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

Project Completion Report
Alaska Sustainable Salmon Fund Grants 53011 and 51012
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Alaska Center for Conservation Science

1. Final Synopsis

This project characterized stream temperature regimes in the Bristol Bay, Kodiak Island, Cook Inlet, Copper River, and Prince William Sound regions to better understand thermal habitats for spawning and juvenile salmon. We aggregated 1,691 summertime stream temperature time series from 420 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 using metrics including temperature range, stability, and timing. Thermal regimes represent a gradient of cold to warm habitats with Groups 1 and 6 experiencing the coldest temperatures, and 2, 3, 4, and 5 ranging from colder to warmest. Group 1 had the latest timing of maximum stream temperatures and Group 6 had the most stable stream temperatures. A comparison of stream thermal regimes among regions showed that cold habitats with later timing of maximum temperatures, compared to other thermal regime types, were most common in all regions and that cold stable habitats were most common in the Copper River and Prince William Sound regions. However, all regions included all six thermal regimes described in our classification.

Thermal sensitivity measures how responsive water temperature is to air temperature, which can help reveal the processes that govern stream temperature and how readily water temperature will be affected by air temperature changes. We calculated stream thermal sensitivity ($\boldsymbol{\tau}$) across monitoring sites. Estimated $\boldsymbol{\tau}$ 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 $\boldsymbol{\tau}$ using geomorphic, hydrologic, climatic, and landcover covariates. The model was used to map thermal sensitivities across 1,597 salmon streams for high and low scenarios of spring snowpack and summer precipitation. Thermal sensitivities decreased under higher summertime precipitation but changed minimally between years with low and high snowpack. The strongest control on $\boldsymbol{\tau}$ was watershed slope, with a lower $\boldsymbol{\tau}$ in streams draining steeper watersheds. This result 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 for all species, while rearing habitats and Chinook, coho, and sockeye salmon habitats all had higher **τ**. Thus, in a warming future, salmon may face tradeoffs between physical habitat preferences for low gradient systems with adaptations for cold water.

2. Project Activities and Results

Build a regional temperature database and summarize temperature metrics associated with salmon life histories

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 (Cook Inlet, Prince William Sound, Copper River, Bristol Bay, and Kodiak). Stream thermal regimes included 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, 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, given that the number of years of data varied among sites. 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 missing data could 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. The final dataset included 230 sites in Cook Inlet, 20 in Prince William Sound, 26 in Copper River, 113 in Bristol Bay, and 31 in Kodiak.

We calculated 37 initial 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. To describe differences among regions, we reduced the full list of metrics to a smaller subset of 11 non-redundant (pairwise correlations less than 0.8) metrics (Table 1).

Table 1. 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
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

Boxplots indicated broadly similar distributions of individual thermal metrics across the different study regions (Figure 1). An abundance of outliers for the frequency and duration of events greater than 18°C signifies that a small proportion of sites within each region are above this threshold for varying lengths of time ranging from only days to most of the summer (Figure 1). Median values indicated that the coldest sites and latest timing of maximum temperatures were in the Copper River and Prince William Sound regions (Figure 1). Sites in the Prince William Sound region also had the lowest median value for the maximum daily range suggesting 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. Visual inspection of daily temperatures indicated these maximums occurred in early summer, possibly due to low water in rainfed streams and minimal shade.

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 as well as 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, and 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 representing the different study regions had significant overlap, indicating that thermal regimes were broadly similar among regions. Copper River and Prince William Sound were the only ellipses to include the top left corner of the ordination, however, confirming our previous result that these regions include sites with colder temperatures and later timing of maximum temperatures (Figure 2).

