human modified river basins.

Methods and Data

We train an LSTM on 481 natural river basins from the CAMELS dataset.[3]

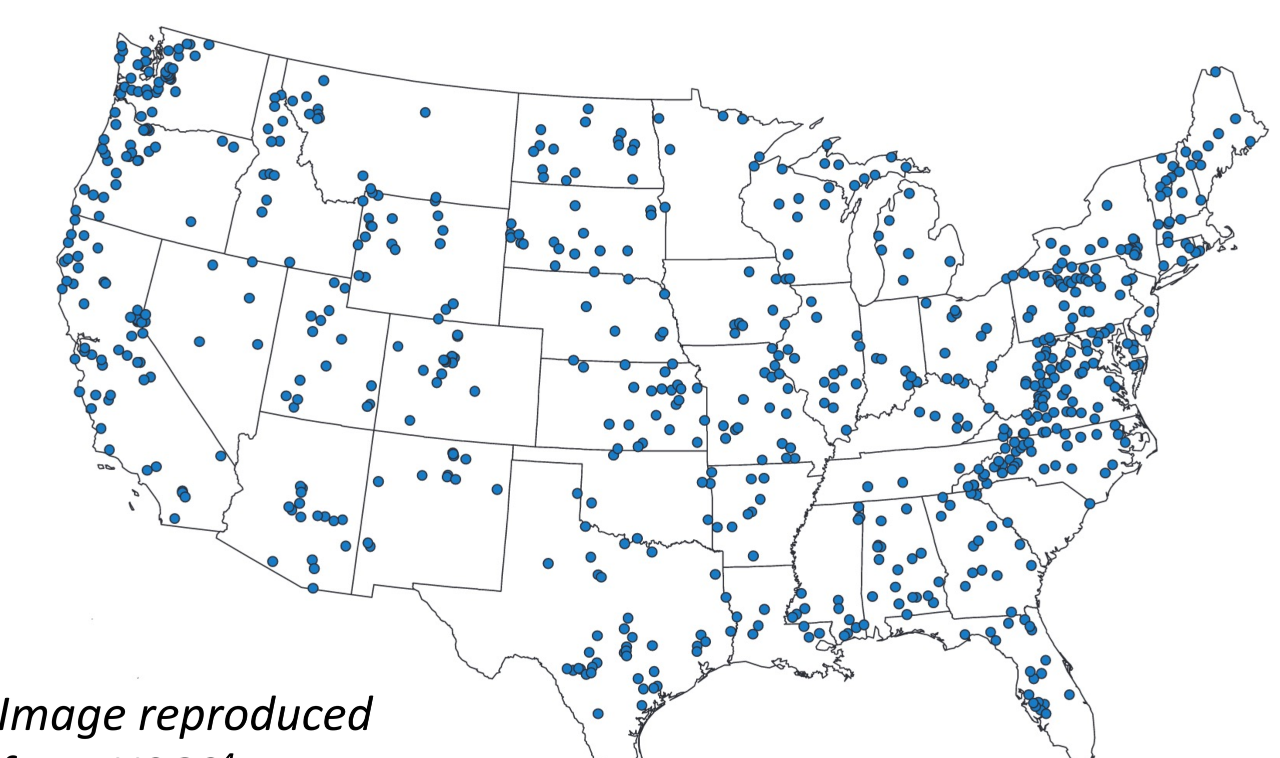
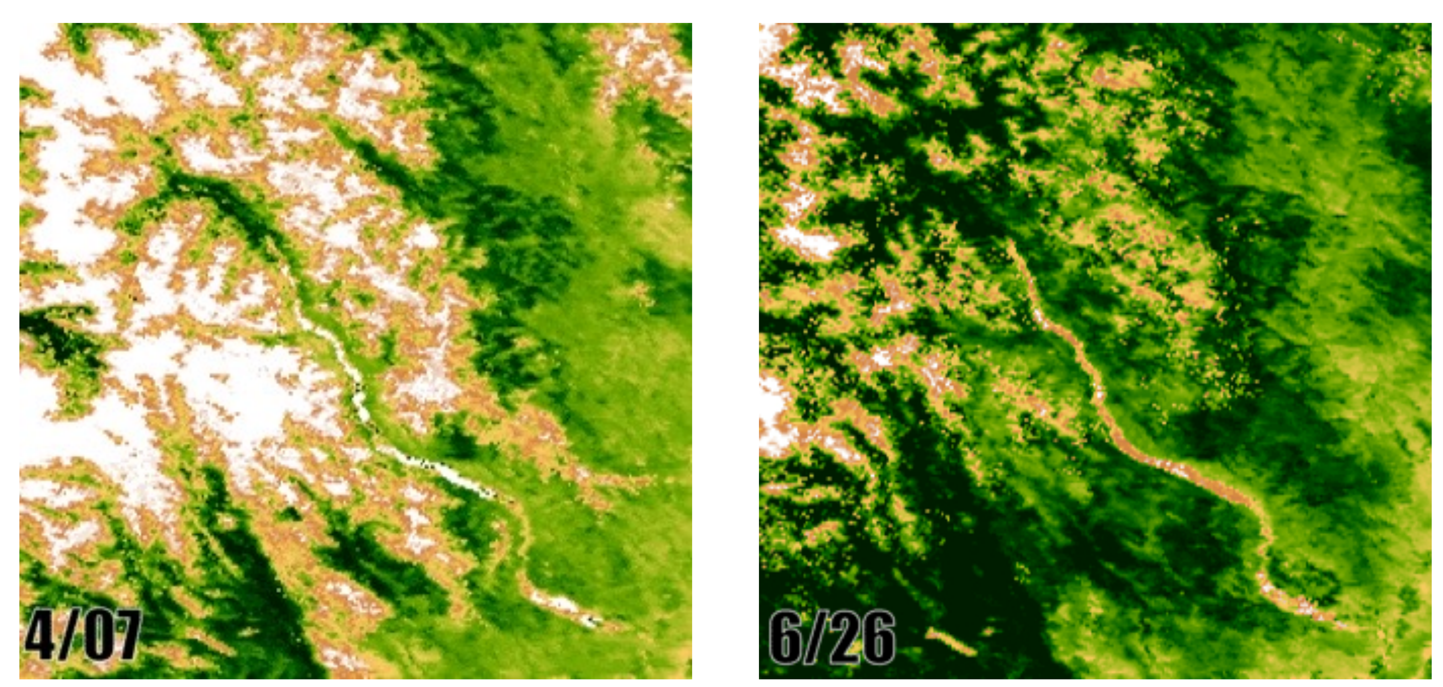


