Assessing Thermal Sensitivities of Salmon Habitats in the Cook Inlet, Copper River, and Prince William Sound Watersheds

Project Completion Report
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Alaska Center for Conservation Science and the Wild Salmon Center

1. Final Synopsis

This project characterized stream temperature regimes in the Cook Inlet, Copper River, and Prince William Sound regions. We aggregated 1,548 summertime stream temperature time series from 355 monitoring locations across southwestern and southcentral Alaska and calculated a suite of metrics related to the magnitude, frequency, duration, timing, and variability of stream temperatures. We categorized streams into one of six different thermal regimes. A comparison of stream thermal regimes among regions showed that cold habitats with later timing of maximum temperatures were most common in all regions, cold stable habitats were more common in the Copper River and Prince William Sound regions, and all regions included all six thermal regimes described in our classification.

We also calculated stream thermal sensitivity (**τ**) across monitoring sites to describe how closely stream temperatures track air temperatures. Estimated **τ** was highest in the Cook Inlet and Kodiak regions, followed by Bristol Bay and Copper River, and was lowest in Prince William Sound. We modeled variation in **τ** using geomorphic, hydrologic, climatic, and landcover covariates. The model was used to map thermal sensitivities across 966 salmon streams for high and low scenarios of spring snowpack and summer precipitation. Thermal sensitivities decreased under higher summertime precipitation and changed minimally between years with low and high snowpack. The strongest control on **τ** was watershed slope. Streams draining steeper watersheds had lower **τ**, which may be due to snowmelt contributions later in the summer period, shorter water residence times, and deeper flowpaths that experience less solar radiation. Chum and pink salmon habitats had the lowest **τ**, followed by spawning habitats. Rearing habitats and Chinook, coho, and sockeye salmon habitats all had higher **τ**. In a warming future, salmon may need to balance physical habitat preferences for low gradient systems with adaptations for cold water.

2. Project Activities and Results

Characterize thermal regimes

We characterized stream thermal regimes as they relate to salmon life histories - specifically juvenile rearing, spawning, and adult migration; using empirical stream temperature data from five regions of southwestern and southcentral Alaska. Stream thermal *regimes* include descriptors of the magnitude, frequency, duration, variability and timing of stream temperatures. We requested stream temperature datasets from data providers identified through the Alaska Online Aquatic Temperature Site (AKOATS, https://accs.uaa.alaska.edu/aquatic-ecology/akoats/). Data were received from state and federal agencies, universities, local monitoring groups, and non-profit agencies working throughout the five study regions. We reviewed all stream temperatures from the summer months for data quality and anomalous or suspect data were flagged and excluded from further analysis. Temperature data anomalies can occur when temperature loggers become exposed to air during low flows or buried by sediment during floods. After reviewing all datasets provided by the many organizations monitoring stream temperature, we developed a final dataset of daily minimum, maximum, and mean temperatures for 470 stream temperature monitoring sites across multiple years representing a total of 2,132 summer seasons. For our analysis of stream thermal regimes, we further screened data sets and excluded time series with less than 80% of days in the months from June, July, and August because we expected that missing data would bias calculations of stream temperature metrics (e.g. miss the summer maximum). The final dataset that we used to calculate our suite of temperature metrics included 420 sites and 1,691 summer seasons.

For our characterization, we calculated 37 metrics that represent stream thermal regimes based on previous work examining thermal diversity in the Mat-Su Basin of Southcentral Alaska. Metrics describing the frequency and duration of warm water events were associated with thresholds of 13°C and 18°C (e.g. number of days greater than 18°C). The 13°C threshold protects habitats used for salmon spawning and the 18°C threshold is protective of salmon rearing habitats and migration corridors. We reduced the full list of metrics to a smaller subset of 11 non-redundant (pairwise correlations less than 0.8) metrics to describe differences among regions (Table 1).

Table 1. Final list of 11 non-redundant stream temperature metrics used to explore differences in stream thermal regimes among five study regions.

Group	Metric	Units
Magnitude	MWMT, maximum weekly rolling average of daily maximum temperatures	°C
Magnitude	Average summer temperature	°C
Magnitude	Minimum of mean daily temperature	°C
Frequency	Number of days greater than 13°C	Count
Frequency	Number of days greater than 18°C	Count

Group	Metric	Units
Duration	Duration of longest event greater than 13°C	Days
Duration	Duration of longest event greater than 18°C	Days
Variability	Maximum daily range	°C
Variability	Variance of maximum daily temperatures	$°C^2$
Timing	Timing of MWMT	Julian day
Timing	Timing of highest maximum daily temperature	Julian day

We used boxplots to examine differences in distributions of individual thermal metric among five study regions: Cook Inlet (230 sites), Prince William Sound (20 sites), Copper River (26 sites), Bristol Bay (113 sites), and Kodiak (31 sites). Boxplots indicated broadly similar distributions of stream thermal metrics across the different study regions (Figure 1). For the frequency and duration of events greater than 18° C, the abundance of outliers indicates that a small proportion of sites within each region are above this threshold for multiple weeks each summer (e.g. the 75th percentile for days greater than 18°C is ~20 days or less for all five regions, Figure 1). Median values indicated that the coldest sites were in the Copper River and Prince William Sound regions and these sites also had the latest timing of maximum temperatures (Figure 1). Sites in the Prince William Sound region also had the lowest median value for the maximum daily range indicating that these monitoring sites were generally more stable than those in other regions (Figure 1). Some sites had very large maximum daily ranges, especially in Bristol Bay, and visual inspection of daily temperatures indicated these maximums occurred in early summer. Low water in rainfed streams and minimal shade in early summer could have caused the large daily temperature swings.

In order to examine differences in thermal *regimes*, we used principal components analysis (PCA). PCA is an ordination method used to identify correlations among variables and reduce large multivariate datasets into a smaller set of synthetic axes that represent important environmental gradients. We scaled the final set of 11 metrics and used a correlation matrix for the PCA. The first two axes of the PCA explained 70% of the variation in stream thermal regimes among the sites. Temperature metrics associated with summer maximum and minimum temperatures and the frequency and duration of warm events loaded positively on the first PC axis (Figure 2). Metrics related to the timing of maximum temperatures loaded positively on the second axis, whereas the maximum daily range loaded negatively on the second axis, indicating that these metrics were inversely related (e.g. streams with large daily ranges had earlier timing of maximum temperatures, Figure 2). Variance of maximum daily temperatures loaded positively on the first and second axes and was most closely correlated to sites that stayed warmer for longer periods (e.g. high duration of longest events above 13 and 18°C, Figure 2). Ellipses indicated that thermal regimes were broadly similar across the five study regions, although the ellipses for Copper River and Prince William Sound included the top left corner of the ordination, confirming our previous result that these regions include sites with colder temperatures and later timing of maximum temperatures (Figure 2).

