H45I-1484

Incorporating Physics-Based Temperature Predictions Into the National Water Model Framework

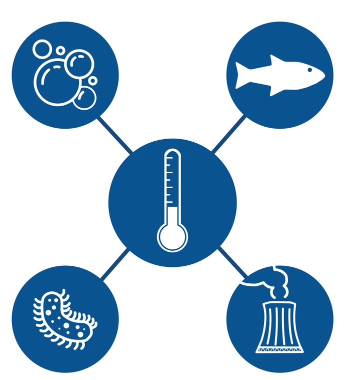
Jeffrey Wade[1,2], Fred L. Ogden[2], Christa Kelleher[3]

(1) Department of Earth and Environmental Sciences, Syracuse University, Syracuse, NY
(2) NOAA/NWS Office of Water Prediction, National Water Center, Tuscaloosa, AL
(3) Lafayette College, Easton, PA

OWP OFFICE OF WATER PREDICTION

Syracuse University

High-Resolution River Water Temperature Modeling at a Nationwide Scale



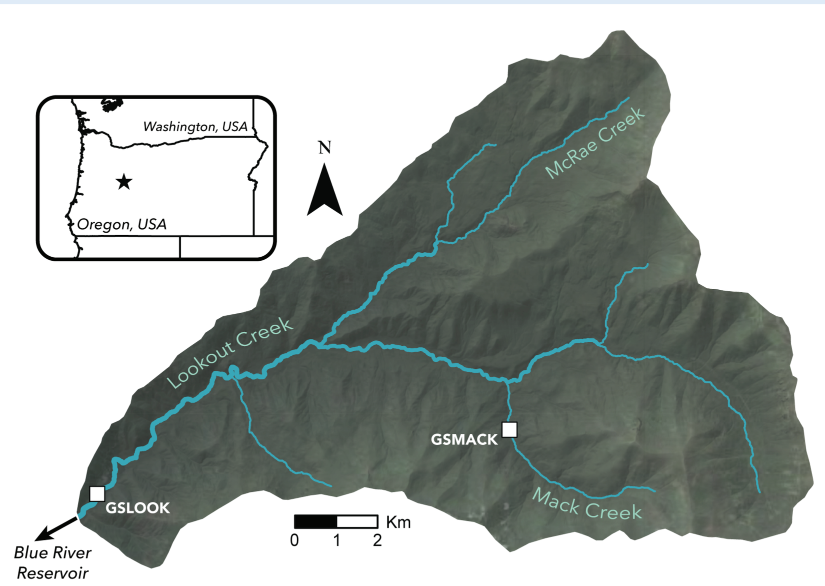
Water temperature is an influential component of and control on water quality, mediating the rate of solute processing, the health of micro- and macrofauna, and other ecosystem services[1]. Despite the significance of water temperature to the health of riverine systems, our knowledge of stream thermal regimes is limited, with some states and regions only having a handful of monitoring locations. Recent advances in high-resolution nationwide hydrologic models such as NOAA's National Water Model (NWM) provide a promising foundation for the development of physics-based water temperature models at similar scales. Using data derived from the NWM in a single test basin, we explore the validity of a mechanistic water temperature model that is transferable to all U.S. river reaches.

Can the National Water Model be leveraged to predict water temperatures at all U.S. river reaches?

Objective 1: Develop a physics-based water temperature model using NWM forcings.

Objective 2: Evaluate model performance in a test basin through sensitivity analysis.

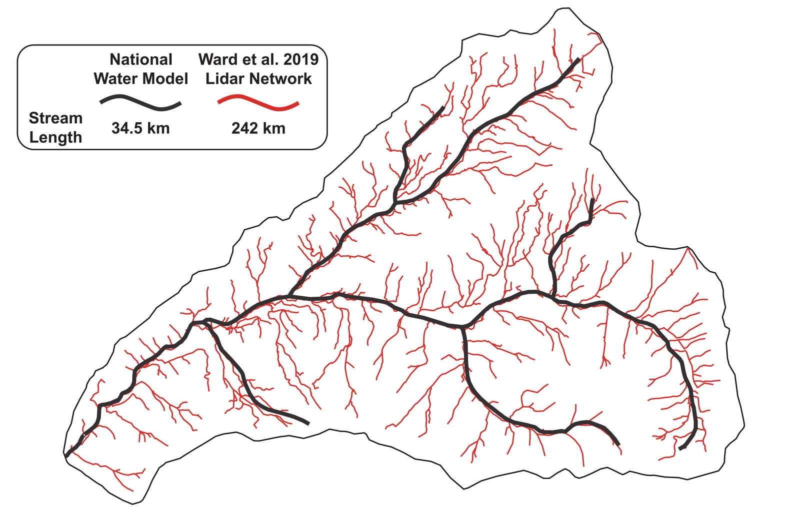
A Headwater Case Study: H.J. Andrews Experimental Forest



