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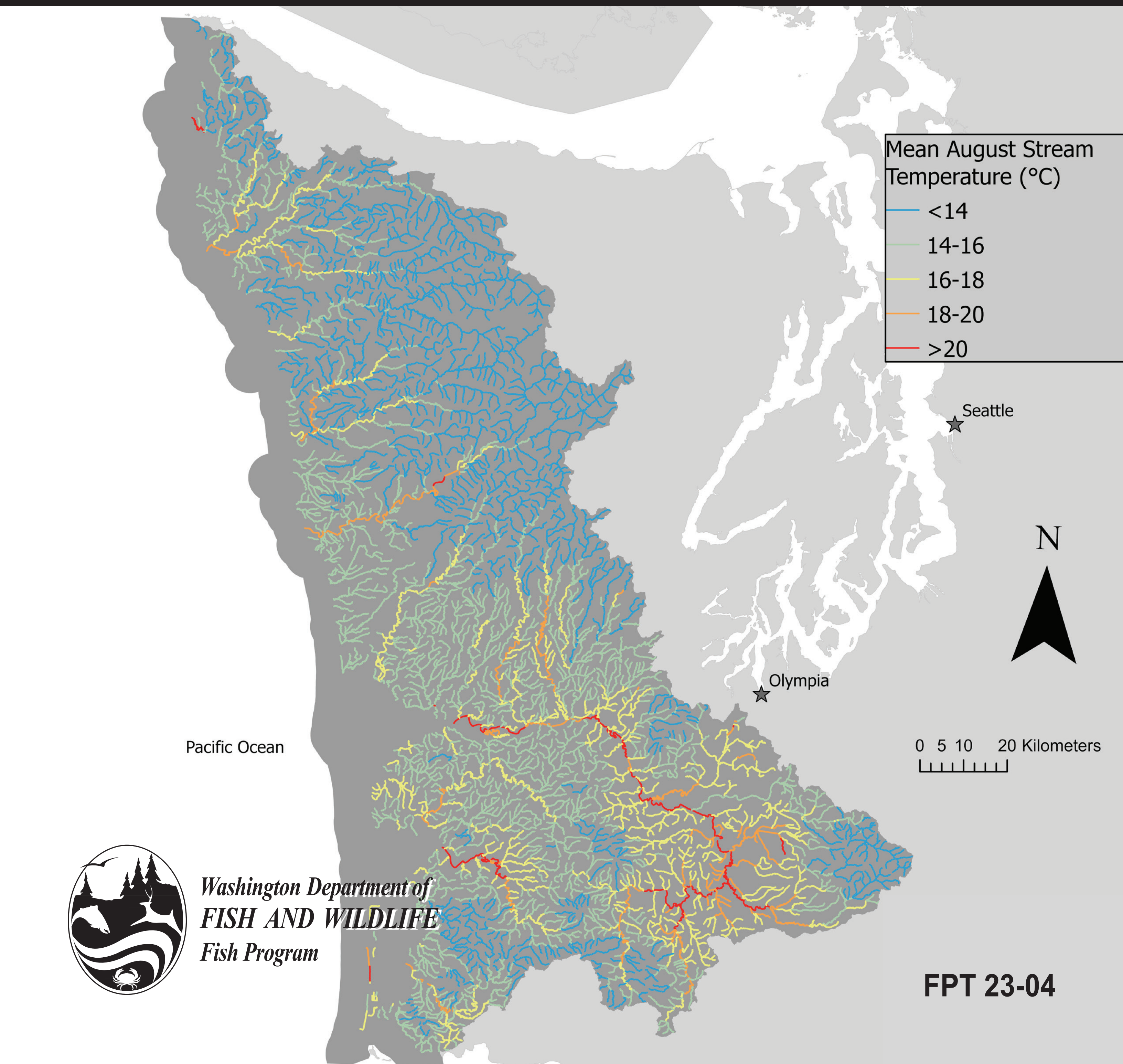
Updating Spatial Stream Network Models of August Stream Temperature for the Washington Coast Salmon Recovery Region



Washington Department of
FISH AND WILDLIFE
Fish Program

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Updating Spatial Stream Network Models of August Stream Temperature for the Washington Coast Salmon Recovery Region

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Olympia, WA

August 2023

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Table of Contents

List of Figures

List of Tables

Executive Summary

Background - In 2017, Isaak et al. (2017) published the NorWeST model of mean August stream temperatures for the Pacific Northwest that provided aquatic resource managers, researchers, conservation organizations, and other stakeholders a valuable and easily accessible geospatial tool for conservation planning. Despite the many contributions of this model, an analysis of local conditions in the Chehalis River Basin identified that the NorWeST model predictions were on average 2.7°C lower than observed current stream temperatures in this basin. A similar analysis of regional conditions from the Washington Coast Salmon Recovery Region followed a similar trend where 83% of NorWeST predictions were cooler than observations and underpredictions were on average 2.1°C and up to 5.6°C cooler than observations. These discrepancies coupled with increased availability of stream temperature data in Western Washington since NorWeST was published warrants the development of an updated regional model, informed with additional data, which should improve understanding of summer stream temperature conditions within the Washington Coast Salmon Recovery Region.