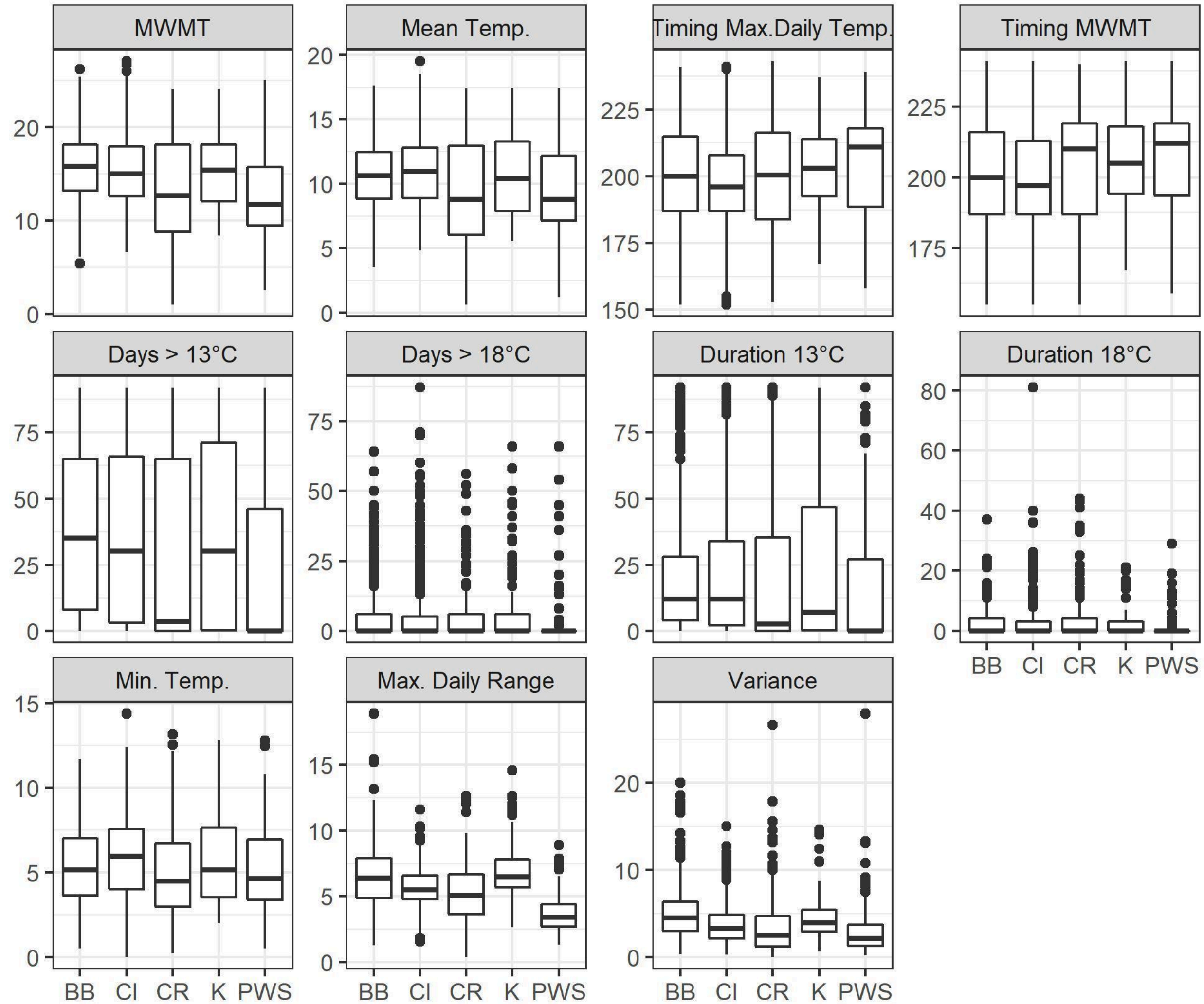

Figure 1. Boxplots showing distributions of 11 stream temperature metrics across five study regions: BB = Bristol Bay, CI = Cook Inlet, CR = Copper River, K = Kodiak, PWS = Prince William Sound. See table 1 for temperature metric units. Points represent outliers, with the box representing the interquartile range, and the thick horizontal line representing the median.

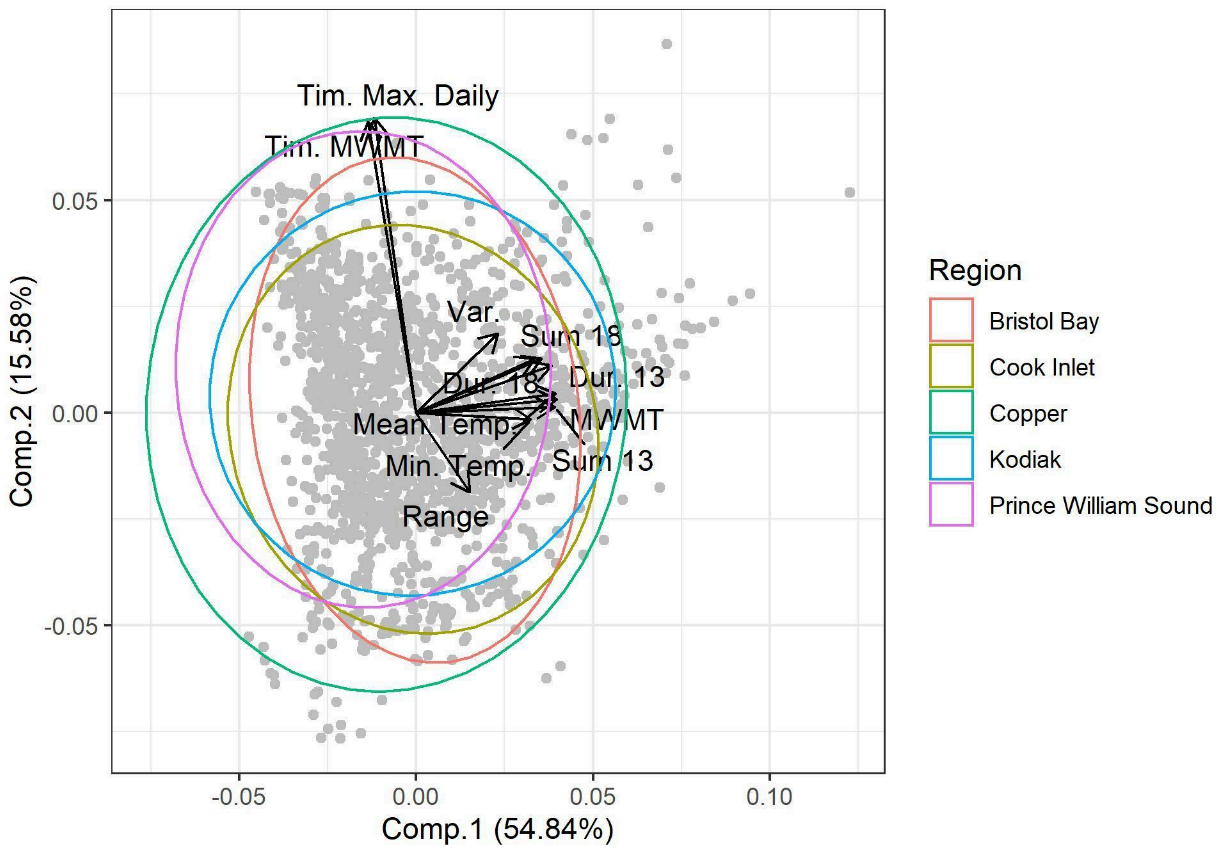

Figure 2. Principal Components Analysis ordination of 11 stream temperature metrics. Sites within regions are indicated by colored ellipses. Arrows indicate stream temperature metric loadings onto the two principal components. The magnitude, frequency, and duration metrics all load positively on the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

Sites were classified into different thermal regimes following methods in Shaftel et al. (2020). 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 stable cold-water habitats that provide important cold water refugia for salmon. Group 1 included the most site-years (35% of total) that were generally cold and had 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 exceeded 13°C (Figure 3 and Table 2).