Location of H.J. Andrews water temperature gages in relation to channels identified by the National Water Model.

H.J. Andrews (HJA) Experimental Forest is a 6400 ha catchment in the Western Cascades, Oregon[2]. As an NSF Long-Term Ecological Research site, the streams draining HJA have been intensively studied over the past 60 years, providing detailed records of climate, discharge, and in-stream ecology. Comprehensive understanding of hydrological processes from numerous studies in the basin makes HJA an ideal site to test the performance of a water temperature model in forested headwater reaches.

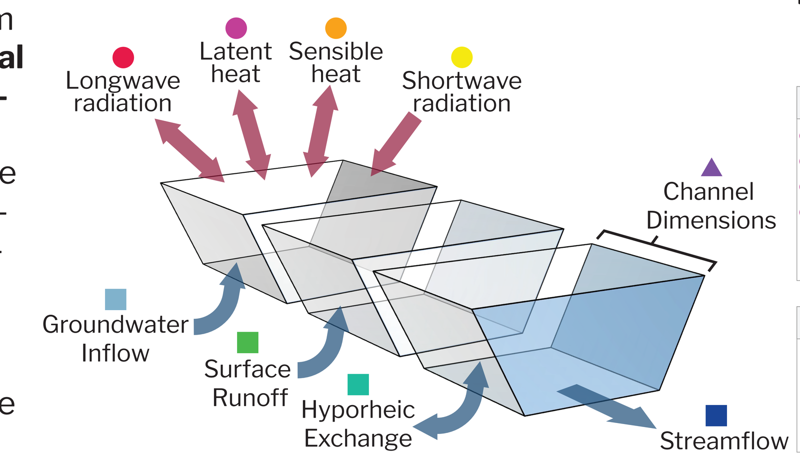
The National Water Model simulates HJA as a third-order stream network, giving predictions of discharge and other hydrological variables at 11 reaches in the basin. Two onsite gages, **GSMACK (located on Mack Creek)** and **GSLOOK (located on Lookout Creek)**, record water temperatures at 5-minute intervals. We use records from these gages to evaluate predictions made by our water temperature model.



Comparison of stream network extent at H.J. Andrews Experimental Forest between the National Water Model (NHD) and onsite estimates via Lidar (Ward et al., 2019)[2].

Semi-Lagrangian Water Temperature Model

Using forcings and model output from the **NOAA National Water Model Retrospective Data-set Version 2.1**, we extract hourly meteorological and hydrologic variables within our test basin to drive a water temperature model.



