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Calibration optimization of a stream temperature model applied to the Nooksack River

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1. Introduction

The River Basin Model (RBM) is used to assess how stream temperatures will change in the Nooksack River due to warming climates. Before modeling forecasted climate scenarios, I first calibrated the model to observed historical stream temperatures. The calibration of the RBM to a stream network involves the adjustment of many different variables until the simulated temperatures match the observed historical stream temperatures. Because the manual process of calibrating the model is extremely time consuming, I developed a Python script to converge on the optimal variables required for the RBM calibration.

I used my optimization script to calibrate the RBM in each of the three sub-basins in the Nooksack River basin: the South Fork, Middle Fork, and the North Fork. I used outputs from hydrology models produced by Murphy (2016) as inputs to the RBM and calibrated to observed temperatures from USGS gauges in each of the sub-basins (Figure 1).

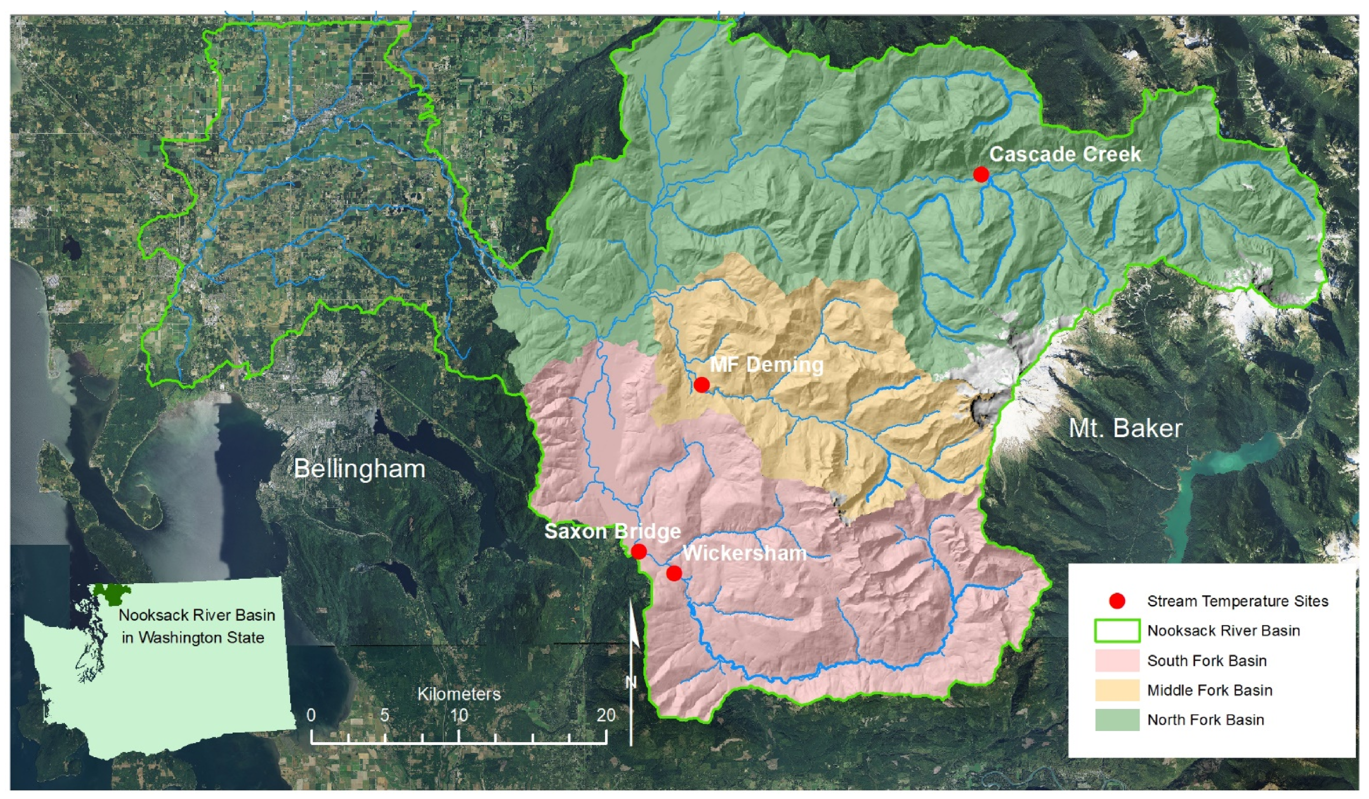

Figure 1. Location of the North, Middle, and South Fork basins in the upper Nooksack River watershed and USGS stream gauge sites, northwest Washington State.