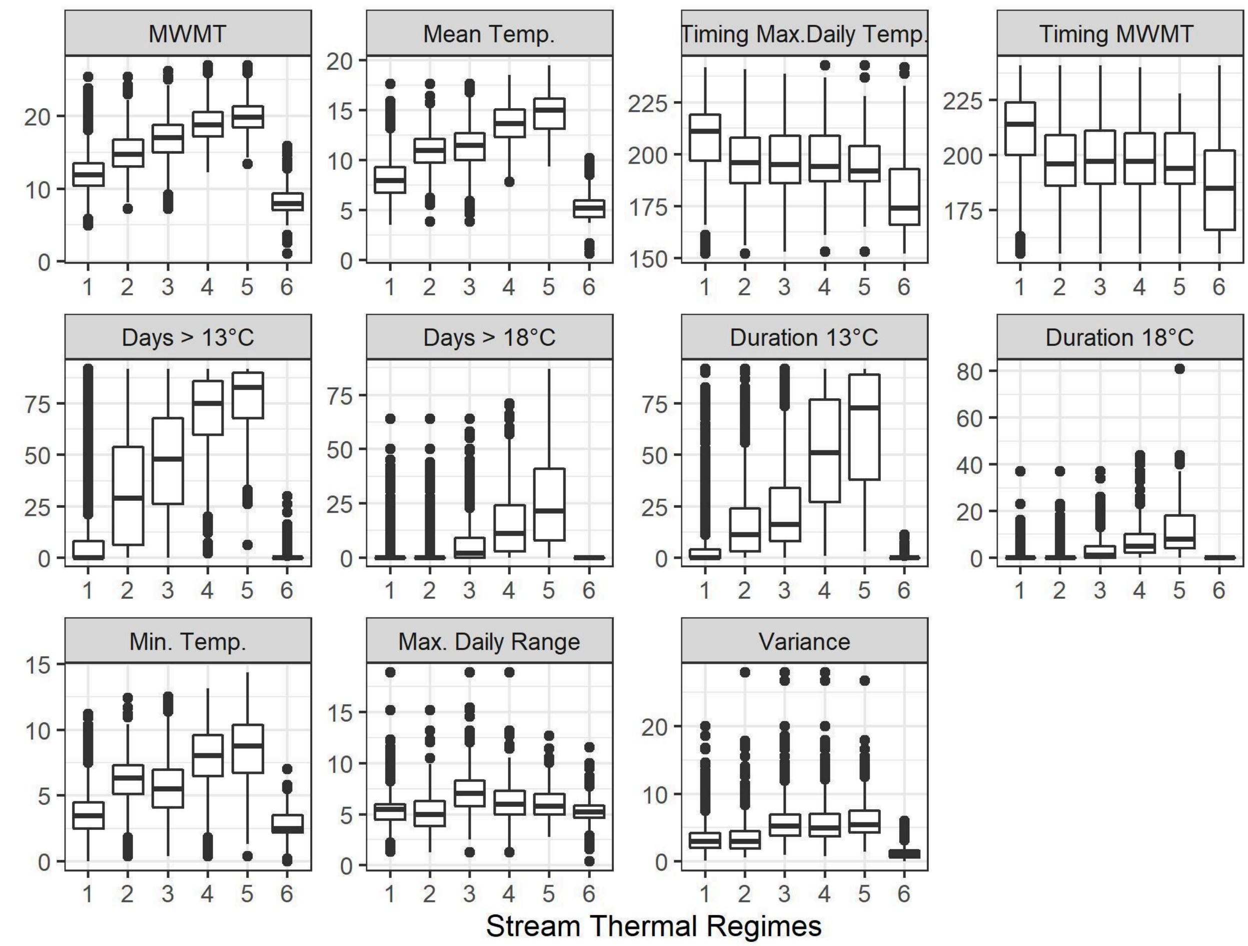

Figure 3. Differences in stream thermal regimes for six groups and 11 stream temperature metrics. See Table 1 for stream temperature metric units. Points represent outliers, with the box representing the interquartile range, and the thick horizontal line representing the median.

To compare the importance of different thermal regimes within each region, we calculated the percentage of different thermal regimes present using the total number of summer stream temperature time series for each region. Group 1 habitats were the most common across all regions, highlighting the importance of high elevation snow, which drives 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 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 and year combinations in each thermal regime group are also provided.

Thermal Regime	Number of Site-Years (count)	MWMT (°C)	Timing of MWMT (day of year)	Days Greater Than 18°C (count)	Variance (°C^2)
1	534 (35%)	11.9	214 (Aug. 1)	0	3.0
2	268 (17%)	14.7	196 (July 14)	0	3.0
3	380 (25%)	17.0	197 (July 15)	2	5.2
4	254 (16%)	18.8	197 (July 15)	11	4.9
5	49 (3%)	19.8	194 (July 12)	22	5.4
6	63 (4%)	8.0	185 (July 3)	0	1.1