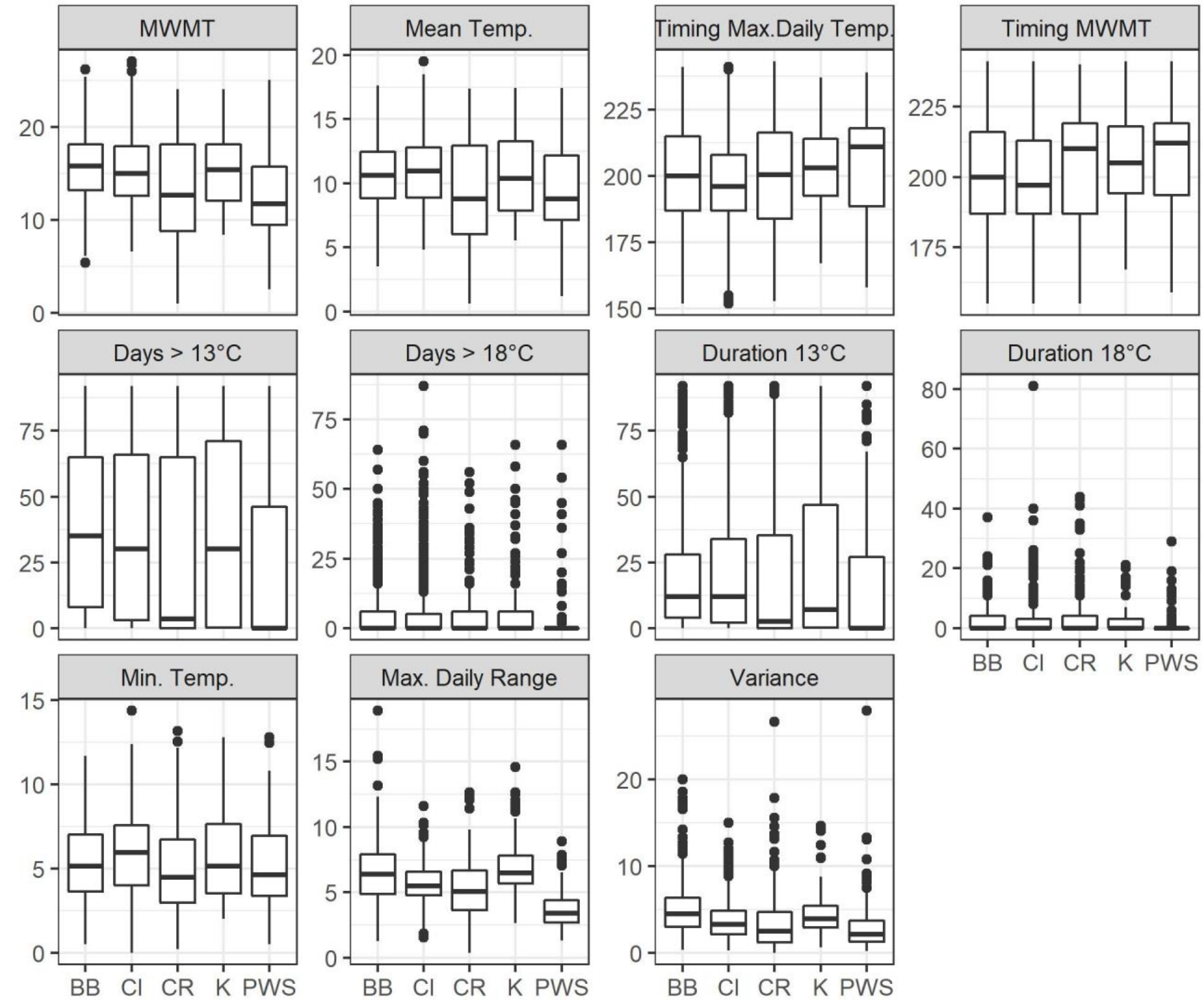

Figure 1. Boxplots showing distributions of 11 stream temperature metrics across five study regions: BB = Bristol Bay, CI = Cook Inlet, CR = Copper River, K = Kodiak, PWS = Prince William Sound. See table 1 for temperature metric units.

