<u>Controls on Stream Temperature and Groundwater Contributions to Streamflow in Rocky Mountain National Park, Colorado</u>

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Summary

Stream temperature is an important ecological variable that affects most ecosystem functions, including mass and energy fluxes of organisms and their environments, phenology, and species fitness. Stream temperature measurements can also provide insight into hydrological processes, especially when paired with air temperature and water chemistry measurements. This study uses measurements of each of these variables to better understand water temperature dynamics in the headwater streams of Rocky Mountain National Park, Colorado. In part one of this study, we use GIS data to identify catchment-scale controls on summer stream temperatures, finding that lake area and basin elevation are particularly strong predictors; lakes produce a net warming effect, while higher elevation sites tend to have cooler stream temperatures. In part two of this study, we characterize trends in stream temperature over the last ~fifteen years across the park and explore potential causes of long-term change, finding that 21st-century wildfire was likely responsible for warming in several streams.

Funding from RMHRC was essential in completing the research described in this report, but equally importantly, it allowed for the collection of critical pilot data in Rocky Mountain National Park. I used this pilot data, collected in the summer of 2024, to successfully apply for a research grant from the Rocky Mountain Conservancy to pursue a much more extensive field

campaign in the park this year (2025). This data will be the subject of my first dissertation chapter, as I plan to start a PhD program at CU Boulder in the fall of 2025. Without RMHRC's help, this exciting early-career research probably wouldn't have been possible, and I am deeply grateful for the support. I will be sure to acknowledge RMHRC's contributions in any publications that originate from this work and to send manuscripts to RMHRC once published.

Part 1. Catchment controls on summer stream temperature in Rocky Mountain National Park

1.1 Introduction

Temperature has been referred to as a "master variable" (Kingsolver, 2009) for its wide-ranging influence on biological and ecological processes, including species phenology, metabolic rates, and nutrient cycling. Water temperature in streams is no exception, as stream temperature shapes the ranges of river fish, macroinvertebrates and primary producers and is an important component of conceptual models of how lotic ecosystems vary from headwaters to large lowland rivers (McManamay and DeRolph, 2019; Vannote et al., 1980). Hence, understanding the spatiotemporal distribution of stream temperature is essential for many aquatic biologists, ecologists, and resource managers whose areas of interest are influenced by this important water quality parameter.

Stream temperature depends on a range of physical factors (Figure 1). Heat transfers consist of radiative, convective, latent and sensible heat fluxes from the atmosphere, banks and streambed, as well as advective heat fluxes from upstream and from groundwater - surface water exchange (Caissie, 2006). These fluxes are related to reach- and catchment-scale characteristics, including climate, surface and subsurface hydrology, riparian shading, and basin morphology. For a full list of variables considered in this study and their conceptual relationship to stream temperature, see Table 1. Which variables are the best predictors of stream temperature depends on location and time. While air temperature is often the strongest predictor of stream temperature—univariate models of stream temperature using only air temperature may perform well (Mohseni et al., 1998; Webb and Nobilis, 2007)—confounding factors necessitate the consideration of other variables, especially in complex mountainous topography where inter-basin differences in hydrology and climate can be drastic. Previous work in small mountain streams in Colorado found that while stream temperature increased downstream as expected within individual basins, between basins, hydrological and geomorphic variables such as discharge, drainage area and residual pool volume were more important (Laurel and Wohl, 2017).

One factor confounding the air-stream temperature relationship is groundwater influence, which dampens temperature variability at the seasonal and daily timescales, keeping stream temperatures relatively cool in summer and warm in winter (Snyder et al., 2015). Previous work in Rocky Mountain National Park (RMNP) has found that greater proportions of subsurface-derived streamflow are associated with larger amounts of young surficial deposits (Suecker et al., 2000) and especially talus (Clow et al., 2003; Clow and Sueker, 2000), which may be the result of these areas storing and slowly releasing snowmelt. Another confounding factor is water's residence time as it flows from relatively cool higher elevations to warm lower elevations. Steeper stream segments more efficiently transmit cold water downstream, potentially causing a stronger decoupling of stream and air temperature. In contrast, lakes, wetlands and low gradient stream segments give water more time to equilibrate with ambient air temperatures, which in summer can lead to water : air temperature ratios closer to one (Dripps and Granger, 2013; Webb et al., 2008).

Understanding catchment controls on stream temperature is important not only for understanding the present landscape of this important ecological parameter, but also for predicting how stream ecosystems will respond to warming air temperatures in a changing climate. Certain catchment characteristics may cause greater or lesser sensitivity to changing air temperatures, but how exactly this sensitivity varies is debated (Isaak et al., 2016; Steel et al., 2019).

To better understand how mountain topography, hydrology, land cover and climate influence stream temperature in a high mountain environment, in this study we sought to identify controls on August stream temperature in RMNP. Our hypotheses were that:

1) Air temperature, lake area and runoff curve number would exert positive influences on stream temperature.
2) Surficial deposits, stream slope, and discharge would exert negative influences on stream temperature.

Air temperature was hypothesized to have a positive influence as it is a proxy for the sensible and radiative heat fluxes primarily controlling stream temperature. We hypothesized lake area would have a positive influence due to its positive effect on time-to-equilibrate, while stream slope and discharge have negative effects on time-to-equilibrate and were therefore hypothesized to have a negative influence on stream temperature. Discharge was also expected to have a negative effect because larger volumes of water in the stream are slower to respond to warm air temperatures. Lastly, surficial deposits were hypothesized to cause colder stream temperatures due to their known relationship with subsurface flow generation in RMNP which would theoretically cool streams in the summer.