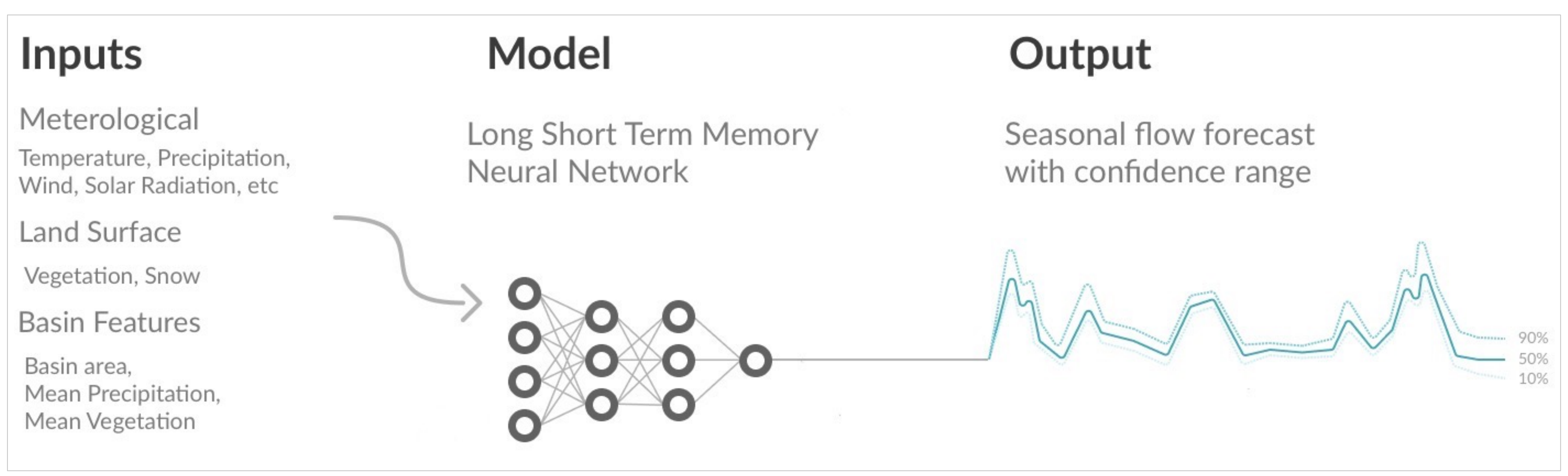
Image reproduced from USGS[4]