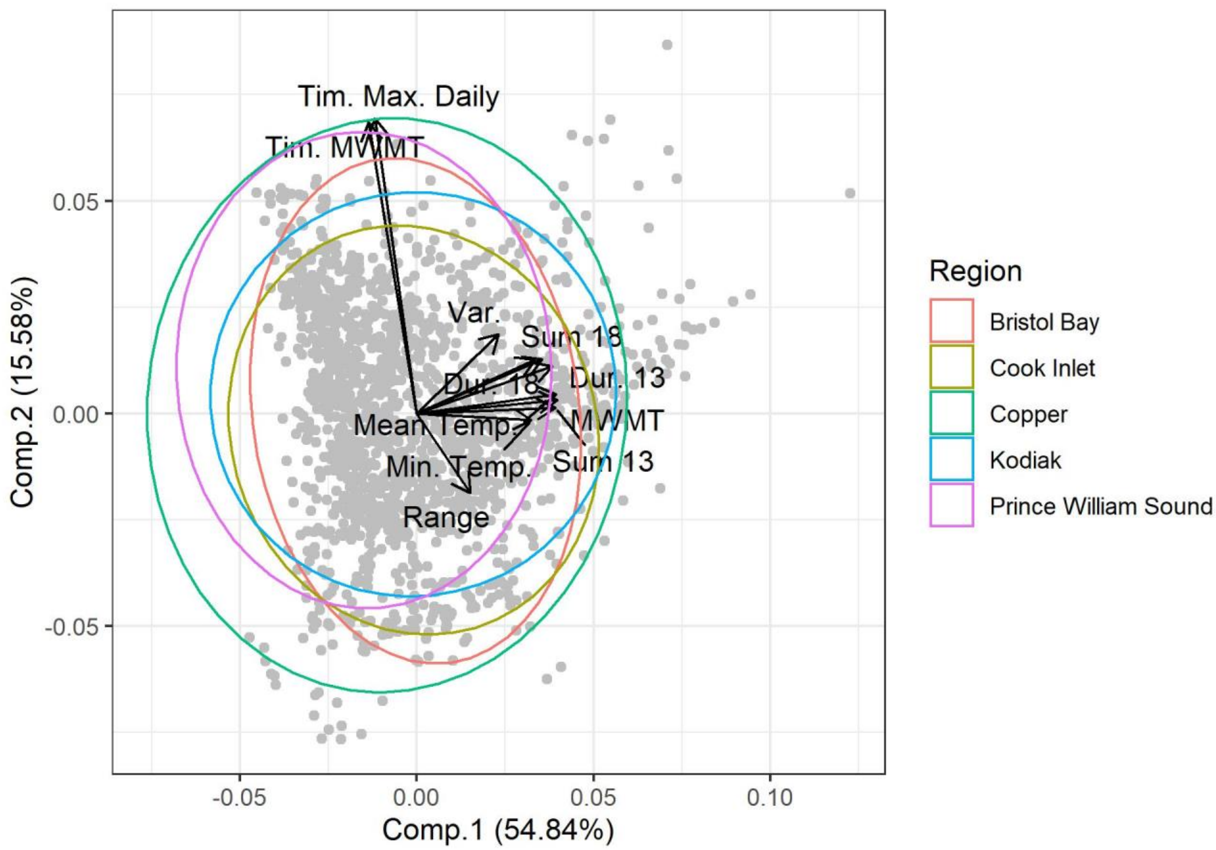

Figure 2. Principal Components Analysis ordination of 11 stream temperature metrics. Sites within regions are indicated by colored ellipses. Arrows indicate stream temperature metric loadings onto the two principal components. The magnitude, frequency, and duration metrics all load positively on the first axis, indicating that these variables are correlated. The timing metrics loaded positively on the second axis.

As a secondary tool to compare differences in stream thermal regimes, we followed methods in Shaftel et al. 2020 to classify sites into different thermal regimes. The final set of 11 temperature metrics were scaled and converted into a distance matrix using Euclidean (straight-line) distances. We used hierarchical cluster analysis to sequentially merge sites or groups of sites using Ward's method, which minimizes the distance between each site and the centroid of its group. We cut the final dendrogram (i.e., decision tree) at six groups because that solution included important stable cold-water habitats that we wanted to explore across regions. We used boxplots to examine differences in the distributions of our 11 stream temperature metrics among the six groups. Group 1 included the most site-years (35% of total) and were generally cold with the latest timing of maximum summer temperatures (Figure 3 and Table 2). Groups 2 through 5 all had similar timing of maximum temperatures and represented a gradient of stream thermal regimes from cold to warm (2 < 3 < 4 < 5, Figure 3 and Table 2). Groups 4 and 5 had the most days greater than 18°C, indicating the presence of thermally stressful habitats in the dataset (Figure 3 and Table 2). Group 6 represented the coldest and most stable habitats with low variance and stream temperatures that rarely exceed 13°C (Figure 3 and Table 2).

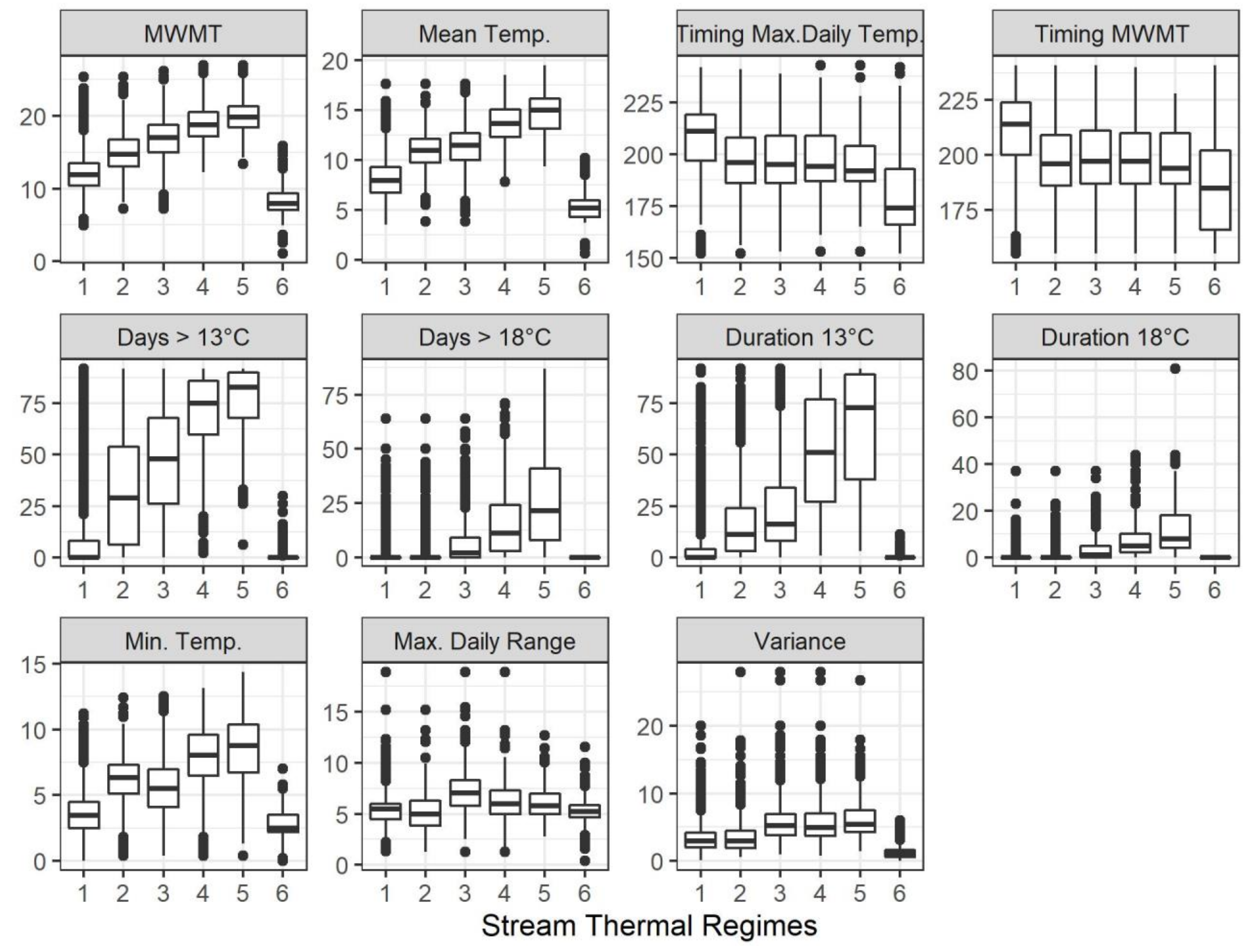

Figure 3. Differences in stream thermal regimes for six groups and 11 stream temperature metrics. See table 1 for stream temperature metric units.

To compare the importance of different thermal regimes within each region, we calculated the percentage of different thermal regimes present based on the total number of summer stream temperature time series for each region. Group 1 habitats were the most common across all regions indicating the importance of high elevation snow influencing colder stream temperatures and later timing of maximum summer temperatures (Figure 4). Group 3 habitats were more common in Bristol Bay and group 4 habitats were more common in Kodiak (Figure 4). The cold and stable habitats represented by group 6 were most common in the Copper River and Prince William Sound regions (Figure 4). These results confirm our previous analyses indicating a diversity of stream thermal regimes among regions in southwestern and southcentral Alaska.