1.2 Study Area

RMNP spans 1074 km^2 of high-elevation forests, meadows and alpine tundra on both sides of the Continental Divide in the central Rocky Mountains, Colorado, USA. The Colorado River headwaters are located on the west side of the park, while the Big Thompson River is the largest stream draining the east side of the park. The park receives most of its precipitation as snow with a smaller proportion coming from monsoon rain in the summer. Average streamflow peaks in May or June during peak snowmelt, recedes through the summer, and remains low through fall and winter. Mean annual precipitation ranges from <50 cm at lower elevations to >100 cm along the Continental Divide (Daly and Bryant, n.d.).

Stream temperature data from 22 basins within the park were analyzed in this study (Figure 2). Basin drainage areas ranged from 0.7 to 63.9 km^2. Measurement sites were in subalpine and alpine forest and meadow streams (mean elevation = 2892 m; SD = 262 m). Geology within the basins is mostly Precambrian gneiss and granite, with variable amounts of surficial deposits including till, colluvium, talus and landslide deposits (mean basin surficial deposit coverage = 18%; SD = 16%). Rock glaciers are found in the headwaters of most basins, as are permanent snow and ice fields and several small cirque glaciers (Homer et al., 2015). Lakes are abundant in some watersheds and absent in others (mean lake coverage = 2.7%; SD = 2.4%). West of the Continental Divide, the vulnerable Colorado River Cutthroat trout inhabits the upper portions of many basins, while the critically imperiled Greenback Cutthroat Trout is the focus of reintroduction and conservation efforts east of the divide.

1.3 Methods

Overview: We used multiple linear regression with a best subsets variable selection process to identify important drivers of summer stream temperature throughout RMNP.

Stream Temperature Data: Stream temperature data gathered by the NPS and US Geological Survey (USGS) were accessed via the public NPS Aquarius web portal, while data gathered by the US Fish and Wildlife Service (FWS) was received via personal communication. August stream temperature was chosen as the temperature metric to be analyzed, which is a commonly used indicator of near-maximum water temperature during the short growing season of mountain streams (Isaak and Hubert, 2001). Stream temperature was collected at sub-hourly intervals over a period spanning 1999-2024 (mean record length = 14 years), averaged at the daily and then monthly intervals, and the median monthly mean for August was the stream temperature value used in analysis.

Predictor Variables: Data describing catchment characteristics to be considered for predicting August stream temperature were gathered for each basin from publicly available sources, including USGS StreamStats, surficial geology maps, lakes delineated in QGIS based on aerial imagery, a 1m digital elevation model (DEM). Climate variables (air temperature, precipitation, vapor pressure and solar radiation) were averaged for August from DAYMET climate reanalysis data only across those years with stream temperature data at each site. To satisfy the normality assumption required by linear regression, non-normally distributed variables were transformed by log, square-root, or power (up to fifth power) transformations; those variables that were still not normally distributed (Shapiro-Wilkes test $p > 0.10$) were removed from consideration.

Variables passed to the next step of variable selection (best subsets) and their reason for consideration (conceptual relationship to stream temperature) are presented in Table 1.

Variable Selection: The best linear regression models composed of one, two, three, four and five predictor variables were chosen using the best subsets method using the 'leaps' package in R, as has been done previously (Laurel and Wohl, 2017). In this procedure, linear regression models are fitted for all possible combinations of variables, up to a user-specified maximum number of variables; five variables were chosen as the largest set of models to be fitted to avoid overfitting given the relatively low number of observations (n = 22). Models of each size were then ranked based on the Bayesian Information Criterion (BIC) and the best model was chosen as that with the lowest BIC. To limit collinearity between predictor variables, any models with Variance Inflation Factors (VIF) > 4 were removed from consideration.

Model Validation: Once the best model was selected, validation was performed by randomly splitting observations into 12 training and 10 validation data points, training the model with the training set and then predicting stream temperature for the validation set, with root mean squared error (RMSE) calculated for the difference between the predicted and observed values of the validation set. This was repeated 500 times and the mean RMSE of all validation model fits was calculated.

1.4 Results

The best model (lowest BIC) included five variables (Figure 3). The equation of that model is:

$$
\begin{aligned}
T = -0.014 \cdot (\text{Mean Elev}) + 3.89 \cdot (\text{Lake Area}) \\
+ 3.4 \times 10^{-3} \cdot (\text{Max Elev}) - 2.59 \cdot \log(\text{Grass Area}) \\
+ 0.015 \cdot (\text{Solar Rad})
\end{aligned}
$$

Mean and maximum elevation are in units of meters, lake area and grass area are a percent of total basin area, and solar radiation is in W/m^2. Based on standardized beta coefficients, mean elevation has the largest effect on August stream temperature, followed in decreasing order by lake area, max elevation, grass area, and solar radiation. Sqrt(stream slope) is included in the best model of four variables (negative effect) and sqrt(% basin storage) is included in the best model of three variables (positive effect). The best overall model predicts stream temperature well with a mean RMSE of 0.77 °C (Figure 4).

1.5 Discussion

Stream temperature in RMNP primarily depends on landscape factors, as demonstrated by the low prediction errors of the final model. This is in keeping with the findings of previous work that found a model incorporating basin elevation, watershed slope, valley constraint, grass, cattle density, and riparian trees could predict stream temperature maxima (Isaak and Hubert, 2001).