Using remote sensing inputs, we capture real time changes in land surface characteristics such as snow and vegetation.



Satellite imagery above and graphic below produced at Upstream Tech

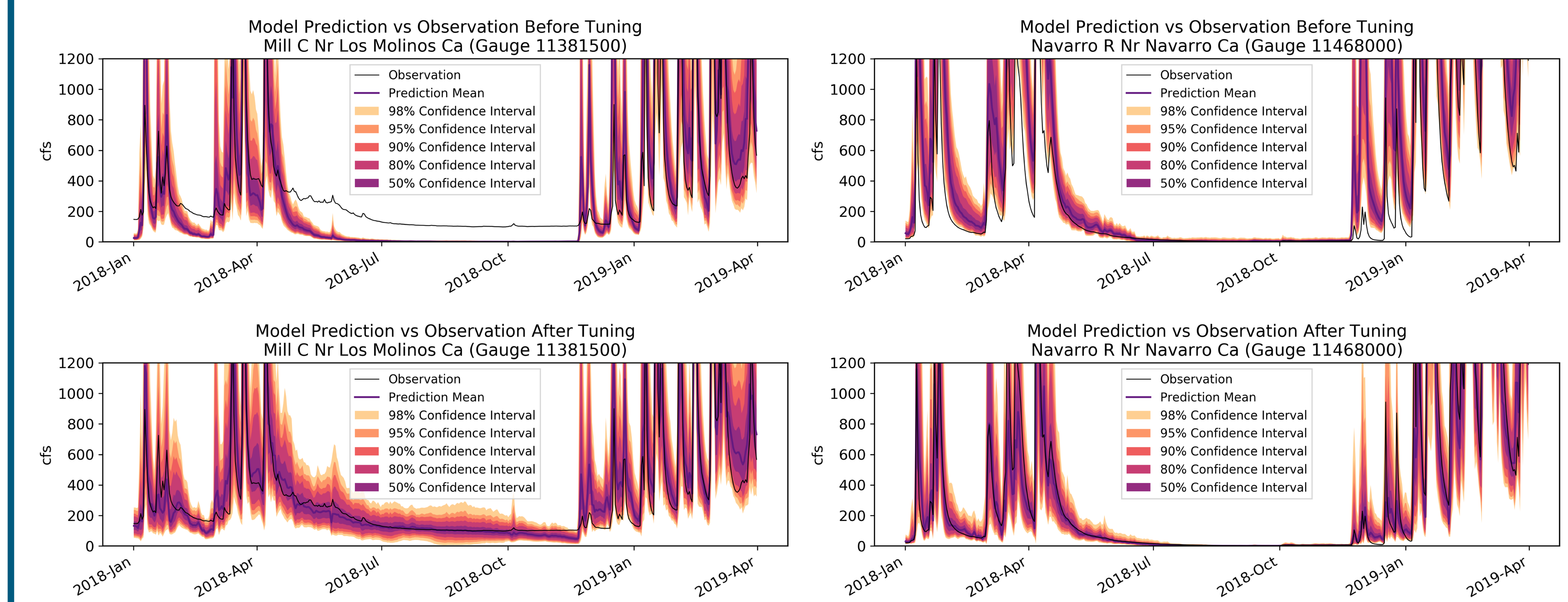
Model predictions are evaluated on human modified basins both before the model has seen the basins, and after the model is tuned on previous years' data from the same basins.