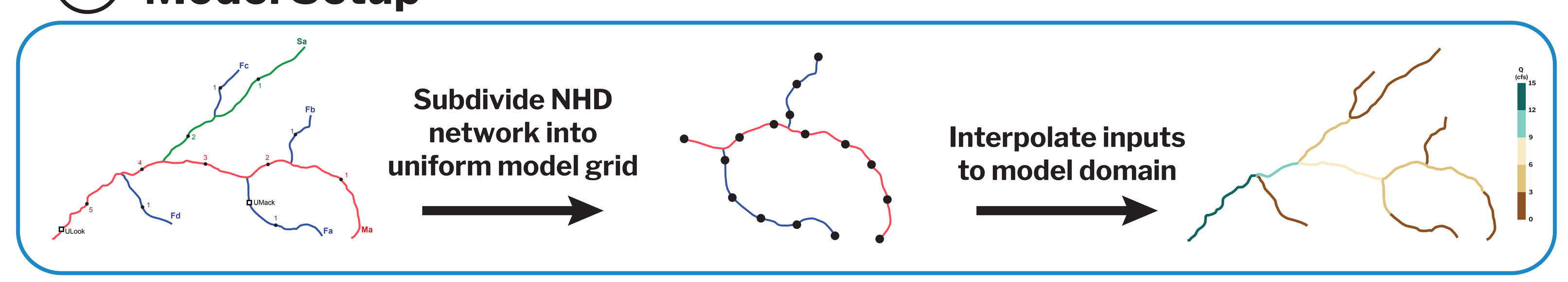
Model Data Sources

● = Color and shape of symbol reflects how each variable is used in the model

NWM Forcings	NWM Route Link
Incoming Shortwave	Channel Location
Incoming Longwave	Reach Length
Air Temperature	Channel Width
Relative Humidity	Channel Depth
Air Pressure	Channel Side Slope
Wind Speed	Stream Order

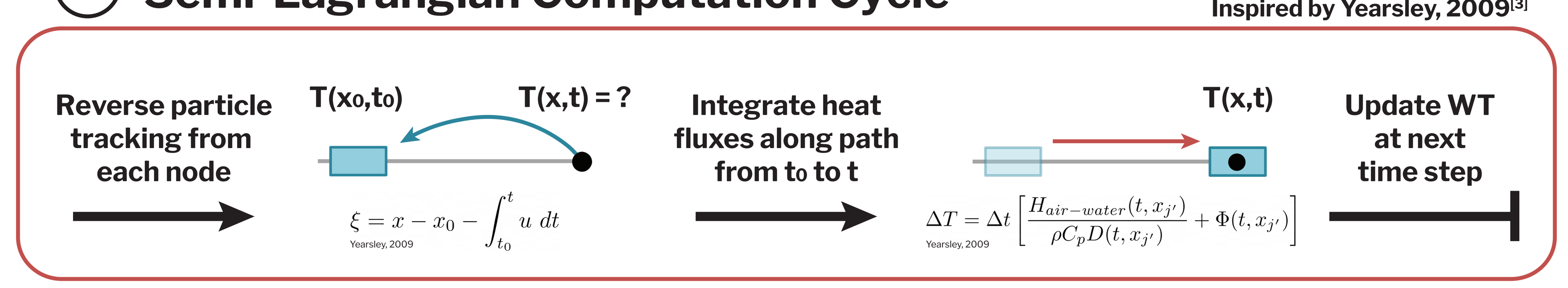
NWM Model Output	Unconstrained by NWM
Discharge	Riparian Shading
Stream Velocity	GW Temperature
Groundwater Inflow	Runoff Temperature
Surface Runoff	Hyporheic Lag
	Hyporheic Flow

1 Model Setup



2 Semi-Lagrangian Computation Cycle

Inspired by Yearsley, 2009[3]



$$\xi = x - x_0 - \int_{t_0}^{t} u \, dt$$

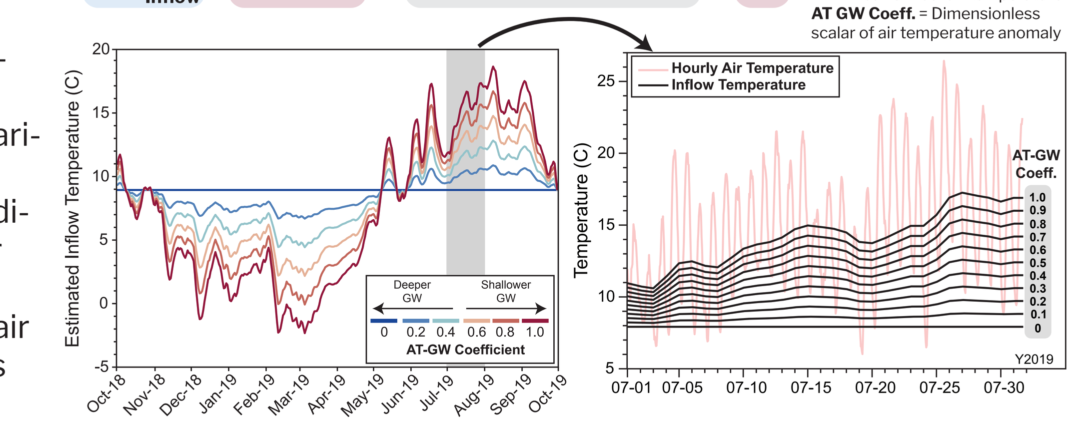
$$\Delta T = \Delta t \left[\frac{H_{air-water}(t, x_{j'})}{\rho C_p D(t, x_{j'})} + \Phi(t, x_{j'}) \right]$$