Mean basin elevation being the single strongest predictor of stream temperature would suggest that this metric is a more accurate representation of the sensible heat fluxes typically represented by air temperature. Contrary to our hypothesis, air temperature is not one of variables with a strong positive effect on stream temperature. In this case, 4 km x 4 km resolution reanalysis-derived air temperature is likely a poorer representation than mean basin elevation, which is more precise and air temperature generally predictably decreases with increasing elevation. Solar radiation having a positive effect on stream temperature likely captures the radiative heat flux element of a stream thermal budget, though in case, the 4 km x 4 km resolution reanalysis-derived solar radiation ended up in the final models rather than aspect directly calculated from a DEM, which should theoretically capture the same effect but be more precise. Paired air temperature measurements may improve predictions of stream temperature, but if mean elevation captures the influence of air temperature effectively, perhaps it can be a useful proxy in future models of stream temperature in the park without requiring costly additional data collection. Like this study, previous work has also found that mean basin elevation is a better predictor of stream temperature than point elevations (i.e., elevation of the stream temperature measurement location) (Isaak and Hubert, 2001; Mauger et al., 2017). However, elevation was found to have a positive effect on stream temperature in another study of several dozen Colorado streams; only within individual streams did elevation have the expected negative effect seen in this study (Laurel and Wohl, 2017). This suggests that the effect of mean basin elevation can be confounded by other variables.

The strong positive influence of lake area supports our hypothesis. This supports the theory that lakes allow water temperatures to equilibrate with relatively warmer ambient air temperatures, increasing stream temperatures lower in the basin. This is in keeping with previous studies that have found a positive influence from lake area and pool volume (Isaak et al., 2017; Laurel and Wohl, 2017).

Contrary to our hypothesis, runoff curve number, surficial deposits, and discharge were not strong predictors of stream temperature. While stream slope did not end up in the final model, it had the expected negative effect on stream temperature in the best model of four variables. The lack of runoff curve number and surficial deposits in any of the best models would suggest that either these metrics do not best reflect the ability of basins to store snowmelt and release subsurface water through the summer, or that subsurface storage and release is not among the five most important factors influencing summer stream temperature in RMNP. However, grass area may be representing the effect of subsurface storage and release instead. Grass area as classified by the NLCD 2011 land cover dataset used here corresponds primarily to alpine tundra within the park, which may be areas of snow accumulation, increased infiltration and storage.

The exclusion of discharge or any related variable such as drainage area is surprising given that flow is often considered an important mediator of the air-water temperature relationship (Webb et al., 2003). One hypothesis to explain the exclusion of both discharge and air temperature is that these variables influence stream temperature on shorter time scales, but these effects diminish relative to other variables when averaging across the long (multi-year) timescale considered in this study.

Maximum basin elevation has a positive effect on stream temperature, something that was not predicted beforehand. This may be the result of a combined effect of mean and maximum basin elevation, in which the larger the difference between the maximum and mean basin elevation, the longer water has to travel to reach the observation point, allowing it to equilibrate with air temperatures. Another possible interpretation is that maximum basin elevation is correlated with some other unknown variable not considered here that has a more direct positive influence on stream temperature.

1.6 Conclusions

August stream temperature in RMNP is largely determined by landscape factors that can be easily derived from publicly available datasets. Lake area and mean basin elevation are dominant controls on stream temperature, along with grass area, solar radiation, maximum basin elevation, stream slope, and basin storage (lake + wetland) area.

Future work should focus on which predictor variables are important for other important stream temperature metrics like maximum 7-day mean stream temperature. For sites with sufficiently long datasets, variation in the stream temperature – air temperature slope, i.e. stream temperature sensitivity, should be analyzed. Identifying landscape factors associated with greater or lesser sensitivity to changing air temperatures will inform predictions of future habitat suitability in a warming and potentially drying climate.

1.7 Figures

Variable	Trans.	Rationale	Source
August median air temperature		Sensible heat flux	DAYMET
August median vapor pressure		Sensible and latent heat fluxes	DAYMET
August median solar radiation		Radiative heat flux	DAYMET
August median total precipitation		Streamflow quantity + source temperature	DAYMET
Mean annual precipitation		Streamflow quantity + source temperature	StreamStats
Longitude		East-west differences in climate + basin morphology	StreamStats
Elevation (mouth)		Dependence of air temperature on elevation	StreamStats
Basin elevation (mean)		Dependence of air temperature on elevation	StreamStats
Basin elevation (maximum)		Distance from streamflow source	StreamStats
Area-weighted mean lake elevation	fifth	Air temperature where water has time to equilibrate with atmosphere	DEM
Lake area	log	Area where water has time to equilibrate with atmosphere	DEM
% Basin lake area	sqrt	Area where water has time to equilibrate with atmosphere	DEM
% Basin storage (lake + wetland)	sqrt	Area where water has time to equilibrate with atmosphere	StreamStats

% Basin talus		Areas of subsurface water storage	Surficial geology (ROMN)
% Basin surficial deposits	log	Areas of subsurface water storage	Surficial geology (ROMN)
% Basin soil type A	sqrt	Subsurface vs. surface streamflow generation	StreamStats (SSURGO)
% Basin soil type D		Areas of subsurface water storage	StreamStats (SSURGO)
<u>% Basin grass</u>	log	Shading; areas of subsurface water storage	StreamStats (NLCD)
% Basin greater than 30 degree slope		Areas of subsurface water storage	DEM
% Basin snow & ice	log	Areas producing near-freezing streamflow	StreamStats (NLCD)
Basin aspect		Solar radiation; snow	DEM
Basin aspect	sqrt	Solar radiation; snow	DEM
Stream slope (from 10th to 85th % along longest flow path)		Time to equilibrate with atmosphere	StreamStats
Longest flow path length	log	Time to equilibrate with atmosphere	StreamStats
Time of concentration	log	Time to equilibrate with atmosphere	StreamStats
Runoff curve number		Subsurface vs. surface streamflow generation	StreamStats

<u>Table 1.</u> Variables included in best subsets model selection process. Variables included in final five-variable model **<u>bolded and underlined.</u>** Trans. = transformation. NLCD = National Land Cover Database 2011. ROMN = NPS Rocky Mountain Inventory & Monitoring Network.