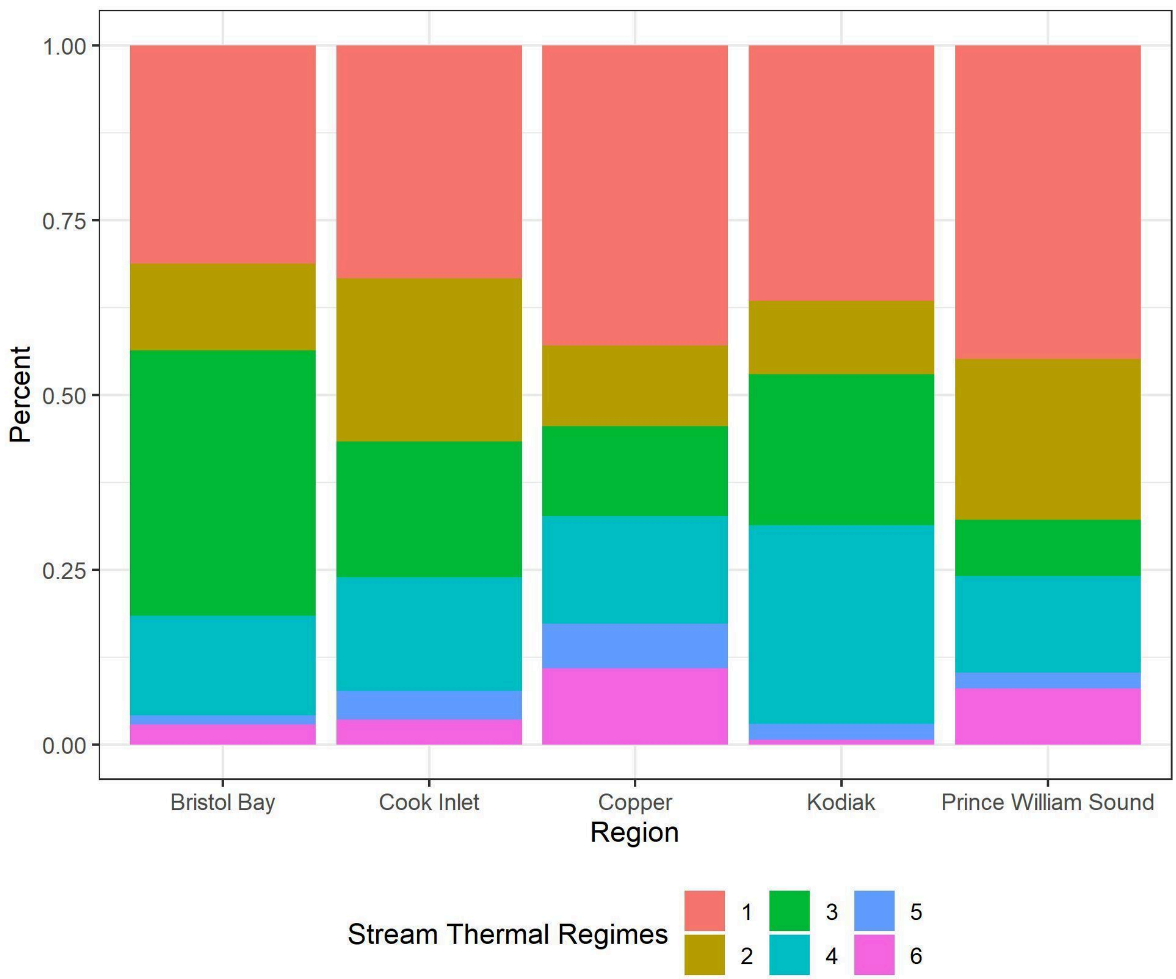

Figure 4. Distribution of stream thermal regimes by region. Thermal regimes represent a gradient of cold to warm habitats from 6 < 1 < 2 < 3 < 4 < 5. Group 1 had the latest timing of maximum stream temperatures and group 6 had the most stable stream temperatures.

Estimate thermal sensitivities of salmon streams to warming air temperatures and declining snowpack

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 temperature as a variable to explain patterns in annual stream temperatures, which allows for the calculation of site-specific stream thermal sensitivities. 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 not 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 temperature 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 and Bristol Bay, while Prince William Sound had much lower $\boldsymbol{\tau}$ (Figure 6). We used $\boldsymbol{\tau}$ values from the model that controlled for differences in daylength to map stream thermal sensitivities. This method allowed us to explore $\boldsymbol{\tau}$ that was strictly associated with climate warming and not daylength, across salmon habitats in the region.

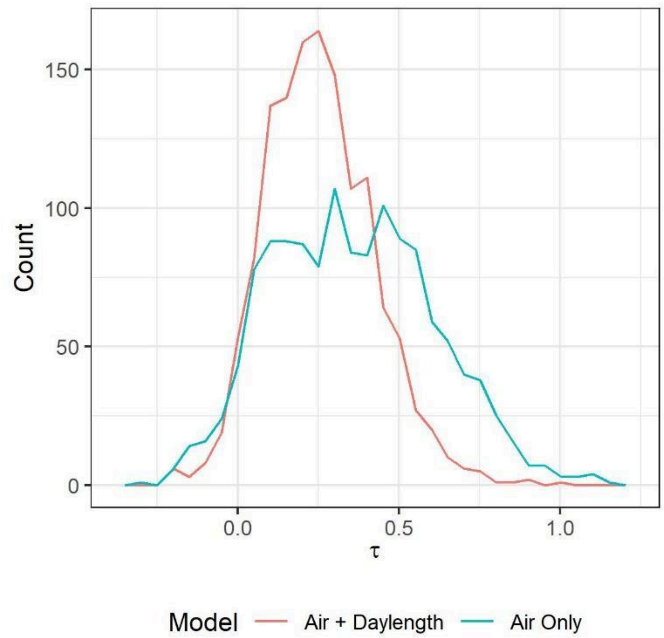

Figure 5. Frequency distribution of the differences in stream thermal sensitivities in DFA models with daylength as a covariate. Sensitivities decreased when daylength was added to the DFA model.

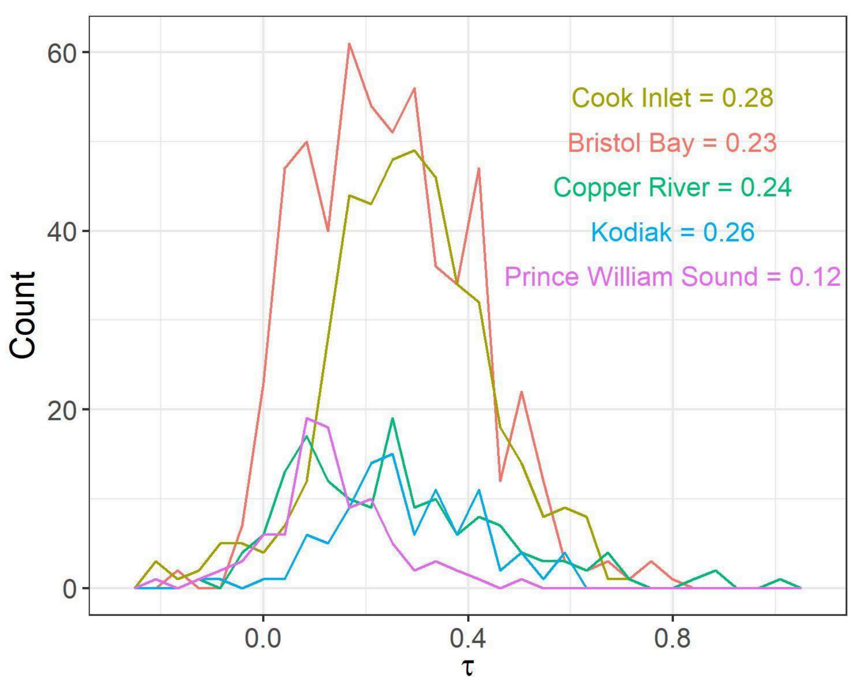

Figure 6. Frequency distribution of estimated stream thermal sensitivities across five regions used in the dynamic factor analysis model. Median values are shown as text for each region. Sensitivities are from a model that included daylength.