Constraining Effective Inflow Temperatures

Although water temperature models often conceptualize subsurface inflow as 'groundwater', the effective temperature of subsurface inflow can be warmer and more variable than deep groundwater temperatures[4]. To reproduce longitudinal patterns of temperature in our model, we estimated inflow temperatures by scaling variability in air temperature with a dimensionless coefficient (*AT-GW Coefficient*).

$$WT_{Inflow} = (AT - \overline{AT}) \times \text{AT GW Coefficient} + \overline{AT}$$

Where:
AT = Mean daily moving window air temperature
$\overline{AT}$ = Mean annual air temperature
AT GW Coeff. = Dimensionless scalar of air temperature anomaly



Estimated inflow temperatures for WY2019 at HJ Andrews headwater for a range of AT-GW coefficients.

Estimated inflow temperatures for July study period at HJ Andrews headwater for a range of AT-GW coefficients.

Evaluating Model Performance Through Monte Carlo Tuning

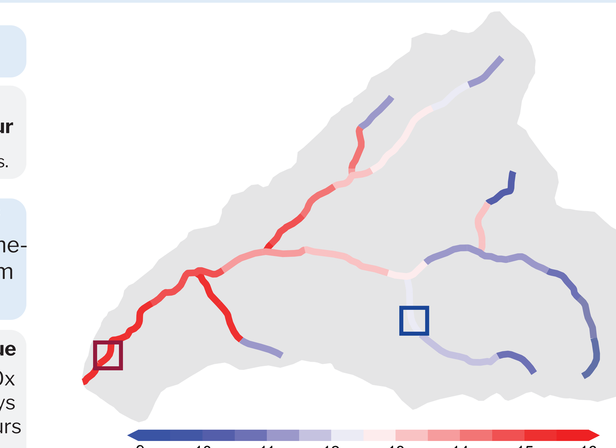
Model Tuning

Spatial Resolution: Predictions every **1 km**
Temporal Resolution: Predictions every **1 hour**

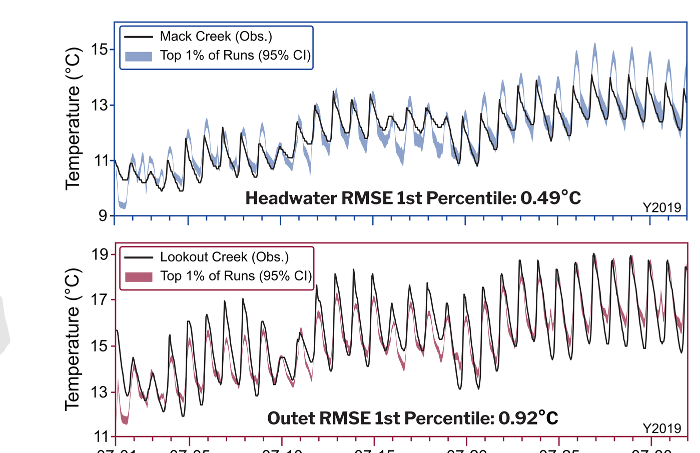
Predictions were stable for range of model resolutions.

Monte Carlo: 5000 runs, varying a set of hydrologic, thermal, and hyporheic parameters across the full network and by stream order (1st, 2nd, and 3rd order)

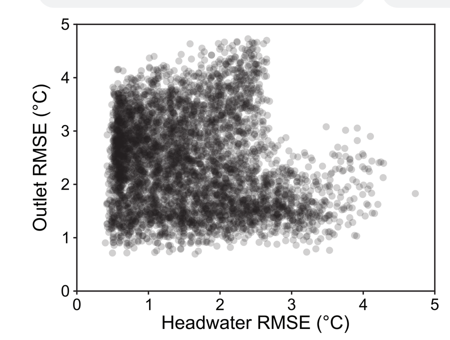
	MC Value
By Full Network:	
Riparian Shading	0.5x-2.0x
AT-GW Temp. Moving Window	2-14 days
Hyporheic Lag	2-24 hours
By Stream Order:	
GW Inflow Rate	0.5x-2.0x
AT-GW Temp. Coefficient	0-1
Hyporheic Exchange Fraction	0-1