Figures

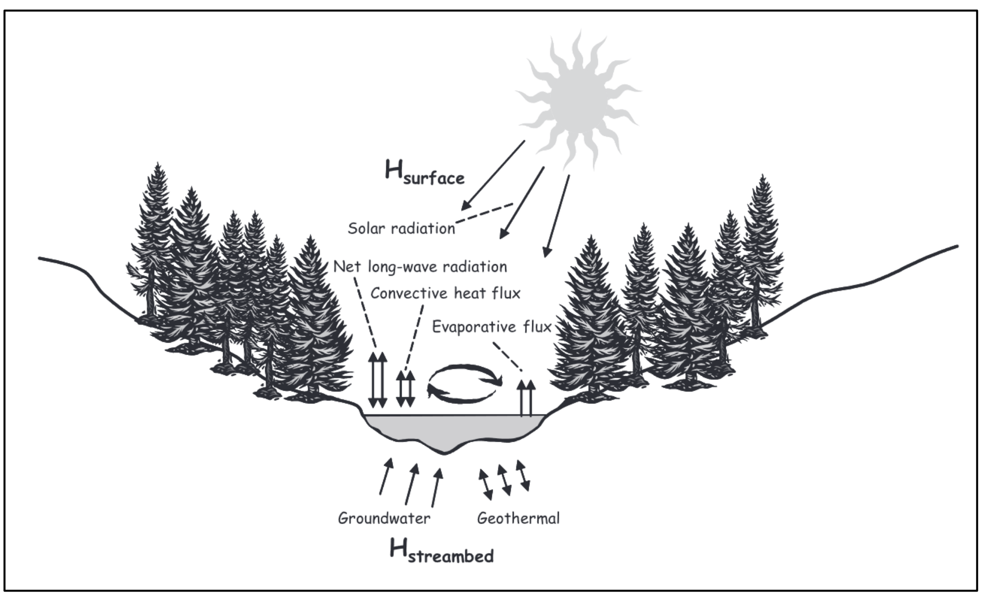
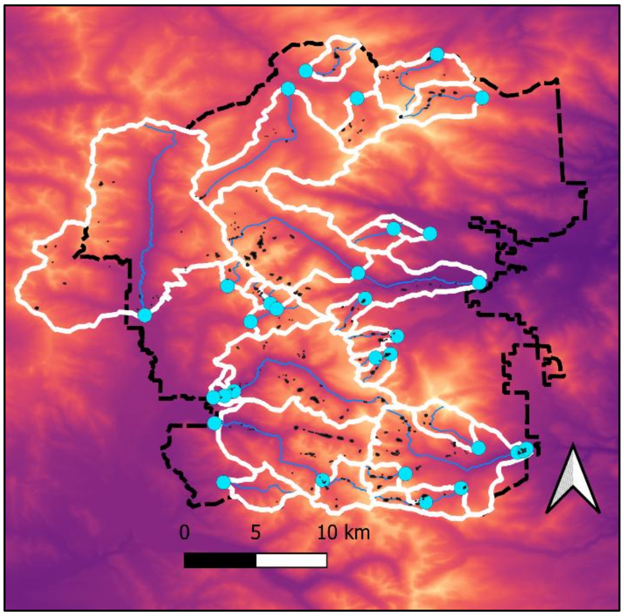


Figure 1. River heat exchange processes, from Caissie 2006. Not pictured: advection of (typically cooler) stream water from upstream.