Map temperature regimes and thermal sensitivities of salmon habitats and identify habitats sensitive (i.e., more at risk) to climate warming, habitats with high potential to provide cold-water refugia under future climate change, and an assessment of the exposure of subsistence fisheries (i.e., populations) to temperature warming

We modeled $\boldsymbol{\tau}$ using covariates that represented important hydrologic, topographic, and climatic drivers, then used the model to map $\boldsymbol{\tau}$ across the study area in habitats that support Pacific salmon. 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 (NHD 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 DEM and TauDEM 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 slightly to intersect the vector stream network being used for each region to generate accurate stream reach, catchment, and watershed attributes.

Our approach relied on identifying correlations between $\boldsymbol{\tau}$ and datasets that serve as proxies for hydrologic and climatic controls. We included 13 predictors in our model after 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 (m), mean catchment slope (%), mean watershed slope (%), percent of the watershed with a north aspect, watershed area (km^2), percent of the watershed covered by glaciers, lakes, or wetlands, spring snow index, total summer precipitation (mm), valley confinement (measured as width in m), and region (Cook Inlet, Prince William Sound, Copper River, Bristol Bay, and Kodiak).

We calculated the spring snow index (last day of the continuous snow season averaged across each watershed) as an initial covariate representing snowpack processes that may buffer stream thermal sensitivities using snow metrics derived from remote-sensing (Lindsay et al., 2015). 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 (hereafter referred to as the spring snow index).

Valley confinement was calculated using the Valley Bottom Extraction Tool, which uses a stream shapefile, DEM, drainage area, and user-defined thresholds to produce estimated valley widths. Valley confinement could influence the amount of solar gain in the channel and have implications for the degree of groundwater influence on temperature in a given reach.

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. Additionally, we dropped variables sequentially until the reduction in prediction 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 (Hijmans et al., 2023).

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 a small amount of bias towards over-predicting tau, but a 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 = 24), watershed size (17), total summer precipitation (16), lake cover (16), mean catchment elevation (15), and the spring snow index (13).

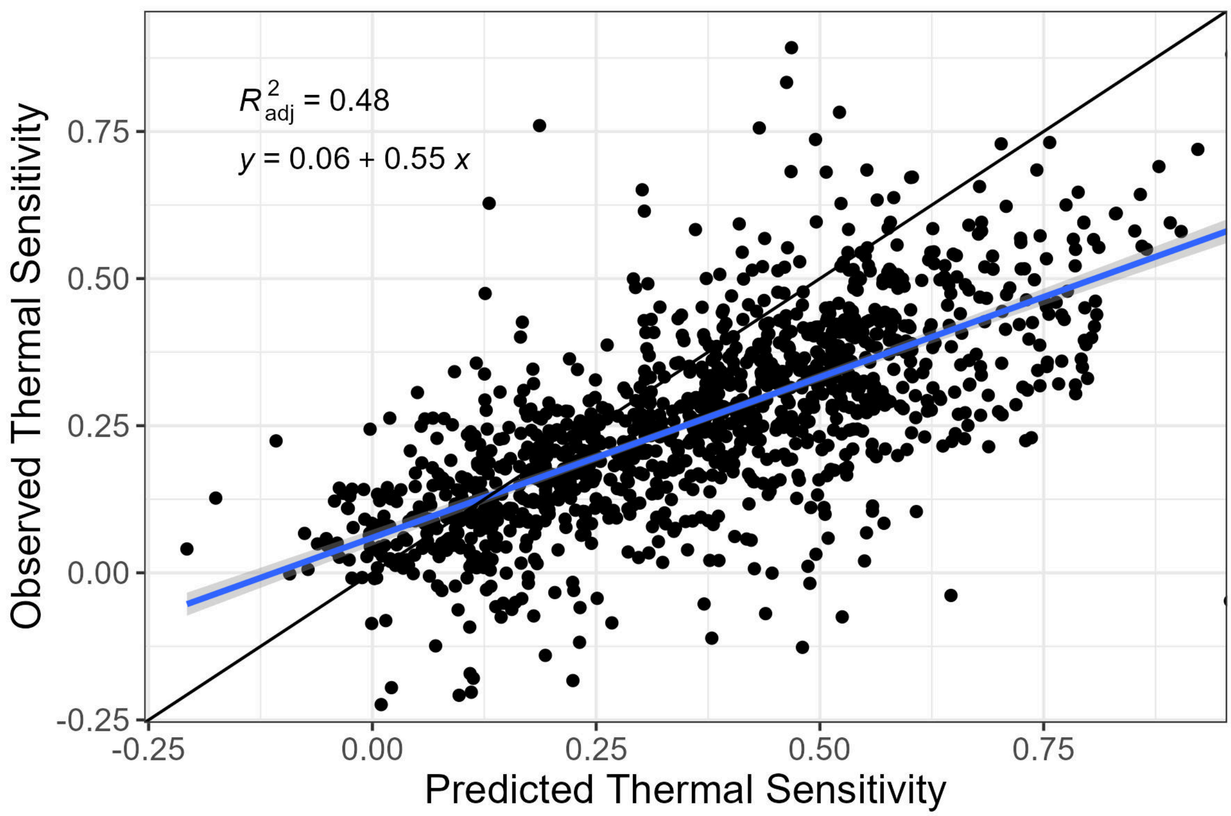

Figure 7. Observed stream thermal sensitivity and predicted thermal sensitivity from boosted regression tree model. Predictions are based on withheld data during cross-validation and represent prediction accuracy to new streams not included in the training dataset for the model. The linear fit between the observations and predictions indicate bias towards overprediction of thermal sensitivity in the model and the R^2 indicates the model explains approximately half of the variation in observed stream thermal sensitivities.

Overall, the model performed best in the Bristol Bay and Cook Inlet regions, and more poorly in the Copper River, Kodiak, and Prince William Sound regions (Figure 8). This difference could be explained by the higher number of sampling sites in Bristol Bay and Cook Inlet compared to the other three regions. More stream temperature data collection could allow for better refinement of these predictive thermal sensitivity models for those regions .