Purpose of the study –The overall goal of this project is to develop an updated spatial stream network model for mean August stream temperature for rivers of the Washington Coast Salmon Recovery Region, specifically Water Resource Inventory Areas (WRIAs) 20-24. The resulting Washington Coast Thermalscape Model includes data sets from 564 stream temperature monitoring locations and downscaled climate projections from 5th Climate Model Intercomparison Program (CMIP5), thus improving the spatial coverage and updating the climate change projections available when the NorWeST model was published.

Methodological approach – Stream temperature data were collated from multiple organizations collecting data in our study area. Data were examined for outliers and organized into a database for modeling. The modeling steps (e.g., geospatial preprocessing, covariate selection and evaluation, and model fitting and evaluation) essentially followed the approach of Isaak et al. (2017) We evaluated models for subregions in addition to the region in its entirety (e.g., North Coast [WRIAs 20 and 21], Chehalis Basin [WRIAs 22 and 23], and Willapa Bay [WRIA 24], and full Washington Coast [WRIAs 20-24]). A model selection approach was followed to select the best fitting models at each spatial scale and then examined spatial and temporal factors associated with summer stream temperature. Model performance was then compared among all models and the best performing model was selected to predict August stream temperatures for the region under current and future climate scenarios. Model structure was similar to that previously developed for the NorWeST model of summer stream temperatures in the Pacific Northwest.

Results – Fit of the Thermalscape Model was evaluated for sub-regions as well as for the region in its entirety. The final regional spatial stream network model showed high predictive performance in terms of precision (root mean square predicted error = 0.6°C, r^2 = 0.95) and accuracy (mean absolute prediction error = 0.01°C) and was selected to develop Thermalscapes of current and future stream temperature conditions for the Washington Coast Salmon Recovery Region. Significant warming effects on mean August stream temperatures (*$p<0.05$*) were associated with August air temperature, cumulative drainage area, and lake % and significant cooling effects were associated with stream flow, elevation, riparian canopy cover, and mean annual precipitation. Current maximum, minimum and mean August stream temperature across the Washington Coast Salmon Recovery Region were estimated at 25.0, 1.8, and 14.9°C, respectively. Late century predictions (2080s) of maximum, minimum, and mean August stream temperature across the Washington Coast were 25.8, 2.4, and 15.6°C, respectively.

Conclusions – Model results are a geospatial resource available for many applications of riverine research and fish and habitat management on the Washington Coast. The results also highlight areas where uncertainty in stream temperature projections is high, and this information may inform priorities for future temperature monitoring activity.

Introduction

Understanding the riverine landscape that supports aquatic species is critical for management and conservation strategies. Stream temperatures figure prominently in helping to understand ecological traits and biological processes of ectothermic species, like Pacific salmon (*Oncorhynchus spp*). Within the last decade, Isaak et al. (2017) released the NorWeST model that predicted summer stream temperatures (mean August) across the western USA, spanning a geographic area of 2,584,000 km^2. The NorWeST model and associated mean August stream temperature predictions provide aquatic resource managers, researchers, conservation organizations, and other stakeholders a valuable and easily accessible geospatial tool that has been widely applied to conservation planning, including Endangered Species Act consultations, National Forest Plan's, species distribution mapping, and climate refugia and species vulnerability assessments (Isaak et al. 2017). Despite the many data contributions of the NorWeST model, an analysis of local conditions in the Chehalis River Basin identified that the NorWeST model predictions were on average 2.7°C and up to 6.1°C cooler than observed current stream temperatures in this basin. Similar inconsistencies were discovered at the broader Washington Coast Salmon Recovery Region scale where 83% of NorWeST predictions were cooler than observations for 2014 and 2015 (Figure 1). NorWeST predictions at the regional scale were on average 2.1°C and up to 5.6°C cooler than observations. These discrepancies coupled with increased availability of stream temperature data in Western Washington since NorWeST was published warrants the development of an updated regional model, informed with additional data, which should improve understanding of summer stream temperature conditions.

The overall goal of this study is to develop an updated spatial stream network (SSN) model for mean August stream temperature (AugST) for rivers of the Washington Coast Salmon Recovery Region, specifically Water Resource Inventory Area's (WRIAs) 20-24. Models are "updated" by 1) fitting newly acquired stream temperature data since NorWeST was published and 2) updating climate change projections of stream temperature by sourcing downscaled climate change projections of air temperature from the 5th Climate Model Intercomparison Program (CMIP5) and hydrological projections from the recently updated (2022) Variable Infiltration Capacity (VIC) model. The analysis allows for describing 1) factors correlated with variability in AugST at sub regional and regional spatial scales, 2) evaluating the predictive performance of SSN models at sub regional and regional spatial scales, and 3) developing predictive maps (or "Thermalscapes") of AugST for current and future scenarios across the Washington Coast Salmon Recovery Region.