2. Modeling Tools

Hydrology modeling using the DHSVM

The hydrology of the basin was simulated by Murphy (2016) using the Distributed Hydrology Soil Vegetation Model (DHSVM; Wigmosta et al., 1994). The DHSVM is a physical based model that performs an energy and mass balance at the grid scale. Using digital spatial characteristics and meteorological inputs, the DHSVM simulates streamflow at thousands of stream segments (Figure 2).

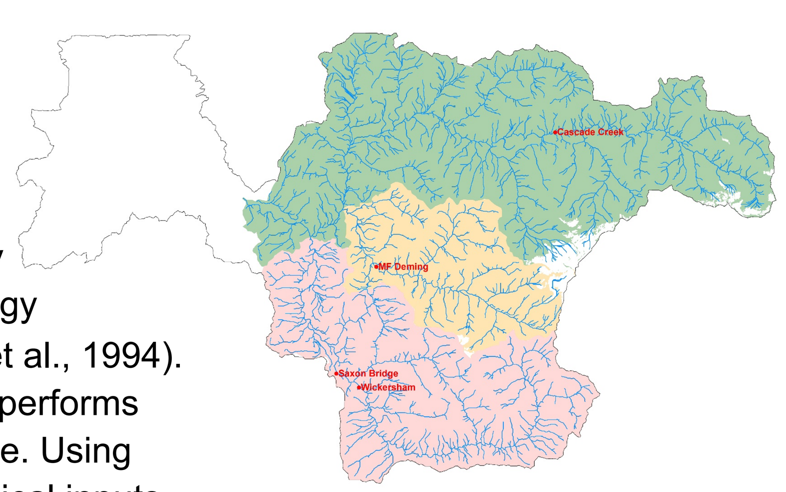

Figure 2. Stream network and USGS stream gauge locations.

Stream temperature modeling using the RBM

DHSVM stream discharge, energy, and riparian vegetation characteristics at each stream segment are used as inputs for the RBM (Figure 3).

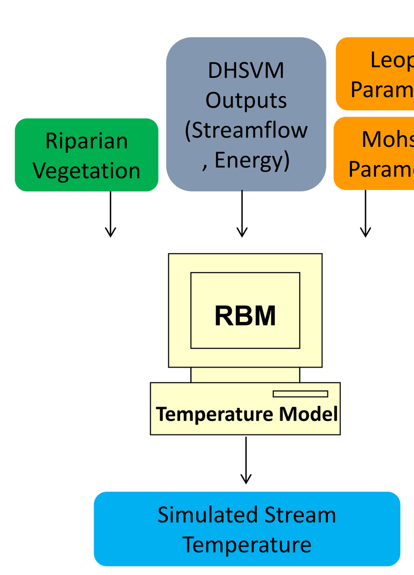

Figure 3. RBM input requirements.

The RBM is a semi-Lagrangian, one-dimension model that is scalable in space and time (Yearsley, 2009, 2012; Sun et al., 2014). The model requires initial headwater temperatures that are estimated using Mohseni parameters.

Steam velocities and depths and required for each stream segment and are estimated from the DHSVM discharge values using Leopold parameters.

The model tracks parcels of water through the river basin and estimates stream segment temperatures as influenced by net solar radiation, net longwave radiation, sensible heat flux, latent heat flux, groundwater, and advected heat from adjacent tributary segments (Figure 4).

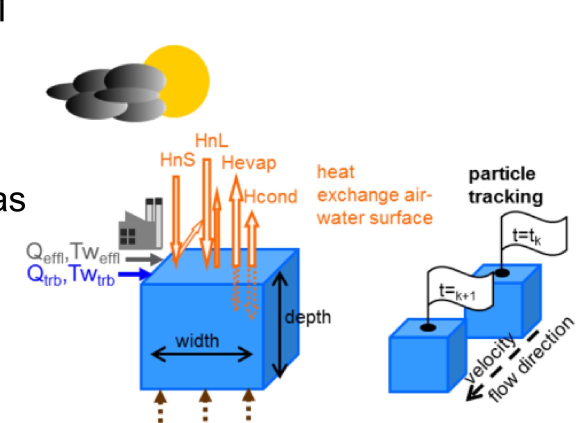

Figure 4. Conceptual model of the RBM (from Yearsley et al., 2009, 2012).