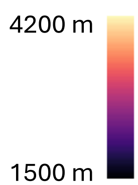
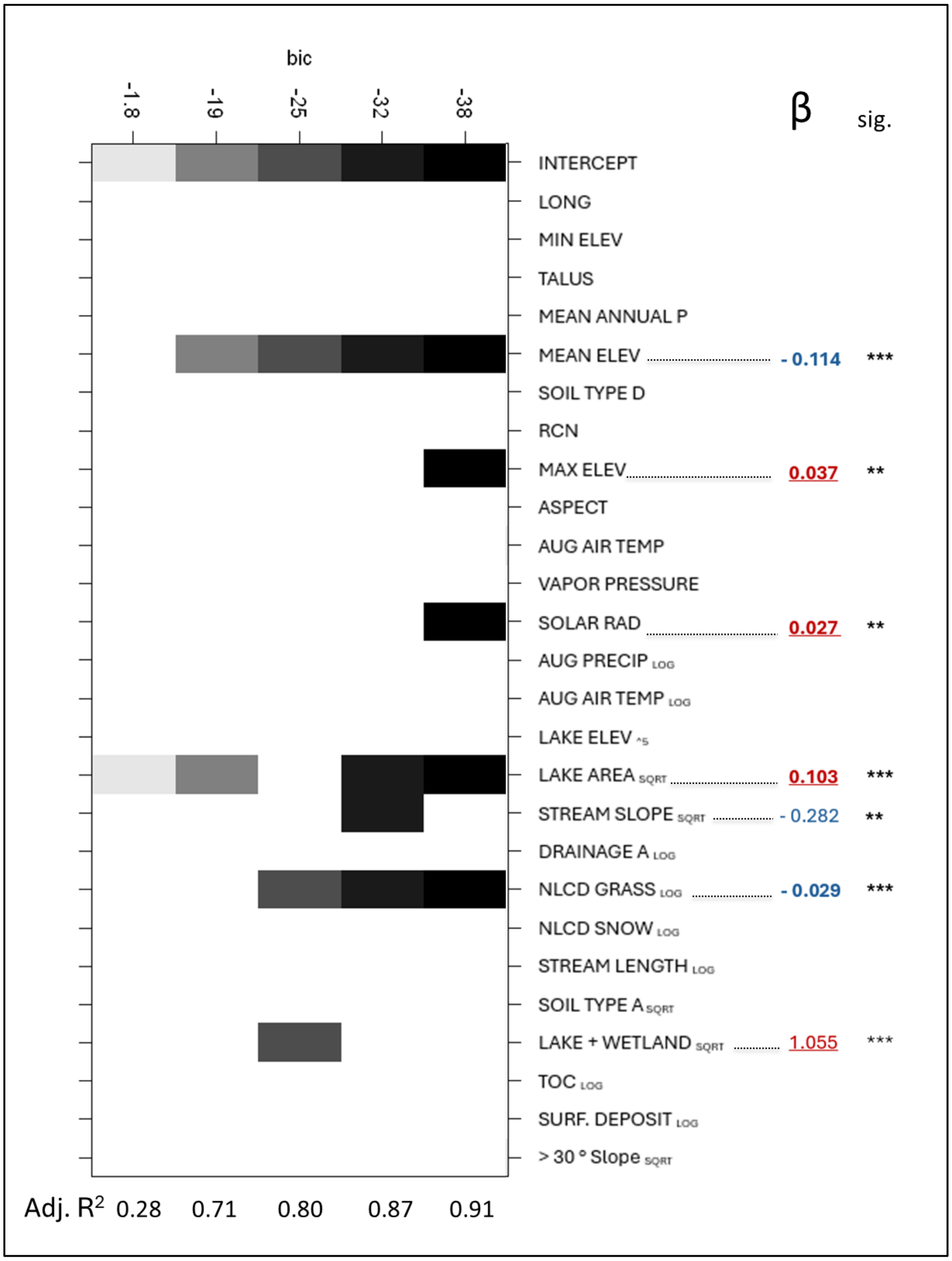


Figure 2a. Study Area. RMNP elevation w/ study basins outlined in white, temperature measurement locations in blue, lakes in black, and park boundary outlined with dotted line.

Figure 2b. Fern Creek in the Big Thompson watershed near the Fern Creek temperature monitoring site.



<u>Figure 3:</u> Multiple linear regression variable selection. Moving left to right, shaded boxes mark variables included in best models (lowest BIC) of 1, 2, 3, 4, and 5 variables. Standardized beta coefficients reported in red/underlined (positive) and blue (negative). Variable significance ** p < 0.01, *** p < 0.001.

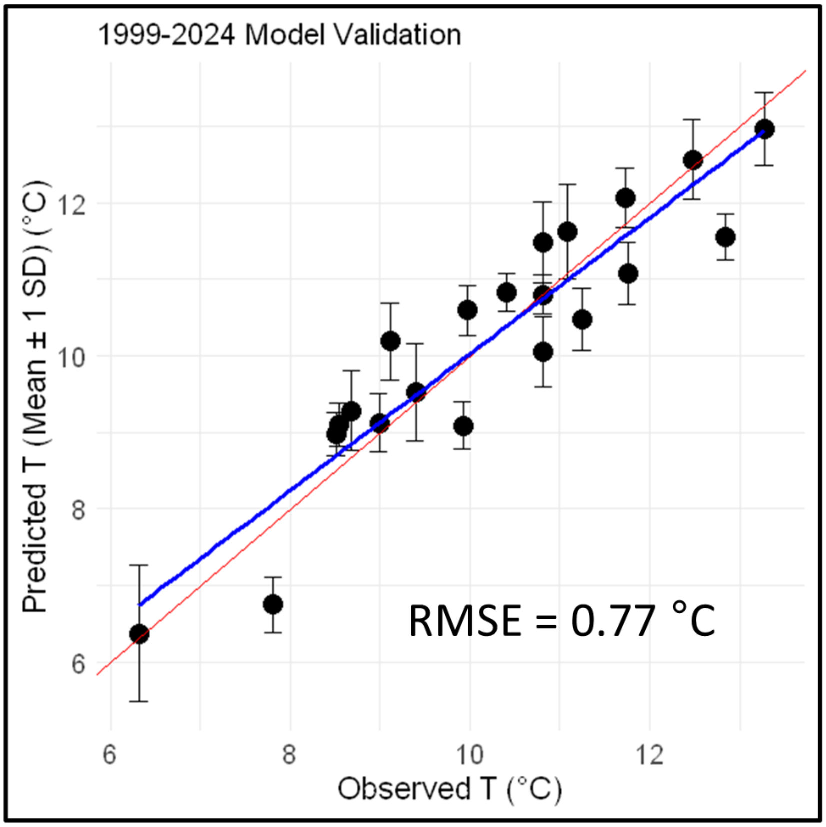


Figure 4: Model validation of best model for median August stream temperature (model equation written above). 22 observations randomly split into 12 training and 10 validation observations and RMSE calculated. Repeated 500 times, RMSE is avg. across all trials and error bars are 1 SD above and below avg. predicted value.