Table 2. Median values of four metrics describing important differences in six stream thermal regimes identified using hierarchical cluster analysis. The number and percentage of site-years in each thermal regime group are also provided.

Thermal Regime	Number of Site-Years (count)	MWMT (°C)	Timing of MWMT (julian day)	Days Greater Than 18°C (count)	Variance (°C^2)
1	534 (35%)	11.9	214	0	3.0
2	268 (17%)	14.7	196	0	3.0
3	380 (25%)	17.0	197	2	5.2
4	254 (16%)	18.8	197	11	4.9
5	49 (3%)	19.8	194	22	5.4
6	63 (4%)	8.0	185	0	1.1

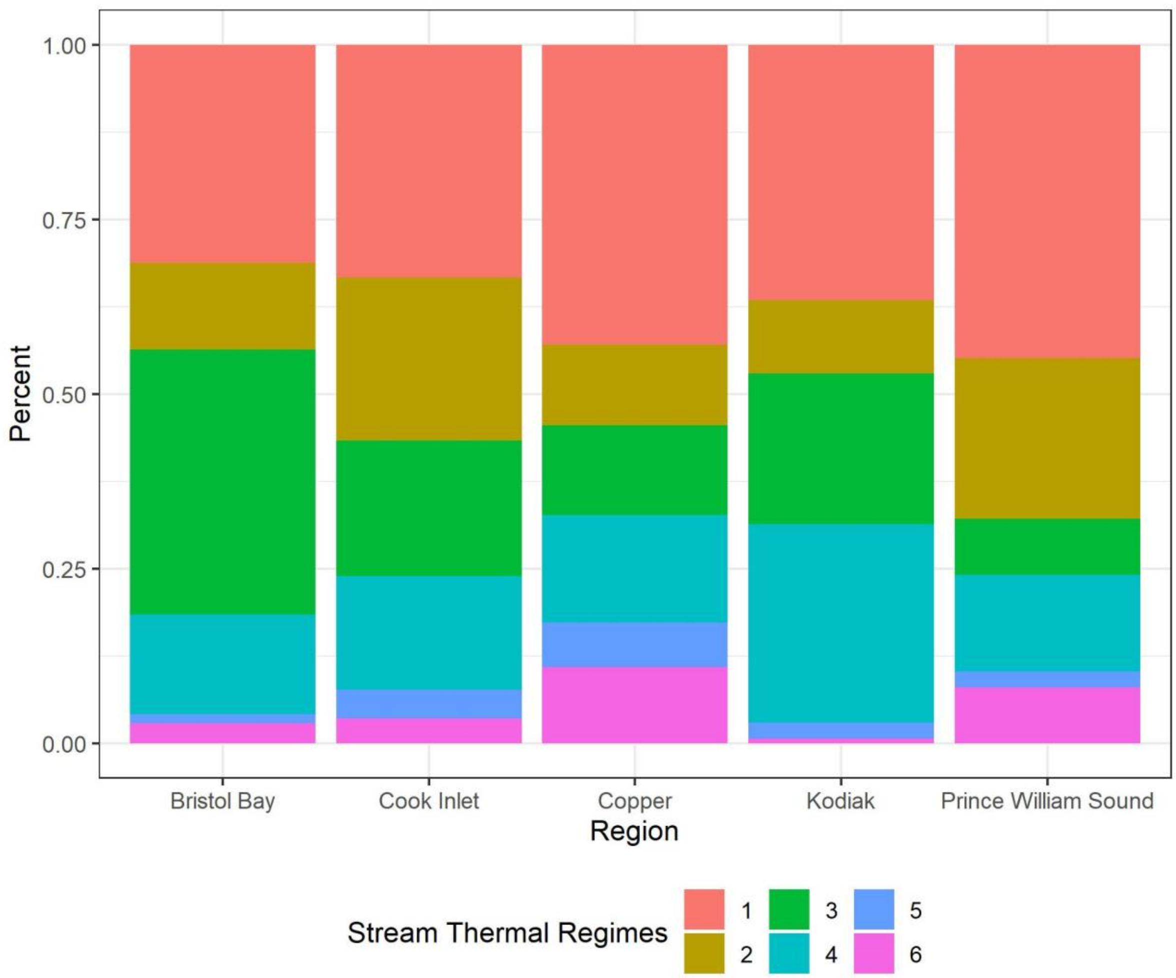

Figure 4. Distribution of stream thermal regimes by region. Thermal regimes represent a gradient of cold to warm habitats from 1 and 6 < 2 < 3 < 4 < 5. Group 1 had the latest timing of maximum stream temperatures and group 6 had the most stable stream temperatures.

Estimate thermal sensitivity of salmon habitats to climate change

We followed methods in Cline et al. (2020) and used dynamic factor analysis (DFA) to calculate stream temperature sensitivities for a subset of sites across the five study regions. Most of the data collection in our study area began in 2008 or later (first year with greater than 50 monitoring sites). We selected 2011 to 2019 for our DFA modeling of stream thermal sensitivities as those years consistently had approximately 100 or more monitoring sites. Our final dataset included 1,224 complete (> 80% of days in June, July, and August) summer stream temperature time series from 319 sites across all five study regions. The number of years of complete summer stream temperature data ranged from one to nine and 60% of sites had three or more complete summers of data.

DFA models daily stream temperatures as a linear combination of an underlying regional trend, explanatory variables, and observation or sampling errors. We developed two DFA models for the years 2011-2019. In both models, we included air temperatures as a variable to explain patterns in annual stream temperatures, which allows for the calculation of site-specific stream thermal sensitivities. Air temperature was used as a proxy for solar radiation as both air temperatures and stream temperatures are warmed by longwave radiation, which is a major input warming stream water. In the second model, we added site-specific daylength as a secondary variable to account for changes in the duration of solar radiation that vary by latitude but do not vary from year to year. Time series were z-scored (subtract mean and divide by standard deviation) prior to input to the DFA. Site specific coefficients for air temperature were back-transformed to generate raw stream temperatures sensitivities ($\boldsymbol{\tau}$) expressed as a $°C_{stream}/°C_{air}$.