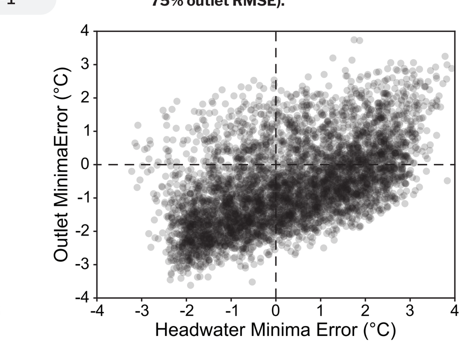
Mean simulated temperature at each reach across top 50 (1st percentile) model runs ranked by weighted error (25% headwater RMSE, 75% outlet RMSE).



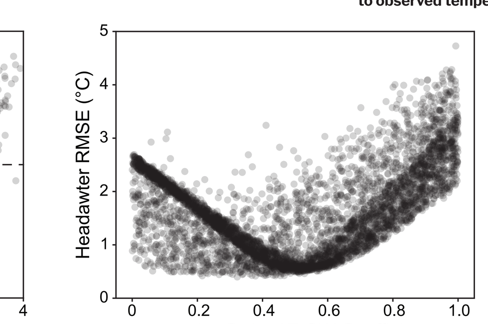
95% confidence intervals of predictions for top 50 (1st percentile) model runs ranked by weighted error (25% headwater RMSE, 75% outlet RMSE) compared to observed temperatures at headwater (Mack) and outlet (Lookout) gages.



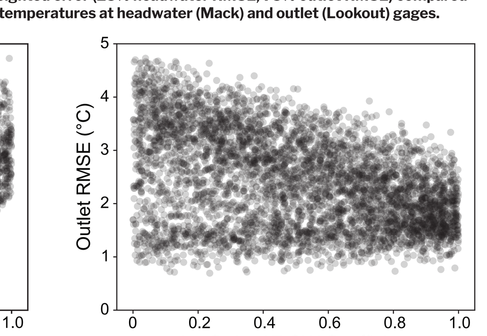
Tradeoffs in headwater and outlet error across 5000 Monte Carlo runs.



Tradeoffs in headwater and outlet error in predicting daily minimum temperatures.



Sensitivity of headwater prediction error to AT-GW Coefficient (control on GW temperature).

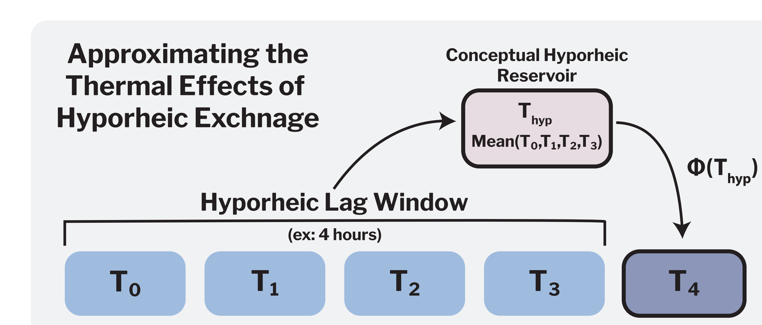


Sensitivity of outlet prediction error to AT-GW Coefficient (control on GW temperature).