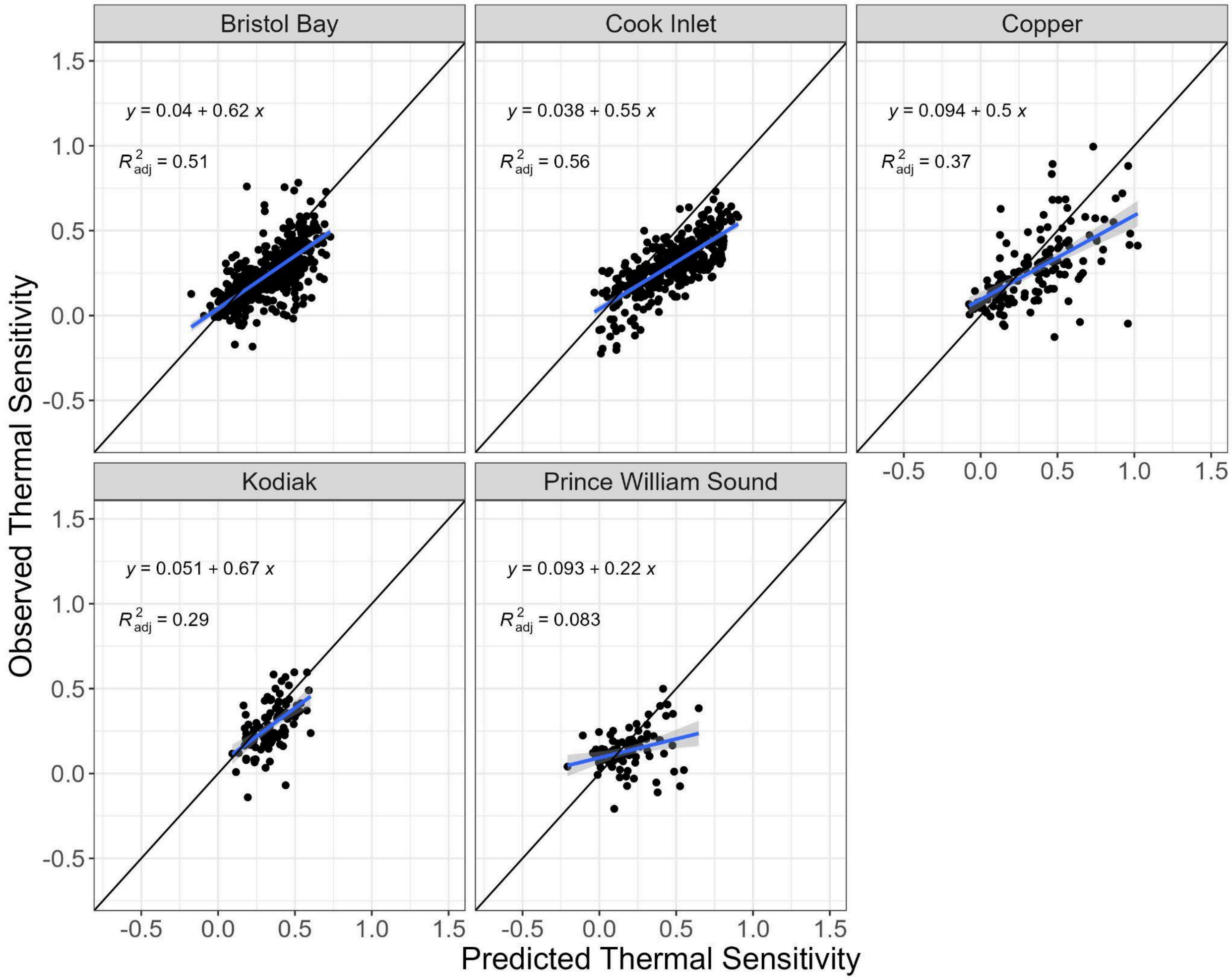

Figure 8. Observed stream thermal sensitivity and predicted thermal sensitivity from boosted regression tree model by region. Predictions are based on withheld data during cross-validation and represent prediction accuracy to new streams not included in the training dataset for the model. The model performs relatively well in Bristol Bay and Cook Inlet, as indicated by the R^2 values for those regions, but less well in Kodiak, Prince William Sound, and the Copper River watershed.

We selected 1,597 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 by 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 1,597 salmon streams so we could predict **τ**. We calculated the spring snow index as before, but for all years from 2011 through 2019. This provided us with a long term, consistent history of snowpack and precipitation variability across all streams.

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

The model predictions indicated that there was little change in mean **τ** across the five regions over different scenarios of summer precipitation or spring snowpack (Figure 9). Salmon habitats in the Prince William Sound and Kodiak regions had the lowest **τ** under all scenarios, followed by Cook Inlet and Copper River, and Bristol Bay, which had the highest **τ** under all scenarios (Figure 9). Changes in **τ** under the two precipitation scenarios were highest in salmon streams draining low elevation areas, such as the west side of the Susitna River basin, the western Kenai Peninsula, and the lowlands of Bristol Bay (Figure 10). In summers with high precipitation, **τ** decreased, indicating that precipitation may be an important hydrologic input to streamflow and may buffer streams from changes in air temperature.

The salmon habitats with the highest **τ** 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). Together, these geomorphic covariates and hydrologic inputs could all be driving changes in **τ**. 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 earlier snowmelt, and have an abundance of wetlands, so unless deeper upwelling groundwater is present (group 6), there are less cold-water contributions in the summer and more near-surface warming before water enters the streams.