Our final DFA models had a single trend and we compared thermal sensitivities for models with and without daylength. Maximum values for $\boldsymbol{\tau}$ decreased when daylength was added as a secondary covariate to the DFA model, although there was no shift in minimum values (Figure 5). Loadings on the single trend in both models were similar indicating that adding daylength explained variation in $\boldsymbol{\tau}$ only and not in annual trends. The estimated $\boldsymbol{\tau}$ varied across regions with the highest thermal sensitivities in the Cook Inlet and Kodiak regions followed by Copper River, Bristol Bay, and much lower $\boldsymbol{\tau}$ in Prince William Sound (Figure 6). We moved forward with $\boldsymbol{\tau}$ from the model that controlled for differences in daylength for mapping thermal sensitivities. This allowed us to explore $\boldsymbol{\tau}$ across salmon habitats that were strictly associated with climate warming and not daylength.

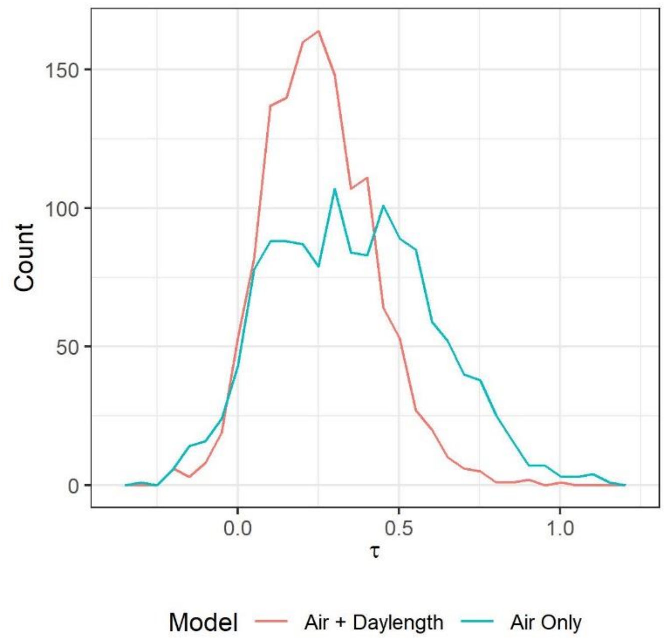

Figure 5. Differences in stream thermal sensitivities in DFA models with daylength as a covariate. Sensitivities decreased when daylength was added to the DFA model.

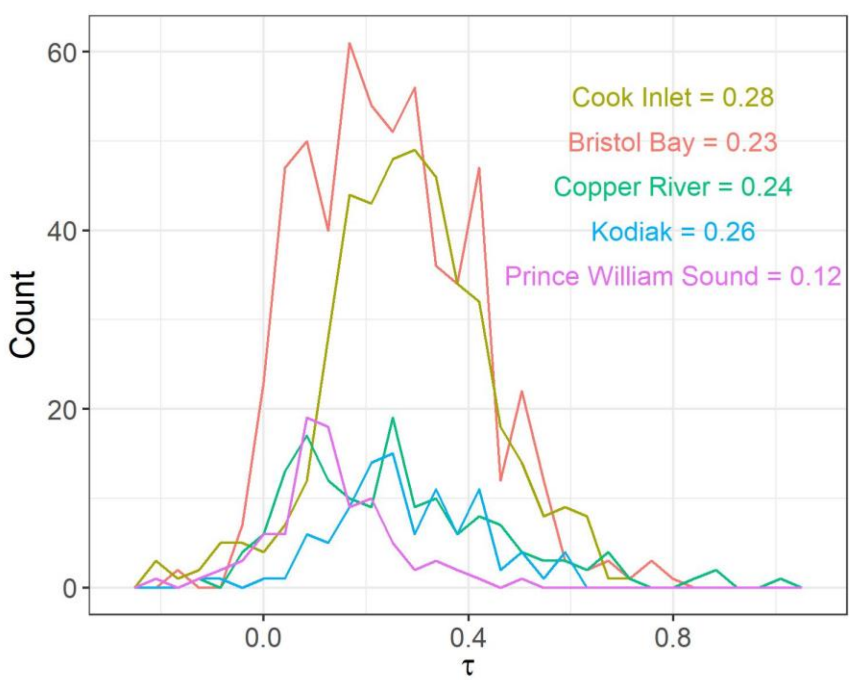

Figure 6. Estimated stream thermal sensitivities across five regions used in the dynamic factor analysis model. Median values are shown as text for each region. Sensitivities are from a model that included daylength.

Map thermal sensitivities of salmon habitats

We modeled τ using covariates that represented important hydrologic, topographic, and climatic drivers and used the model to map τ across the study area in habitats that support Pacific salmon. In order to calculate covariates at different hydrologically meaningful spatial scales, such as stream reaches (confluence to confluence flowlines), catchments (the land area draining to a stream reach), and watersheds; we required datasets that represent the flow of water across the landscape to streams. The U.S. Geological Survey recently developed a high resolution National Hydrography Plus product for the Cook Inlet and Copper River regions that includes the digital elevation models (DEM) used to generate the vector stream network, catchments linked to each stream reach, and attributes that can be used to navigate the stream network. We used a 10-meter composite digital elevation model and τDEM tools to construct synthetic stream networks for the Prince William Sound, Bristol Bay, and Kodiak regions. The five-meter digital elevation models from NHD Plus were resampled to 10 meters to match resolutions for processing of topographic variables. Site locations were examined in a GIS to ensure they matched the sampled stream as described by the data collectors or provided in the metadata. When necessary, sites were shifted to match the vector stream network being used for each region to generate accurate stream reach, catchment, and watershed attributes.

Our approach relies on identifying correlations between τ and spatial datasets that serve as proxies for hydrologic and climatic controls on τ. We included 13 predictors in our model after first eliminating covariates that had strong pairwise correlations or multicollinearity. Covariates with pairwise correlations greater than 0.7 and variance inflation factors greater than three were removed. The final list of predictors included stream slope, mean catchment elevation, mean catchment slope, mean watershed slope, percent of the watershed with a north aspect, watershed area, distance to the coast, percent of the watershed covered by glaciers, lakes, or wetlands; an index of spring snow cover; total summer precipitation; and region (Cook Inlet, Prince William Sound, Copper River, Bristol Bay, and Kodiak).

We calculated the last day of the continuous snow season averaged across each watershed as our initial covariate representing snowpack processes that may buffer stream thermal sensitivities. At higher elevations and in watersheds with steeper slopes, snow lingers longer into the summer season. We removed the effect of watershed slope on snow by fitting a model to our spring snowpack covariate using mean watershed slope as a covariate. We calculated the model residuals per methods in Cline et. al. (2020) as an index of spring snow independent of watershed topography.