Part 2. Long-term changes in stream temperature in Rocky Mountain National Park, CO

2.1 Introduction

Stream temperature has been monitored in Rocky Mountain National Park (RMNP) since at least 2000 by researchers, resource managers and volunteers from the National Park Service, US Fish and Wildlife Service, US Geological Survey, and academic institutions. There are more records longer than a decade in RMNP than in any other national park, making this a uniquely suitable place for studying how long-term stream temperature changes vary across a relatively undisturbed headwater region. These records have been maintained largely for aquatic ecological and fisheries research, as this is a priority area for restoration and preservation of native cutthroat trout populations (Kennedy and Watry, 2022). Changing stream temperatures have the potential to affect cutthroat trout recruitment, growth, and competition with non-native salmonids throughout the Rocky Mountains (Ma et al., 2023; Roberts et al., 2013), including in Rocky Mountain National Park.

As part of an NPS-wide analysis of long-term temperature trends in montane streams, we identified stream temperature trends in eleven streams in RMNP. We compare these trends to those in other park units and investigate possible causes of stream temperature change, including changing air temperature, streamflow, and shading due to wildfire. We find that stream temperatures warmed across most sites in October and at a few sites in June through September too, most of which are distinguished by having burnt in wildfires in the past fifteen years. This suggests that the hard-to-predict occurrence of wildfire may have significant influences on stream temperature within the park in the future.

2.2 Methods

Eleven stream sites were chosen for analysis based on the length and continuity of their stream temperature records. All but one of the water temperature datasets were collected and shared by US Fish & Wildlife Service fisheries biologist Chris Kennedy (personal communication, 2024); the remaining record was collected by the United States Geological Survey and accessed through the publicly available NPS Aquarius web portal (Table 1). To compare temperature trends across a standardized period, trends were estimated for the 2008-2023 period for all sites, and also for the full period of record where longer records were available. We analyzed data from April through October. These months had the most available data, as ice in the remaining months disrupts data collection at many locations.

Trends in water and air temperature were identified using a generalized additive mixed model (GAMM) approach (Ferguson et al., 2008; Orr et al., 2015). A generalized additive model is comparable to a generalized linear model but with an additional relaxation of distributional assumptions. A GAMM was fitted for each site with the following structure:

$$\text{Temperature}_i = \beta_{\text{month}_i} + f_1(\text{yday}_i) + f_{2,\text{month}_i}(\text{time}_i) + \varepsilon_i$$

where βmonth_i is a fixed effect for the month, $f_1(\text{yday}_i)$ is a smooth, cyclic seasonal function of the day of year, $f_{2,\text{month}}(\text{time}_i)$ is a linear function of time representing the long-term trend component, and ε_i accounts for residual autocorrelation using an exponential correlation structure. f_1 accounts for the average seasonal variation in temperature and f_2 estimates a linear slope for temperature in each month across the entire observation period (2008-2023).

To provide a statistically-grounded assessment of confidence in trend directions, we applied Trend Direction Analysis (TDA) (McBride, 2019) to the GAMM-derived trends. Unlike traditional hypothesis test methods for trend analysis like the Mann-Kendall test, which assume a null hypothesis of “no trend” and gives a “yes or no” binary result, TDA provides a percent likelihood of an increasing or a decreasing trend that can be translated into a categorical likelihood descriptor. The likelihood categories used in this study are those used by the Intergovernmental Panel on Climate Change (Mastrandrea et al., 2010) and are shown in Table 2.

To assess possible causes of stream temperature change, air temperature records derived from a 1km gridded reanalysis dataset (DAYMET) were analyzed for each site using the same GAMM and TDA procedure as for stream temperature. Wildfires can increase stream temperatures by reducing shading from vegetation (Hall and Lombardozzi, 2008; Holsinger et al., 2014). To assess potential impacts of wildfires on stream temperatures, wildfire boundaries were downloaded and sites were classified as wildfire-affected or unaffected depending on whether upstream areas of the catchment burnt during the 2008-2023 period. Summer stream temperature sensitivity, calculated as the slope parameter of the water temperature – air temperature relationship in a multiple regression model, was calculated before and after the fires in 2020 and 2010 and compared across wildfire-affected and unaffected catchment to discern if stream’s thermal response to air temperatures changed in wildfire-affected catchments. To account for the potential effects of discharge on this relationship, the multiple linear regression model also included a discharge term. Discharge data from the USGS sites on the Big Thompson River at Moraine Park and the Colorado River below Baker Gulch were used for sites on the east and west sides of the park respectively.

2.3 Results

Over the 2008-2023 period, water temperature trends that were likely, very likely, extremely likely or virtually certainly increasing (hereafter referred to as “probable” increasing) were found at most RMNP sites in October and at several sites in the months of May through September (Figure 1). Probable cooling trends were found at one site, lower Hidden Valley Creek, in April and May. Probable warming trends outnumbered probable cooling trends 27 to 2. The median stream temperature trend across all sites and months was +0.48 °C/decade. October had the largest median temperature change (+0.98 °C/decade), followed by July and August (+0.53, +0.52 °C/decade).

Air temperature trends were similar to stream temperature trends in terms of median (+0.46 °C/decade), but the timing of warming was different: median air temperature trends were largest in May and September (+1.17, +0.65 °C/decade) and the median air temperature trend in October is near zero (+0.04 °C/decade).

Positive air and water temperature trends occurring together are the most common combination (Figure 2). Air temperature trend is a weak but significant positive predictor of stream temperature trend in a univariate linear regression model (Adj. $R^2 = 0.06$; $p = 0.017$).