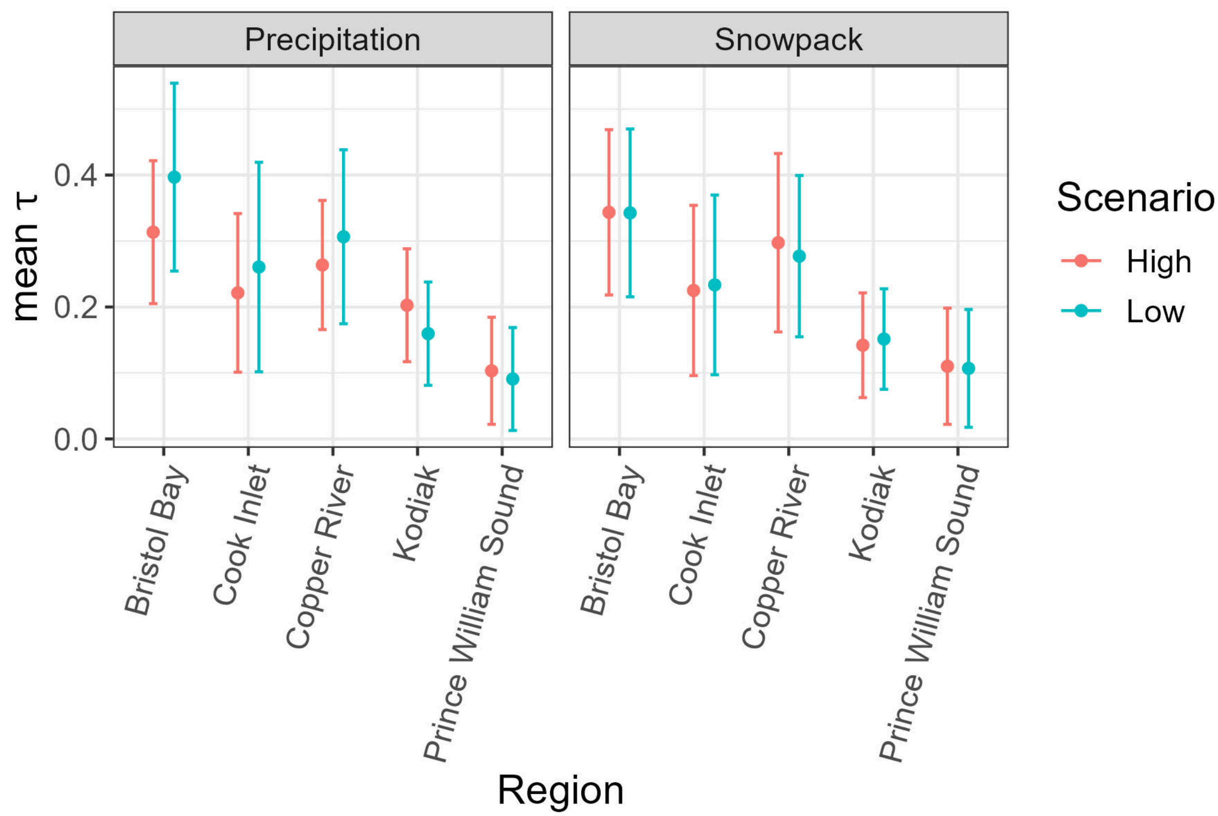

Figure 9. Differences in mean stream thermal sensitivities by region and scenario. The error bars are +/- 1 standard deviation in stream thermal sensitivities. The four scenarios are low and high spring snow and low and high summer precipitation. The highest and lowest values were selected from 2011-2019 climate covariates for each of 966 salmon streams across the five 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.

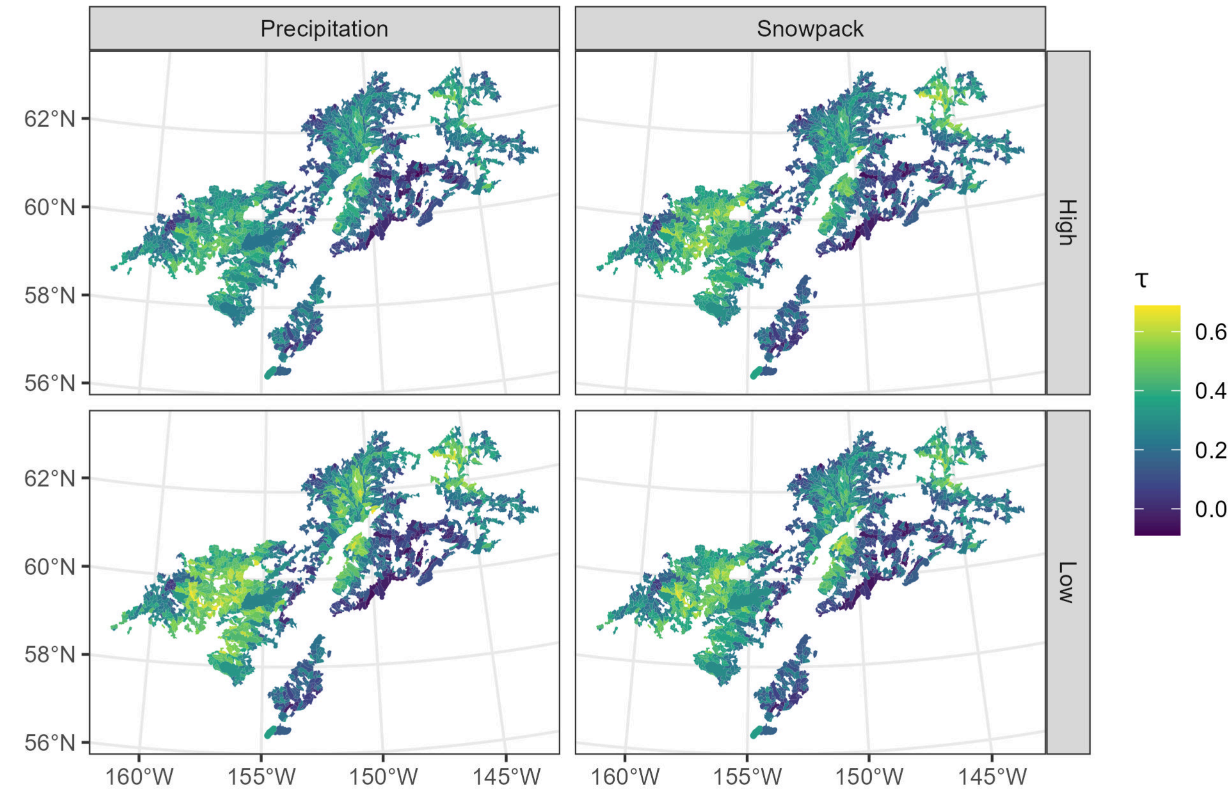

Figure 10. Mapped stream thermal sensitivities for salmon streams in the Cook Inlet, Prince William Sound, and Copper River regions. Thermal sensitivities changed the most from the low to high precipitation scenario, where streams draining low elevation landscapes had lower thermal sensitivities in summers with high precipitation.