We used boosted regression trees to generate a predictive model of τ that could be used to map τ across a spatially balanced set of salmon streams across the study area. For the boosted regression tree model, we used a tree complexity of five to allow for variable interactions, a slow learning rate of 0.005 to stabilize the prediction variance, and a bag fraction of 0.5 (only half of the observations are used in each new tree) to reduce overfitting and improve prediction accuracy. A slow learning rate requires additional trees to identify the best performing model and we used cross validation to determine the total number of trees in the final model. We used 10-fold cross validation and generated models with increasingly larger numbers of trees to identify the optimal number of trees with the lowest predictive performance. We additionally dropped variables sequentially until the reduction in predictive performance exceeded one standard error of the model with the variable retained. Once unnecessary variables were identified, we recreated the optimal boosted regression tree model using cross-validation to select the optimal number of trees. All analyses were run using the gbm.step and gbm.simplify functions in the dismo package in R.

Our final boosted regression tree model for **τ** included six variables and explained 79% of the deviance in the training data and 49% of the deviance in the withheld data used during cross-validation to select the optimal number of trees (Figure 7). Plots of observed versus predicted values on testing data indicated no bias in the model predictions and good model fit (Figure 7). Variable importance calculations were based on the number of times a variable appears in a split, weighted by the increase in model performance, and averaged over all trees. The most important variables in the model in order of decreasing importance were mean watershed slope (relative importance = 25), watershed size (16), total summer precipitation (16), lake cover (15), mean catchment elevation (15), and the snow index (12).

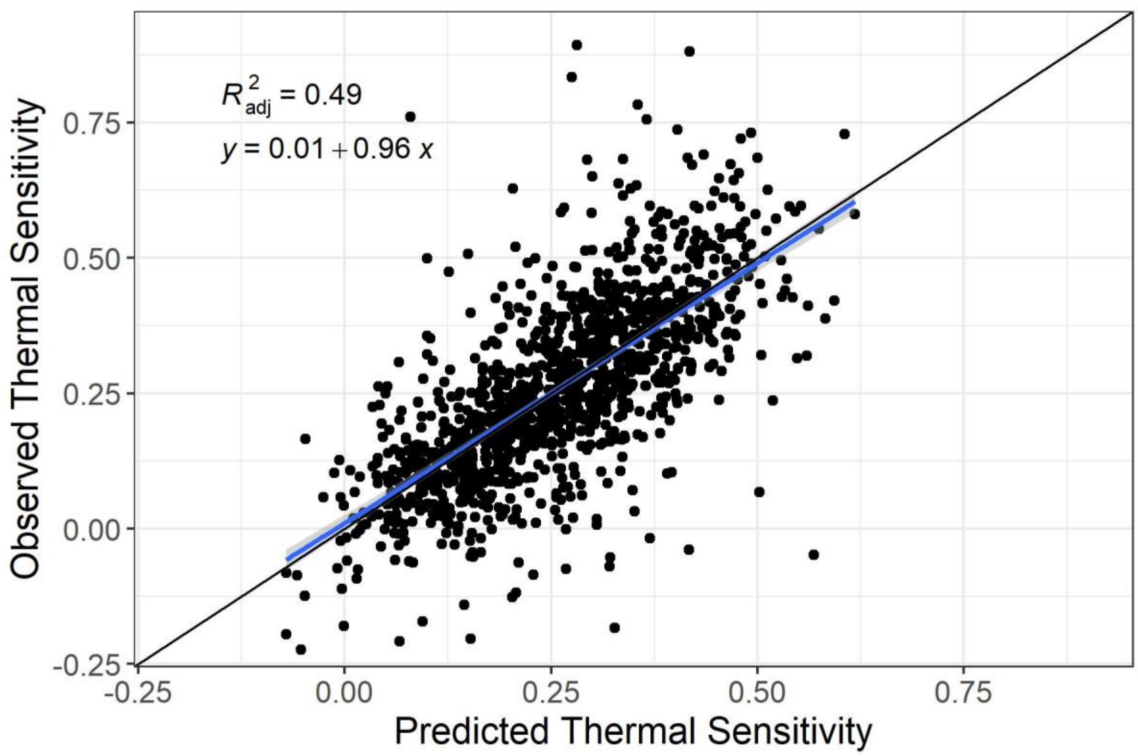

Figure 7. Observed stream thermal sensitivity and predicted thermal sensitivity from boosted regression tree model. Predictions are based on withheld data during cross-validation and represent prediction accuracy to new streams not included in the training dataset for the model. The linear fit between the observations and predictions indicate no bias in model predictions and the R^2 indicates the model explains approximately half of the variation in observed stream thermal sensitivities.

In order to generate scenarios of **τ** across our study area, we selected 966 salmon streams across our study area to explore how **τ** varies under years of high and low snowpack and for different salmon species and life stages. We selected stream reaches that drained Level 12 hydrologic units (HU12), which is a spatial dataset of sub-watersheds generated by the U.S. Geological Survey. The HU12 sub-watersheds are non-overlapping polygons that follow watershed boundaries, but only represent true watersheds when they encompass a headwater stream. We further filtered on stream reaches identified in the ADF&G Anadromous Waters Catalog as supporting salmon and linked species and life stage information to each stream reach. We generated the same thirteen covariates used in our boosted regression tree model for all 966 salmon streams so that we could predict $\boldsymbol{\tau}$ using our model. We calculated our snow index as before, but for all years from 2001 through 2019, which provided us with a longer history of snowpack and precipitation variability across all streams.

For each salmon stream, we selected the year with the smallest and largest snow index and summer precipitation totals and predicted $\boldsymbol{\tau}$ using our boosted regression tree. We mapped $\boldsymbol{\tau}$ across salmon streams using sub-watershed boundaries by the four different scenarios and compared differences in $\boldsymbol{\tau}$ by region. We also explored relationships between stream habitats used by different salmon species or life stages and $\boldsymbol{\tau}$, which may indicate different levels of exposure.

The model predictions indicated that there was little change in mean $\boldsymbol{\tau}$ across the three regions over different scenarios of summer precipitation or spring snowpack (Figure 8). Salmon habitats in the Prince William Sound region had the lowest $\boldsymbol{\tau}$ under all scenarios, followed by Cook Inlet and Copper River, which had similar ranges of $\boldsymbol{\tau}$ across their salmon habitats (Figure 8). Mapped $\boldsymbol{\tau}$ across the study region and under different scenarios indicated that changes in $\boldsymbol{\tau}$ under the two precipitation scenarios were highest in salmon streams draining low elevation areas, such as the west side of the Susitna River basin and the western Kenai Peninsula (Figure 9). In summers with high precipitation, $\boldsymbol{\tau}$ decreased, indicating that precipitation may be an important hydrologic input to streamflow and buffering streams from changes in air temperature.