3. RBM Calibration

Calibration of the RBM requires the manipulation of eleven variables until the simulated stream temperatures match observed stream temperatures within statistical thresholds. Observed stream temperatures were collected at four USGS stream gauge sites (Figures 1 & 2).

The dominant calibration variables are those in the Mohseni relation used to estimate the initial headwater temperatures (T_{head}), and the Leopold parameters used to estimate the stream velocity and depth from the DHSVM discharge values.

Mohseni Parameters Mohseni et al. (1998)

$$T_{head} = \mu + \frac{\alpha - \mu}{1 + e^{\gamma(\beta - T_{smooth})}} \quad (1)$$

α = estimated maximum stream temperature (°C)
β = air temperature at the inflection point (°C)
γ = steepest slope of the function (ratio)
μ = estimated minimum stream temperature (°C)

Leopold Parameters Leopold and Maddock (1953)

$$D = aQ^b \quad (2)$$

$$u = cQ^d \quad (3)$$

Q = discharge (cms)
u = velocity (m/s)
D = depth (m)
a, b, c, and d = empirical constants

A smoothing parameter τ (tau) is used to attenuate high frequency fluctuations in air temperature (T_{air}) and is given as follows:

$$T_{smooth} = \tau \cdot T_{air}(t) + (1 - \tau) \cdot T_{air}(t-1) \quad (4)$$

Where t is time and τ (tau) is estimated by:

$$\tau = \frac{1}{(smoothing\ period)} = \frac{1}{(7\ days * 8\ timesteps\ per\ day)} \quad (5)$$

Two other calibration parameters include the minimum stream depth (D_{min}) and the minimum stream velocity (U_{min}). Riparian vegetation characteristics can also be altered but were held constant in these simulations.

Simulated model accuracy was measured by the Nash-Sutcliffe efficiency (NSE) (Nash and Sutcliffe, 1970), which compares daily mean observed streamflow to simulated daily mean streamflow. NSE values > 0.5 are assumed satisfactory.

Additional statistical tests were evaluated based on the calibration guidelines of Moriasi et al. (2007). Besides the NSE, I examined Pearson's coefficient of determination (R^2), percent bias (PBIAS), and root mean square error standard deviation ratio (RSR) to compare simulated and observed data.

4. Optimization Script

The Python script changes each of the eleven variables based on initial values set by the user and pre-determined maxima and minima (Table 1). The script will adjust the variables until it hits either the imposed limits or until it detects that the summer NSE value begins to decrease. This script is run three times per basin, one with the variables set to their maximum and decreasing, one with the variables set to their minimum and increasing, and one with the variables set at the midpoint. This helps to correct for the possibility of a bimodal distribution in the summer NSE values.

The algorithm steps through the list of variables by first changing Tau until the summer NSE decreases. Then, the algorithm varies Alpha until the statistics begin to decrease, then it adjusts the Tau value to ensure it is still the optimal value. It then changes Beta, then Alpha, then Tau, etc., until it changes each variable. Once it changes each variable and each is at the optimal point, the algorithm ends. The process takes about 12 hours per basin.

Table 1: The starting values for each RBM calibration variable for a midpoint trial.

Variable	Minimum Value	Maximum Value	Starting/Current Value	Step	Change	Increase or Decrease
Tau	0.010	0.020	0.015	12	TRUE	Increase
Alpha	13.000	24.000	17.000	24	TRUE	Increase
Beta	9.000	15.000	11.000	12	TRUE	Increase
Gamma	0.300	0.600	0.450	12	TRUE	Increase
Mu	0.600	3.000	2.000	12	TRUE	Increase
Ua	0.200	0.700	0.350	24	TRUE	Increase
Ub	0.200	0.400	0.300	24	TRUE	Increase
Umin	0.500	1.500	1.000	12	TRUE	Increase
Da	0.500	1.200	0.700	24	TRUE	Increase
Db	0.200	0.400	0.300	24	TRUE	Increase
Dmin	0.500	1.500	1.000	12	TRUE	Increase

5. Calibration Results

Overall, the Python optimization script converged to values within the minima and maxima thresholds for all eleven RBM calibration variables at all four sites in the Nooksack River (Table 2). The comparative statistics in all cases are rated as good to very good according to the performance criteria outlined by Moriasi et al. (2007; Table 3). More importantly, the statistical accuracy improves during the critical summer months, when the temperatures increase. Note that the highest stream temperatures are in South Fork. Elevations in the South Fork Basin reach about 2000 meters where snowpack melts out relatively early in the spring. The headwaters of the Middle Fork and North Fork are in the high snow fields and glaciated areas of Mt. Baker, producing cool meltwater late into the summer months, keeping the streams cooler.