Four of eleven sites were classified as wildfire affected. Of these, three experienced probable stream temperature warming in most months, while only one unaffected site had warming in most months. At sites affected by 2020 wildfires ($n = 3$), the water temperature – air temperature slope (a.k.a., water temperature sensitivity) in a multivariate model that also accounted for discharge remained the same or increased after 2020, while at sites not affected by 2020 wildfires ($n = 6$), water temperature sensitivity decreased (Figure 3a and 3b).

2.4 Discussion

Stream temperatures in RMNP predominantly warmed during the 2008-2023 period, with the largest and highest confidence warming trends occurring at most sites in October and several sites in the summer months of June, July and August. Wildfire appeared to be at least partially responsible for the pronounced summer warming at three sites: the Cache la Poudre River below Hague Creek, West Creek, and Tonahutu Creek at Granite Falls. Each of these sites, along with the Big Thompson River at Moraine Park (portions of this catchment burnt in 2010 and 2020), showed a change in the relationship between air and stream temperature before and after wildfire, either in terms of the slope of the water-air temperature relationship or the intercept. This suggests that the loss of shading due to wildfire produced a measurable change in the thermal regime of these sites, warming the streams relative to pre-fire conditions.

However, warming trends were also present in catchments unaffected by wildfire during the study period, demonstrating that wildfire was not the only driver of warming. The widespread warming in October suggests changes in air temperature, flow, or some other hydroclimatic variable is responsible for the warming, which was uniquely prevalent in RMNP relative to all other NPS units studied as part of the larger analysis. Causes of the widespread warming in October should be studied in greater detail in future work, along with the potential biological implications of wildfire-induced and other stream temperature warming in the park.

Site	Water Body	Elev (m)	Start	End
WST	West C* (2010)	2479	2001	2022
TON	Tonahutu C* (2020)	3013	2002	2023
POU	Cache la Poudre R* (2020)	2989	2003	2019
OUZ	Ouzel C	3187	2000	2023
HVU	Hidden Valley C	2819	2003	2023
HVL	Hidden Valley C	2728	2002	2023
HAY	Haynach Lakes C	3248	2002	2019
CON	Cony C	3279	2003	2023
CHA	Chaos C	2915	2006	2023
BTN	North Fork Big Thompson R	3152	2007	2023
BTM	Big Thompson R* (2010, 2020)	2438	2012	2023

Table 1. Long-term water temperature records used for trend analysis in RMNP. Sites with an asterisk* are downstream of areas affected by wildfires in the years indicated.

Category	Likelihood of outcome
Virtually certain	99-100%
Extremely likely	95-99%
Very likely	90-95%
Likely	66-90%
About as likely as not	33-66%
Unlikely	10-33%
Very unlikely	5-10%
Extremely unlikely	1-5%
Exceptionally unlikely	0-1%

Table 2. IPCC likelihood categories for Trend Direction Analysis (TDA). From Mastrandrea et al. 2010 and McBride 2019.