Across all four scenarios, we examined differences in mean $\boldsymbol{\tau}$ among salmon habitats. Chinook, coho, and sockeye salmon habitats had the highest mean $\boldsymbol{\tau}$, which decreased under the high precipitation scenario (Figure 11). 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 11). Overall, our results indicate that habitats with the highest thermal sensitivities were those draining flatter, low elevation watersheds with high wetland cover, which are the most sensitive watersheds to warming. 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.

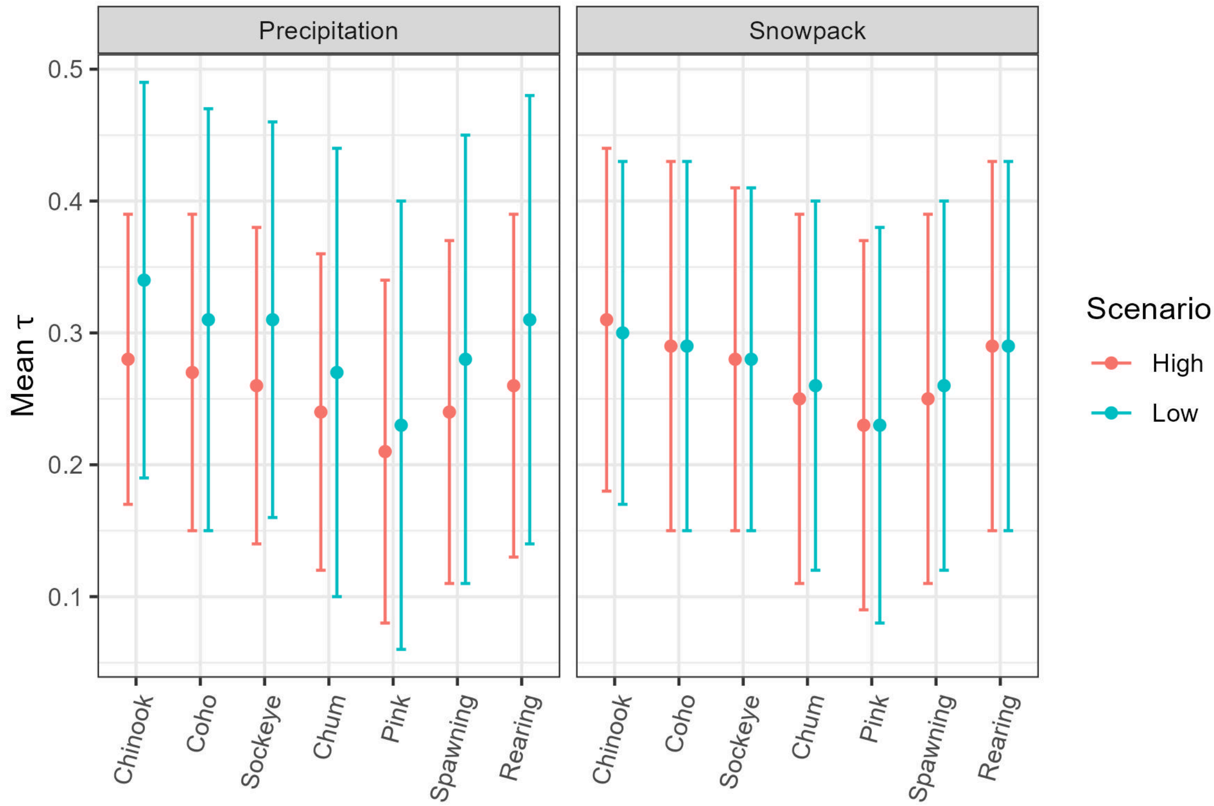

Figure 11. Differences in mean stream thermal sensitivities by scenario and salmon habitat. The error bars are +/- 1 standard deviation in stream thermal sensitivities. The four scenarios are low and high spring snow and low and high summer precipitation. Salmon habitats are attributes for each stream reach assigned from the ADF&G Anadromous Waters Catalog. Species designations include all life stages and life stage designations include all species.

References

Cline, T. J., Schindler, D. E., Walsworth, T. E., French, D. W., & Lisi, P. J. (2020). Low snowpack reduces thermal response diversity among streams across a landscape. *Limnology and Oceanography Letters*, *5*(3), 254–263. https://doi.org/10.1002/lol2.10148

Hijmans, R. J., Phillips, S., & Elith, J. L. and J. (2023). *dismo: Species Distribution Modeling* (1.3-14) [Computer software]. https://cran.r-project.org/web/packages/dismo/index.html

Lindsay, C., Zhu, J., Miller, A. E., Kirchner, P., & Wilson, T. L. (2015). Deriving Snow Cover Metrics for Alaska from MODIS. *Remote Sensing*, *7*(10), Article 10. https://doi.org/10.3390/rs71012961

Shaftel, R., Mauger, S., Falke, J., Rinella, D., Davis, J., & Jones, L. (2020). Thermal Diversity of Salmon Streams in the Matanuska-Susitna Basin, Alaska. *JAWRA Journal of the American Water Resources Association*, *56*(4), 630–646. https://doi.org/10.1111/1752-1688.12839

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 finalize a manuscript with these results in a peer-reviewed journal.

4. Reports and Other Products

We created an ArcGIS online web mapper for this project (https://arcg.is/Xq1fn0) that can be used to explore stream thermal sensitivities in salmon habitats across the Bristol Bay, Kodiak, 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 1,597 salmon streams in the five 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. Stream temperature metrics for all sites and years included in analysis of stream thermal regimes.
3. Estimated stream thermal sensitivities and spatial covariates for 420 sites with data between 2011-2019. Spatial covariates were used in boosted regression tree models.
4. Scenarios of stream thermal sensitivities, spatial covariates, and species and life stage information for 1,597 salmon streams across the Cook Inlet, Prince William Sound, and Copper River regions. Four scenarios included low and high spring snowpack and low and high summer precipitation.