Table 2. Final RBM calibration values.

	Variable	South Fork at Wickersham	South Fork at Saxon Bridge	Middle Fork at Deming	North Fork at Cascade Creek
	Tau	0.017	0.017	0.017	0.017
Mohseni Parameters	Alpha	18.840	20.000	17.000	13.084
	Beta	10.500	11.000	11.000	11.500
	Gamma	0.350	0.410	0.300	2.400
	Mu	2.000	3.000	2.200	2.200
Leopald Parameters	Ua	0.350	0.350	0.370	0.390
	Ub	0.300	0.300	0.290	0.300
	Umin	0.960	0.960	1.120	1.320
	Da	0.700	0.700	0.700	0.800
	Db	0.300	0.300	0.330	0.300
	Dmin	0.920	1.420	1.460	1.500

Table 3. Statistics for the final RBM calibration values.

	South Fork at Wickersham		South Fork at Saxon Bridge		Middle Fork at Deming		North Fork at Cascade Creek	
Statistics	Annual	May-Sept	Annual	May-Sept	Annual	May-Sept	Annual	May-Sept
NSE	0.834	0.681	0.891	0.84	0.809	0.712	0.805	0.732
NSE Monthly	0.909	0.799	0.94	0.907	0.908	0.86	0.873	0.896
R2	0.842	0.682	0.902	0.849	0.817	0.73	0.836	0.761
R2 Monthly	0.921	0.803	0.954	0.918	0.918	0.867	0.914	0.916
RSR	0.406	0.565	0.329	0.399	0.436	0.535	0.437	0.518
RSR Monthly	0.3	0.449	0.244	0.304	0.303	0.374	0.351	0.323
Pbias	-4.701	0.219	-2.94	1.524	-2.133	-1.416	-7.01	-0.396
Pbias Monthly	-4.801	0.158	-3.21	1.434	-2.32	-1.656	-7.15	-0.407

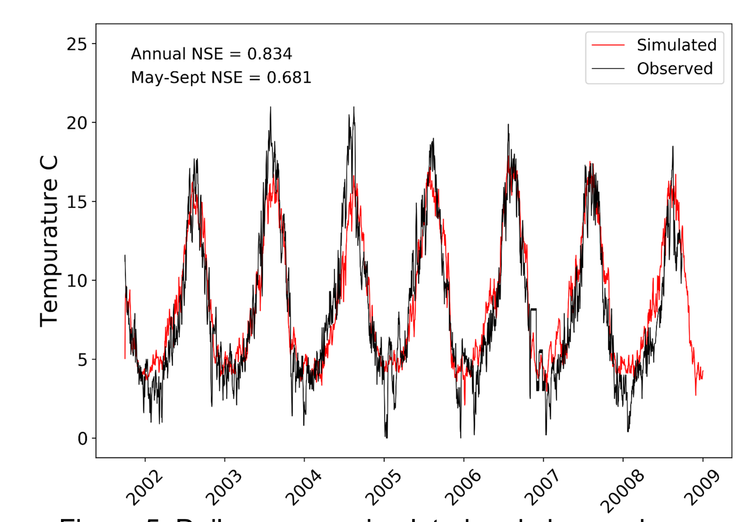

Figure 5. Daily average simulated and observed stream temperatures at the **Wickersham** gauge. South Fork Basin.