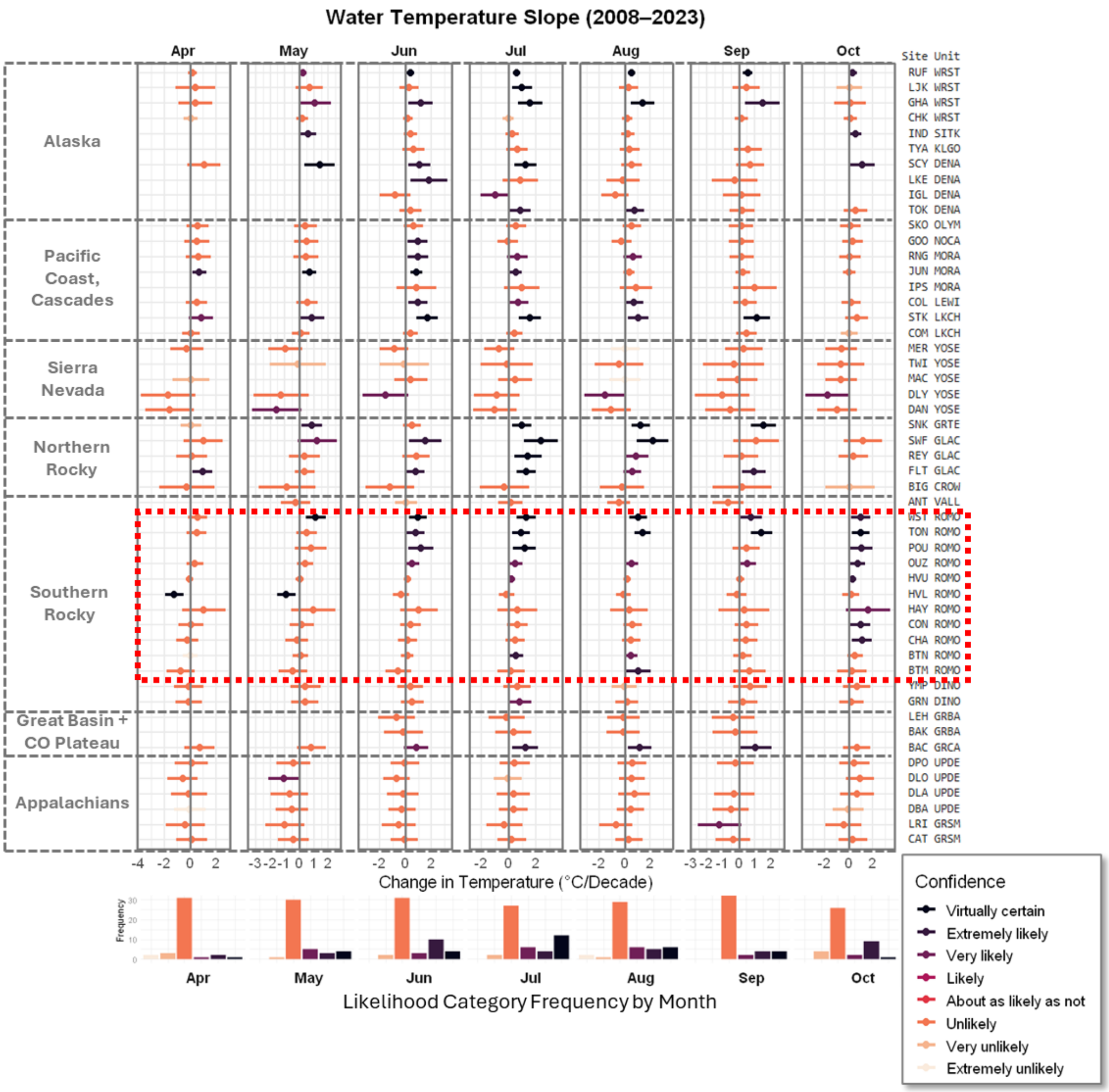


Figure 1. Water temperature slopes and confidence intervals for all sites and months, with the Rocky Mountain National Park sites highlighted in the dotted red box. Colors correspond to categorical likelihood of a warming trend being present determined via Trend Direction Analysis (McBride 2019). Histograms show how frequently each likelihood category occurs in each month.

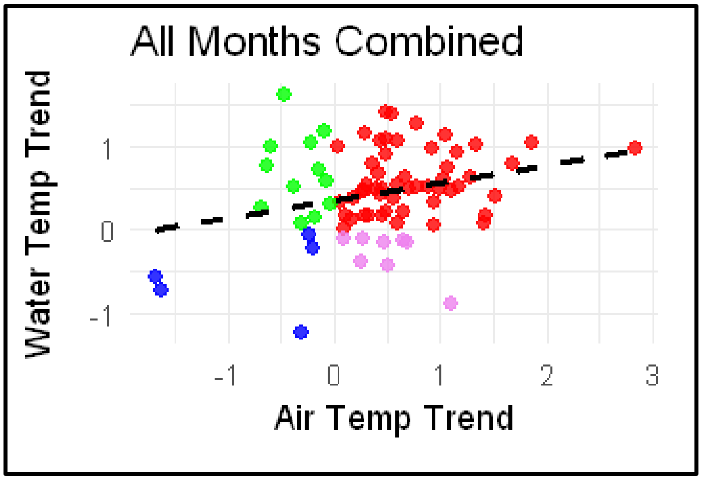


Figure 2. Stream temperature trends vs. water temperature trends in °C/decade for all sites and months. Colors correspond to the quadrant that a point falls in. For example, red indicates both a positive air and water temperature trend.

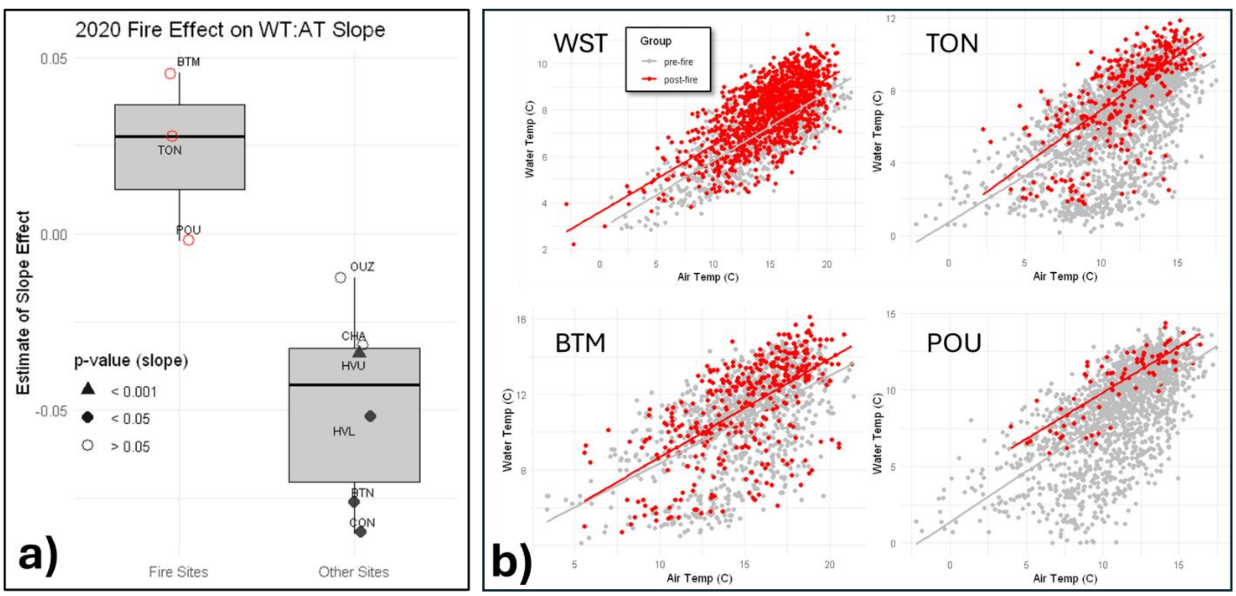


Figure 3a. Comparing estimates of the 2020 fires' effect on water temperature – air temperature slopes for sites that burned in 2020 (left panel, left) and sites that did not (left panel, right).

Figure 3b. Water temperature – air temperature scatter plots for all four sites that experienced wildfire, with post-fire data points in red.

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