The salmon habitats with the highest $\boldsymbol{\tau}$ had low mean watershed slopes. This covariate was correlated with elevation (r = 0.53), end of the snow season (r = 0.48), and wetland cover (r = 0.51). This combination of geomorphic covariates and hydrologic inputs could all be driving changes in $\boldsymbol{\tau}$. Steeper watersheds have lower residence times, more snow, and fewer wetlands, indicating the availability of more cold-water inputs that enter streams quickly and have less opportunity for atmospheric heating. Streams draining flatter watersheds are generally lower elevation, have snow that melts earlier so there are less cold-water contributions in summer, and have an abundance of wetlands where water from precipitation and snowmelt is heated in near surface flowpaths before entering streams.

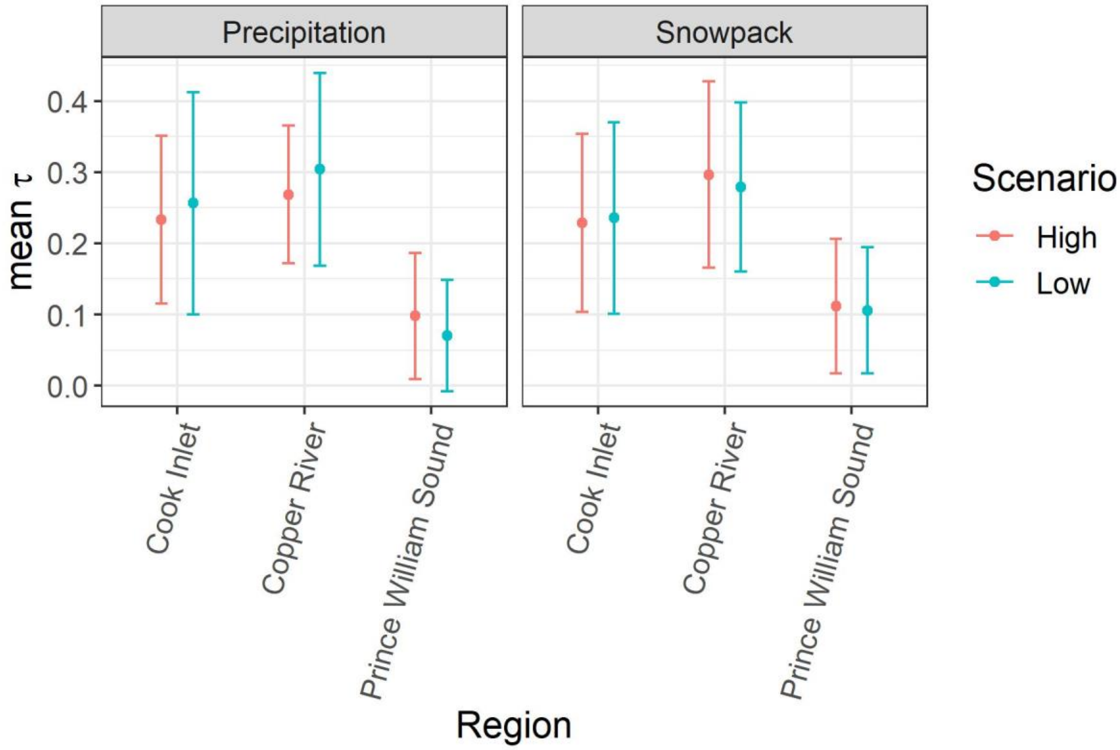

Figure 8. Differences in mean stream thermal sensitivities by region and scenario. The error bars are +/- 1 standard deviation in stream thermal sensitivities. The four scenarios are low and high spring snow and low and high summer precipitation. The highest and lowest values were selected from 2001-2019 climate covariates for each of 966 salmon streams across the three regions. The spring snow index is the last day of the snow season averaged over each watershed after removing the effect of mean watershed slope. The precipitation value is the total summer precipitation at each stream reach summed from daily values from June through August of each year.

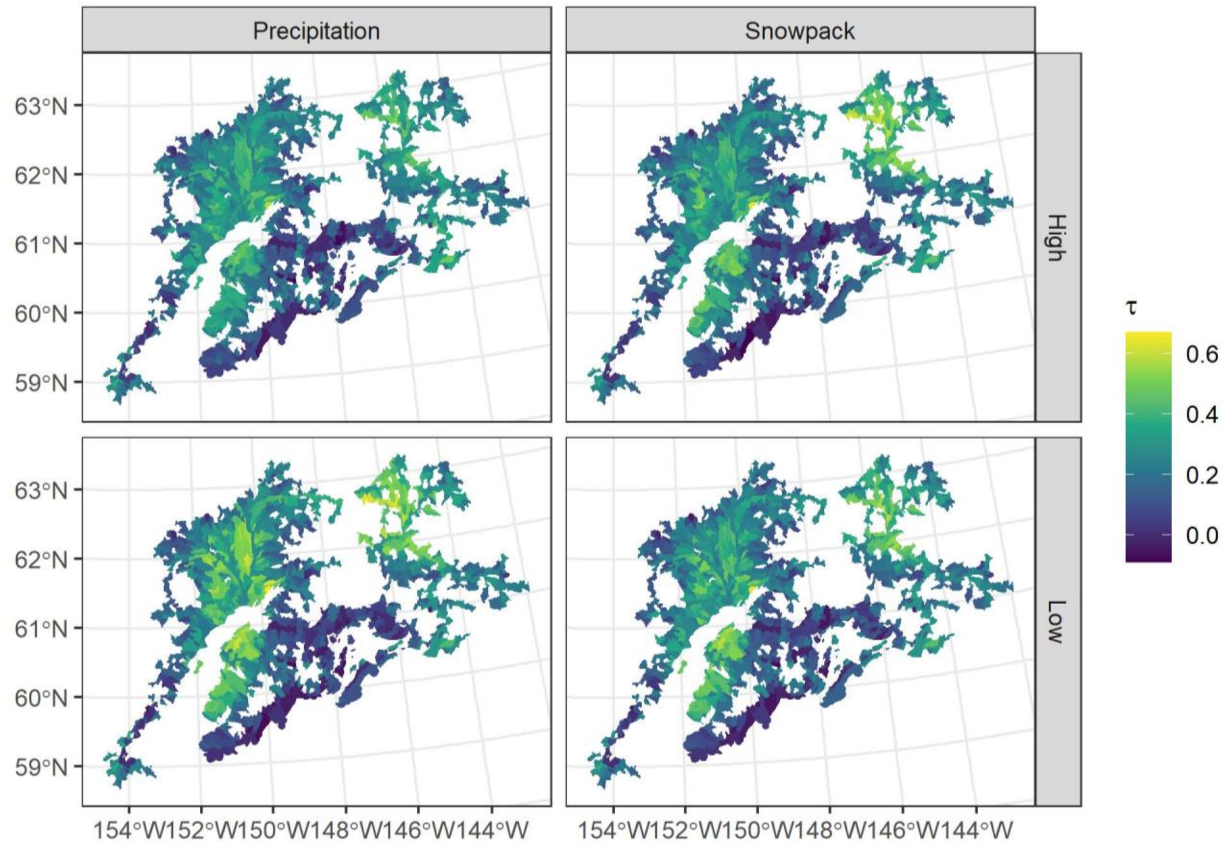

Figure 9. Mapped stream thermal sensitivities for salmon streams in the Cook Inlet, Prince William Sound, and Copper River regions. Thermal sensitivities changed the most from the low to high precipitation scenario, where streams draining low elevation landscapes had lower thermal sensitivities in summers with high precipitation.