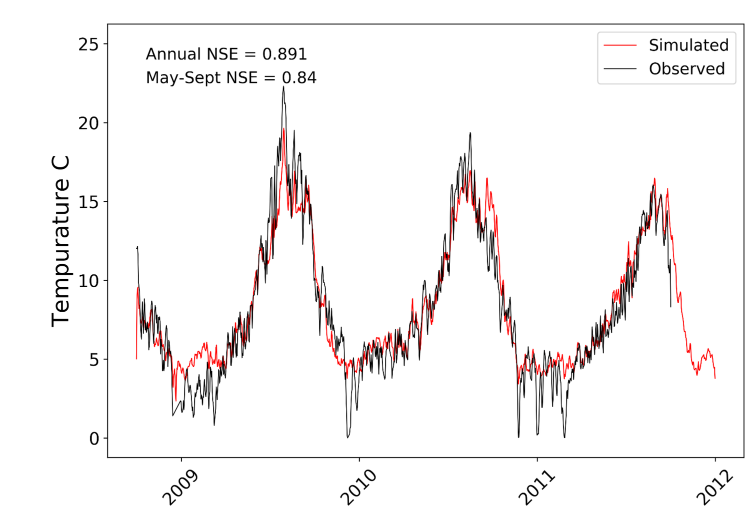

Figure 6. Daily average simulated and observed stream temperatures at the **Saxon Bridge** gauge, South Fork Basin.

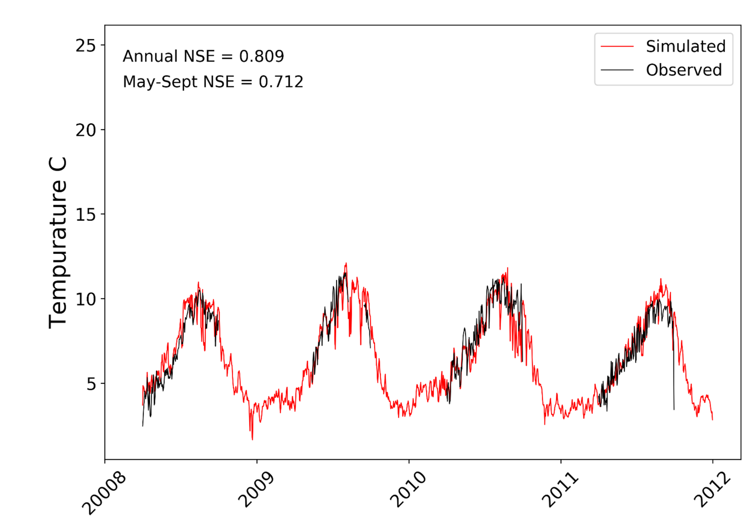

Figure 7. Daily average simulated and observed stream temperatures at the **Middle Fork Deming** gauge. The USGS gauge is missing data from October through April.

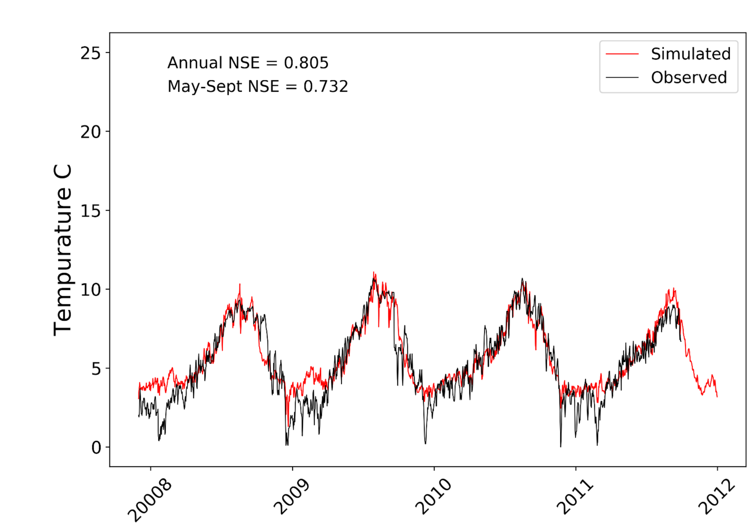

Figure 8. Daily average simulated and observed stream temperatures at the **Cascade Creek** gauge, North Fork Basin.

6. Future Work

Following the methods of Truitt (2018), the calibrated models will be used with forecasted climate data to simulate the hydrology and stream-temperature response in the three forks of the Nooksack River into the 21st century. We will use forecasted meteorological data from 10 global climate models of the CMIP5 with RCP4.5 and RCP8.5 forcing scenarios. Outputs will be analyzed with R scripts to assess hydrology and stream temperature trends in 30-year intervals surrounding 1996 (hindcast) 2025, 2050 and 2075.

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