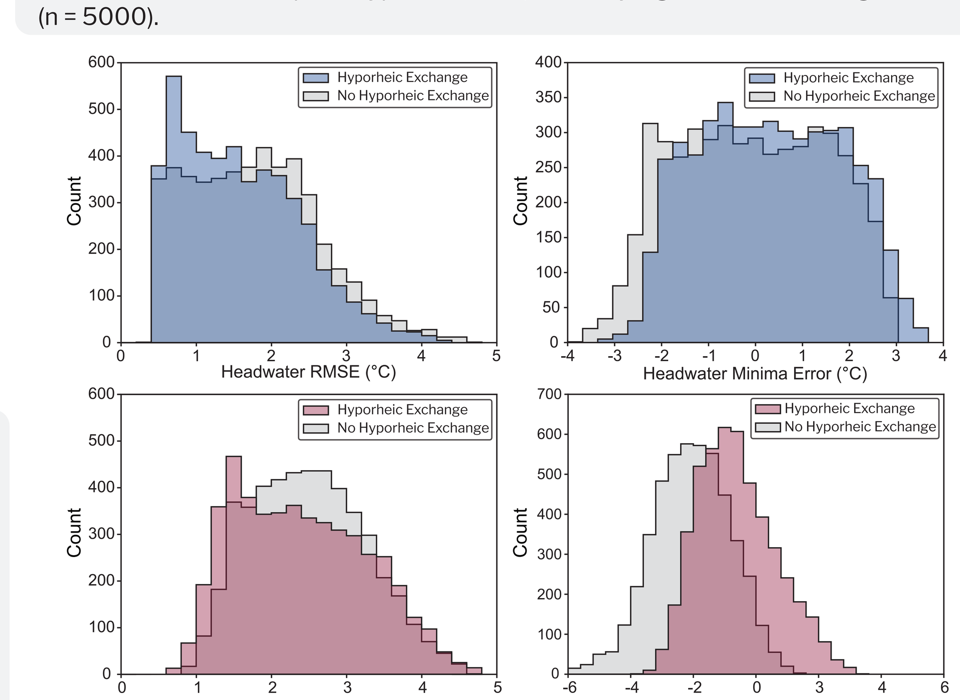
Does Conceptualized Hyporheic Flow Improve Temperature Predictions?

In high-gradient headwater streams, large fractions of streamflow pass through the subsurface as hyporheic exchange. This can have a considerable effect on water temperatures, as returning hyporheic flows typically have temperatures that are lagged compared to the main channel. Without including hyporheic processes, we struggled to recreate patterns of downstream heat transport. By including hyporheic exchange:

- **Headwater error improved**, with a higher frequency of runs under 1°C RMSE
- **Eliminated systematic bias in outlet daily minima**, driven by nighttime heat flux



No Hyporheic Exchange Runs: Tuned shading, GW temperature, and GW inflow variables without hyporheic exchange (n = 5000).
Hyporheic Exchange Runs: Identical Monte Carlo variables as no hyporheic exchange runs, with added conceptual hyporheic zone, tuned by lag time and exchange fraction (n = 5000).



Distribution of RMSE and daily minima error at the headwater and outlet gages across two model configurations (hyporheic exchange and no hyporheic exchange; n = 5000 runs each).

ACKNOWLEDGEMENTS

I would like to thank Peter Roohr, Todd Christenson, and Laura Cutrer for their support in organizing NOAA's William M. Lapenta Student Internship Program. I would also like to thank Jocelyn Burston for welcoming me to the National Water Center.

REFERENCES

[1] Caissie, D. (2006). The thermal regime of rivers: A review. Freshwater Biology, 51(8), 1389–1406. https://doi.org/10.1111/j.1365-2427.2006.01597.x
[2] Ward, A. S., Zarnetske, J. P., Baranov, V., Blaen, P. J., Brekenfeld, N., Chu, R., Derelle, R., Drummond, J., Fleckenstein, J. H., Garayburu-Caruso, V., Graham, E., Hannah, D., Harman, C. J., Herzog, S., Hixson, J., Knapp, J. L. A., Krause, S., Kurz, M. J., Lewandowski, J., … Wondzell, S. M. (2019). Co-located contemporaneous mapping of morphological, hydrological, chemical, and biological conditions in a 5th-order mountain stream network, Oregon, USA. Earth System Science Data, 11(4), 1567–1581. https://doi.org/10.5194/essd-11-1567-2019
[3] Yearsley, J. R. (2009). A semi-Lagrangian water temperature model for advection-dominated river systems. Water Resources Research, 45(12). https://doi.org/10.1029/2008WR007629
[4] Kurylyk, B. L., P.-A. Bourque, C., & Macquarrie, K. T. B. (2013). Potential surface temperature and shallow groundwater temperature response to climate change: An example from a small forested catchment in east-central NB (Canada). Hydrology and Earth System Sciences, 17(7), 2701–2716. https://doi.org/10.5194/hess-17-2701-2013

CONTACT

Email: jswade@syr.edu

View my poster and other AGU materials.