Results

Mill Creek (Sacramento River Tributary) is regulated to maintain a minimum flow.

Agricultural diversions reduce water in the Navarro River.

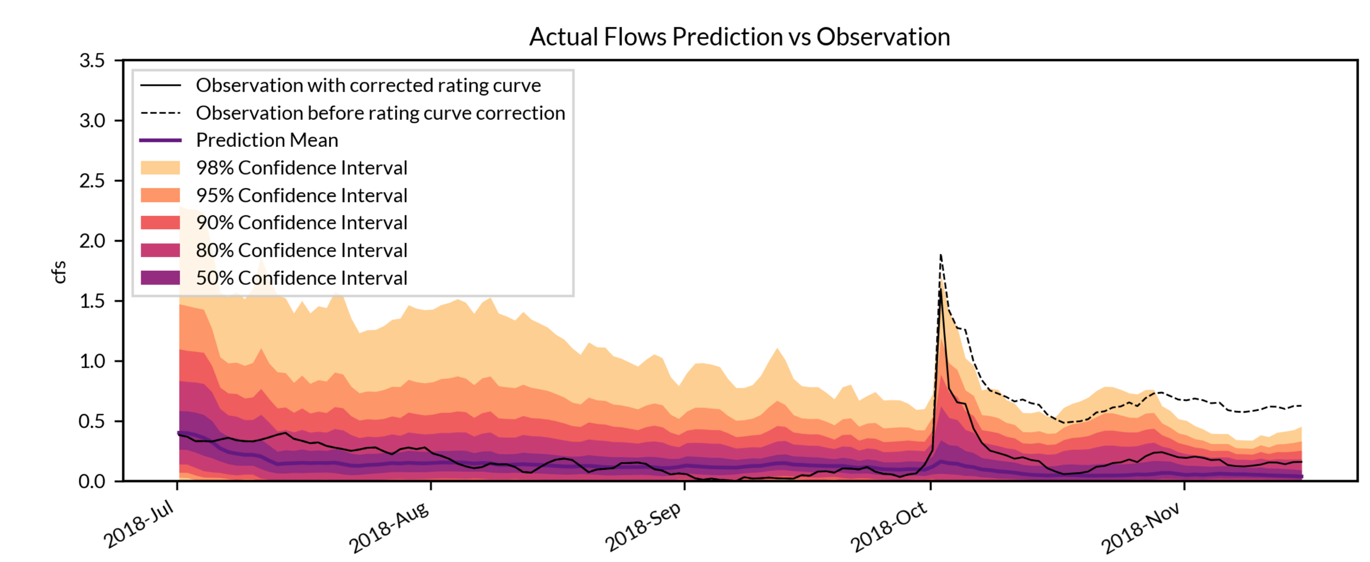


R^2: 0.83 R^2: 0.83

During unseen predictions, the model produces hydrographs representative of unmodified rivers. Upon tuning with previous years data, we can produce reasonable streamflow predictions of the human modified streamflow.

Highlight

Model results at the gauge on the right indicated that an early season storm flood changed the rating curve. The subsequent rating curve correction shows us that the model actually performed better than the initial gauge measurement.



Future work will explore how we can use integrate these models into conservation and management operations.

References

1. Kratzert, F. Benchmarking a Catchment-Aware Long Short-Term Memory Network (LSTM) for Large-Scale Hydrological Modeling. (2019).
2. Kratzert, F. Prediction in Ungauged Basins with Long Short-Term Memory Networks. (2019).
3. Newman, A. A large-sample watershed-scale hydrometeorological dataset for the contiguous USA. (2014).
4. Lins, H.F. USGS Hydro-Climatic Data Network 2009 (2012)

Acknowledgements

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