We examined differences in salmon habitats with mean $\boldsymbol{\tau}$ for our four different scenarios. Chinook, coho, and sockeye salmon habitats had the highest mean $\boldsymbol{\tau}$, which decreased under the high precipitation scenario (Figure 10). These three species all have juveniles that spend a year or more in freshwater and are therefore using habitats across a larger part of the stream network than pink or chum salmon. Spawning habitats had slightly lower mean $\boldsymbol{\tau}$ than rearing habitats and both habitats had decreased $\boldsymbol{\tau}$ under higher precipitation (Figure 10). Overall, our results indicate that habitats with the highest thermal sensitivities were those draining flatter, low elevation watersheds with high wetland cover. These watersheds are most sensitive to warming and our scenarios indicated that snowpack did not change $\boldsymbol{\tau}$, whereas years with higher precipitation did lead to lower $\boldsymbol{\tau}$. Salmon prefer to spawn and rear in low gradient habitats with high floodplain connectivity and off channel habitats, but these types of settings have the highest $\boldsymbol{\tau}$ and could lead to tradeoffs in the future where salmon balance physical habitat preferences against adaptations for cold water.

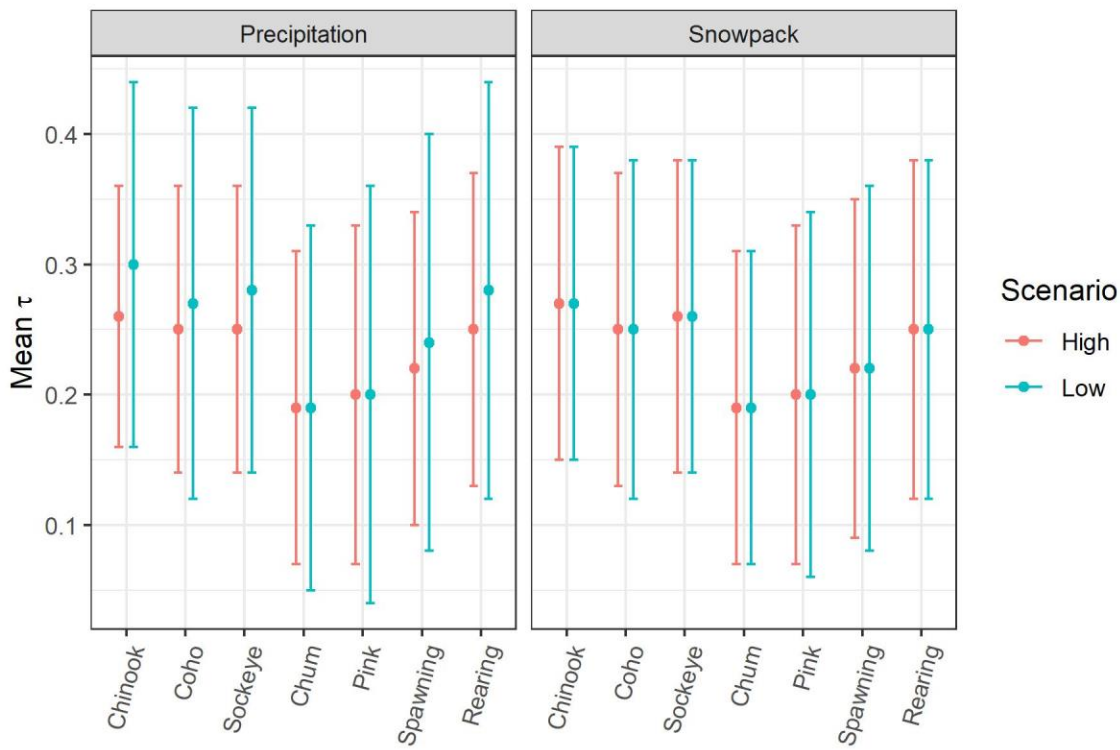

Figure 10. Differences in mean stream thermal sensitivities by scenario and salmon habitat. The error bars are +/- 1 standard deviation in stream thermal sensitivities. The four scenarios are low and high spring snow and low and high summer precipitation. Salmon habitats are attributes for each stream reach assigned from the ADF&G Anadromous Waters Catalog. Species designations include all life stages and life stage designations include all species.

3. Project Dissemination

Project results were presented at the Alaska Chapter of the American Fisheries Society meeting on March 2, 2022. We have created a project entry on the Alaska Center for Conservation Science Data Catalog: https://accscatalog.uaa.alaska.edu/dataset/stream-thermal-sensitivities, which will be updated to include a copy of this completion report and a link to the project web mapper. We plan to publish datasets generated as part of this project to Zenodo, a public data repository, and will include a link to the DOI for the project on the Data Catalog entry when it is available. We are working to create scenarios for the Bristol Bay and Kodiak regions and plan to publish the results in a peer-reviewed journal once all the results are ready.

4. Reports and Other Products

We created an ArcGIS online web mapper for this project (https://arcg.is/0jiG94) that can be used to explore stream thermal sensitivities in salmon habitats across the Cook Inlet, Prince William Sound, and Copper River regions. The mapper includes geospatial datasets of estimated stream thermal sensitivities for stream temperature monitoring sites used in this project in addition to scenarios of stream thermal sensitivities for 966 salmon streams in the three regions.

We plan to archive data created as part of this project on Zenodo, a public data repository. The datasets we will archive include several .csv files:

1. Metadata for 420 stream temperature monitoring sites used in this project as a csv with latitude, longitude, site name, and other information associated with the data collector.
2. Daily minimum, maximum, and mean stream temperatures for all 420 sites.
3. Stream temperature metrics for all sites and years included in analysis of stream thermal regimes.
4. Estimated stream thermal sensitivities and spatial covariates for 319 sites with data between 2011-2019. Spatial covariates were used in boosted regression tree model.
5. Scenarios of stream thermal sensitivities, spatial covariates, and species and life stage information for 966 salmon streams across the Cook Inlet, Prince William Sound, and Copper River regions. Four scenarios include low and high spring snowpack and low and high summer precipitation.