Landscape variables characterize thermal stability in Southeastern US Brook Trout streams

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3.1 Dataset and Study Area

We considered paired air and water temperature data from 168 sites throughout the southern Appalachian region of the USA (Fig. X). Sites were subsetted from 204 randomly selected subwatersheds identified as capable of supporting populations of brook trout [*Salvelinus fontinalis*; (**ebtjv2006?**)]. Located at the downstream outlet of the subwatersheds, at each site a logger underwater was paired with a logger affixed to the bank or a tree. Stream and air temperatures were measured every 30 minutes using remote loggers (Onset Computer Corporation, 470 MacArthur Blvd. Bourne, MA 02532). Loggers were deployed from 2011 to 2015. For model fitting, we summarized temperatures to daily and weekly maximums, a reflection of the thermal sensitivity of coldwater organisms.

Each site was linked using a GIS to the National Hydrography Dataset [NHDplus v2.1; U.S. Geological Survey (2016)] stream segment on which it is located. Using the NHDplus COMID code for each segment, we then accessed associated landscape metrics from the NHDplus and the Environmental Protection Agency StreamCat database (Hill et al., 2016). Together, these sources contributed 174 variables for each segment (Appendix X).

3.2 Principal Components Analysis

We performed a Bayesian principal components analysis (PCA) of the segment-level NHDplus and StreamCat predictors at >9,000 sites of known BKT habitat obtained through EcoSHEDS (www.usgs.gov/apps/ecosheds) and the Eastern Brook Trout Joint Venture (**ebtjv2006?**). We used Bayesian PCA due to its ability to take N/A values in inputs. Analysis was completed using the "pcaMethods" package in R (R Core Team, 2022; Stacklies et al., 2007). We then extracted the top ten loadings by absolute value for the first five principle components (cumulative r^2: 0.61). Lastly, we extracted PCA scores for the stream segments where we had temperature data.

3.3 Hierarchical Model

We used Bayesian hierarchical models to infer stream segment thermal sensitivity and the effects thereupon of local landscapes. We compared linear and nonlinear models fit to daily maximum and weekly maximum temperatures. By fitting a linear model, we gain first-order estimates of the relationship between air and water temperatures (Beaufort et al., 2020; **webb1997?**; **erickson2000?**; **morrill2005?**;

kelleher2012a?). We removed observations where air temperatures were missing or <0° C. We fit observed water temperature T_W (° C) at stream segment $i = 1, ..., 168$ and day/week $t = 1, ..., T$

$$\mathrm{T}_{Wi,t} \sim \mathrm{normal}(g(\alpha_i, \beta_i, \mathrm{T}_{Ai,t}), \sigma^2) \tag{1}$$

where $\sigma \sim \mathrm{uniform}(0, 10)$ and $g(\alpha_i, \beta_i, \mathrm{T}_{Ai,t})$ is a linear function of observed air temperature T_A (°C) and the top five principle components of landscape variables:

$$g(\alpha_i, \beta_i, \mathrm{T}_{Ai,t}) = \alpha_i + \beta_i \mathrm{T}_{Ai,t}. \tag{2}$$

β_i, the slope of the linear air-water temperature relationship at each site, arises from $\beta_i \sim \mathrm{normal}(g(\theta_l, \mathrm{PCA}_{l,i}), \sigma_\beta^2)$ where $\sigma_\beta \sim \mathrm{uniform}(0, 10)$ and $g(\theta_l, \mathrm{PCA}_{l,i})$ for l in $1, ..., 6$ is the linear function

$$g(\theta_l, \mathrm{PCA}_{l,i}) = \theta_1 \mathrm{PCA}_1 + \theta_2 \mathrm{PCA}_2 + \theta_3 \mathrm{PCA}_3 + \theta_4 \mathrm{PCA}_4 + \theta_5 \mathrm{PCA}_5 + \theta_6 \mathrm{PCA}_6. \tag{3}$$

$\boldsymbol{\theta}$, the contribution of each principal component to thermal sensitivity, arises from $\theta_l \sim \mathrm{normal}(0, 100)$.

We also implemented a nonlinear model to relate observed air and water temperatures. We consider the nonlinear model due to the established nonlinear behaviors of water temperature at high and low air temperatures (Mohseni et al., 1998). Following Mohseni et al. (1998), we replace Eq. (2) with

$$g(\epsilon_i, \zeta_i, \beta_i, \kappa_i, \mathrm{T}_{Ai,t}) = \epsilon_i + \frac{\zeta_i - \epsilon_i}{1 + e^{\beta_i(\beta - \mathrm{T}_{Ai,t})}}, \tag{4}$$

where ϵ_i represents the minimum stream temperature (°C) at site i, ζ_i the maximum stream temperature (°C), κ_i the air temperature at the inflection point of the function (°C), and β_i the slope of the function at β_i (°C$\hat{}^{-1}$).

If using C-values, describe null model and C-value equations here

Model fit was assessed using posterior predictive checks of mean and standard deviation. Models were compared by calculating the deviance information criterion (DIC) for each. Lower DIC values indicate better model fit. We implemented our models utilizing Markov Chain Monte Carlo (MCMC) sampling using JAGS with the 'jagsUI' package in R (Kellner, 2021). We provide code in Appendix **??**. After a burn-in period of 1,000 samples, three chains were run until 5,000 iterations were reached. We report posterior means as point estimates and 95% highest posterior density credible intervals as estimates of uncertainty.

4 Results

5 Discussion

6 Conclusion

7 References

Beaufort, A., Moatar, F., Sauquet, E., Loicq, P., & Hannah, D. M. (2020). Influence of landscape and hydrological factors on stream–air temperature relationships at regional scale. *Hydrological Processes*, *34*(3), 583–597. https://doi.org/10.1002/hyp.13608

Hill, R. A., Weber, M. H., Leibowitz, S. G., Olsen, A. R., & Thornbrugh, D. J. (2016). The Stream-Catchment (StreamCat) Dataset: A Database of Watershed Metrics for the Conterminous United States. *JAWRA Journal of the American Water Resources Association*, *52*(1), 120–128. https://doi.org/10.1111/1752-1688.12372

Kellner, K. (2021). *jagsUI: A Wrapper Around 'rjags' to Streamline 'JAGS' Analyses.*

Mohseni, O., Stefan, H. G., & Erickson, T. R. (1998). A nonlinear regression model for weekly stream temperatures. *Water Resources Research*, *34*(10), 2685–2692. https://doi.org/10.1029/98WR01877

R Core Team. (2022). *R: A Language and Environment for Statistical Computing.* R Foundation for Statistical Computing.

Stacklies, W., Redestig, H., Scholz, M., Walther, D., & Selbig, J. (2007). pcaMethods – a Bioconductor package providing PCA methods for incomplete data. *Bioinformatics (Oxford, England)*, *23*, 1164–1167.

U.S. Geological Survey. (2016). *NHDPlus Version 2.*

8 Appendix