Climate Change Impacts on the Occurrence of Riverine Heatwaves

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Abstract

River warming in response to climate change may have far-reaching ecological and socioeconomic consequences.[1] Unfortunately, large temporal gaps in the instrumental record limit the ability to study these systems. To address this, I model daily river temperatures across the U.S. using a long short-term memory neural network with the goal of gap-filling historical records, and I then estimate historical shifts in the probability of extreme heat events. The model achieves high accuracy, with a median R^2 of 0.91 at locations not used to train the model. Results suggest that riverine heatwaves have already increased in duration across much of the U.S., with trends likely to accelerate in the future.

Data

Response variable: Daily riverine temperature [°C] measured by the U.S. Geological Survey, 1981-2017[2]

Predictor variables: Daily air temperature [°C] and daily precipitation [mm] from the 4km resolution PRISM dataset, 1981-2017[3]

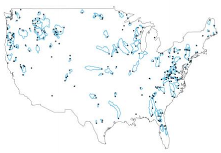

Figure 1. River temperature measurements are available for 254 rivers (points; watershed boundaries in blue) across the U.S. I train my model on one of these, the Deleware R., due to its minimal missing data.

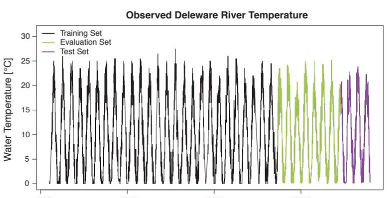

Figure 2. The Deleware River data (n=12,628) used to build the model partitioned into training (70%), evaluation (20%), and test (10%) sets.

Candidate Models

'Naive' baseline: Predict today's water temperature as the average of the past week's air temperature.

Convolutional neural network (CNN): Simple neural network that does not account for temporal dependency

Long short-term memory (LSTM): Allows past information to be reused at a later time.

Gated recurrent Unit (GRU): Similar to LSTM but generally sacrificing accuracy for computation cost.

Results

An LSTM model with one LSTM layer and two deep layers performs best on the evaluation set (n=2600) and is selected as the final model.

Model	Evaluation MSE
Naive Baseline	0.133
CNN	0.069
GRU	0.059
CNN + GRU	0.059
LSTM	**0.055**

Layer	Output Dimension	# Parameters
LSTM	16	1216
Dense	1	17
Dense	1	2

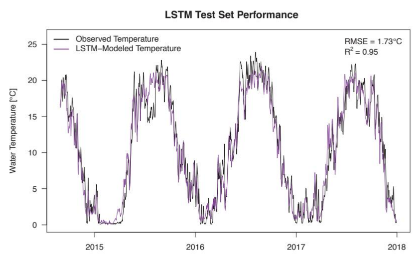

Figure 3. The final LSTM model achieves high accuracy on the test set, capturing both the magnitude and seasonality of temperatures.

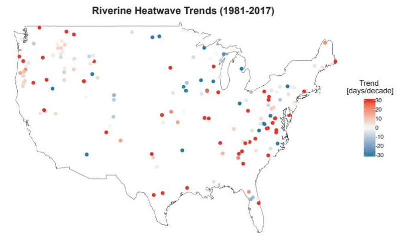

Figure 4. I apply the final LSTM model to estimate daily river temperatures at the remaining 253 sampling locations. The model performs well on these locations, with a median RMSE of 2.1°C and R^2 of 0.91. Then, for each sampling location, I estimate the decadal trend in heatwave days (points), defined as days where river temperatures exceed the local historical 95th percentile for at least 3 consecutive days. The majority of stations have seen increases in the number of heatwave days.

Discussion

One key drawback of the model build is that it only incorporates data from one sampling location, roughly 2.5% of the data available across all sites, so there are opportunities to make the model more applicable to the wide range of rivers in the USGS dataset. Further, attention-based models may better capture seasonality, though accuracy is high already. Last, one hyperparameter with large influence on these recurrent models but whose specification is context-driven rather than performance-driven is the number of previous timesteps allowed to inform the current prediction, here arbitrarily set to to 14 days.

Future Work

To improve generalizability, I will expand the LSTM model to incorporate training data from all rivers as well as additional watershed attributes such as elevation and land use. I will then use global climate models to simulate river temperature responses to future climate change.

References

[1]Frolicher *et al*. Marine heatwaves under global warming. *Nature* (2018).
[2]USGS Water Data for the Nation. waterdata.usgs.gov/nwis/qw
[3]PRISM Climate Group, Oregon State University. prism.oregonstate.edu