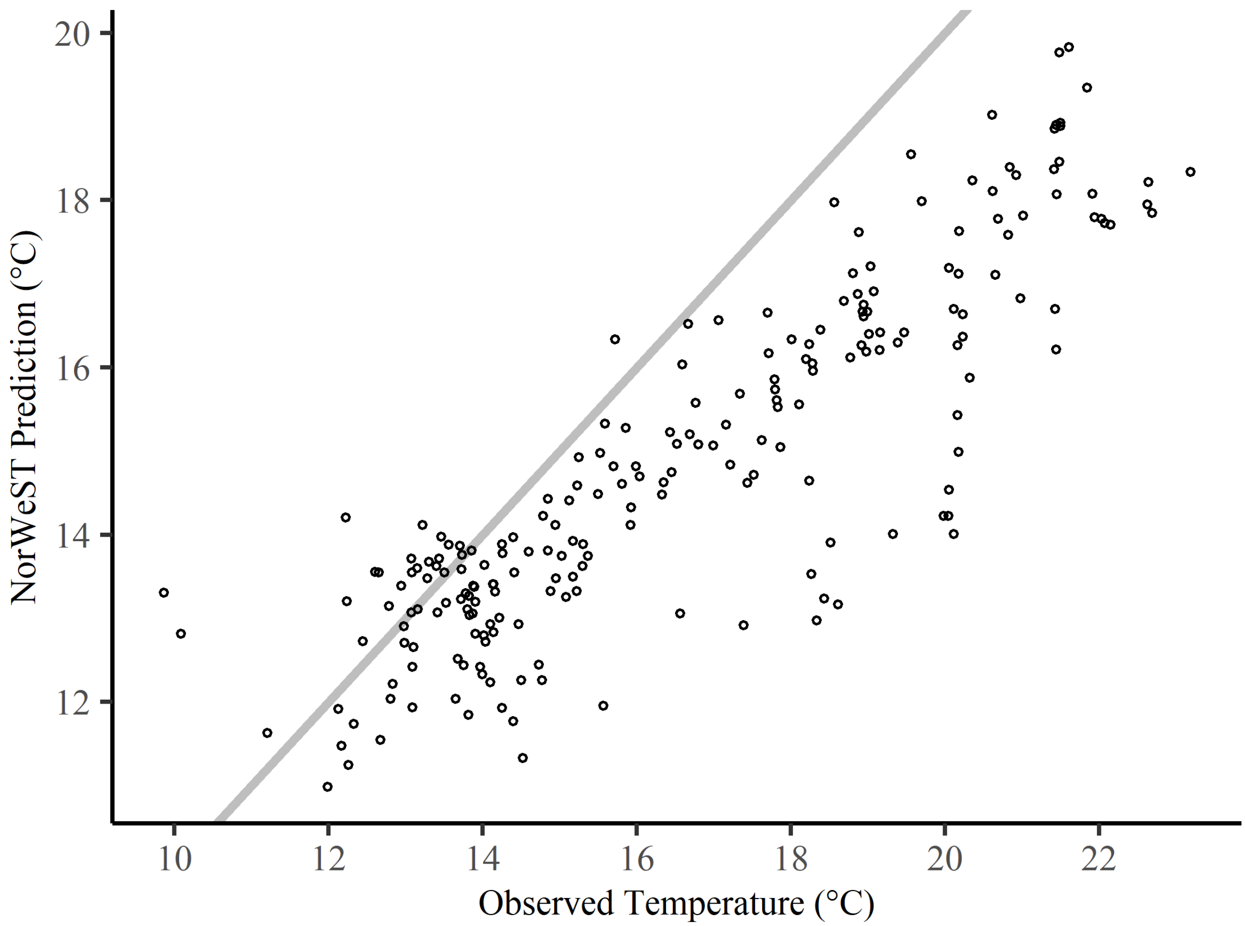

Figure 1. Mean August stream temperature observations in 2014 and 2015 and associated NorWeST predictions (S35_2014 and S35_2015) across the Washington Coast Salmon Recovery Region. Gray line represents hypothetical 1:1 relationship between predictions and observations. Points below or above the line represent cooler or warmer predictions from NorWeST compared to observations, respectively.

Methods

Study Area

The study area is the Washington Coast Salmon Recovery Region (WRIA 20-24) and encompasses a geographic area of approximately 17,845 km^2 (Figure 2). There is considerable heterogeneity across the Washington Coast landscape in terms of land use patterns, watershed size, elevation gradients, and hydrological characteristics (e.g., snow melt vs rain dominant). Table 1 presents descriptive statistics of georeferenced points (n = 12,450) spaced approximately every 1 km on streams throughout the study area. All covariate values were sourced from the USFS NorWeST data repository and specific sources are listed in Appendix Table A.1 (https://www.fs.usda.gov/rm/boise/AWAE/projects/NorWeST.html).

Table 1. Descriptive statistics of landscape covariates in streams of the Washington Coast, WRIAs 20-24 observed via points at approximately every 1km (n = 12,450).

Covariate	Mean	Standard Deviation	Minimum	Maximum
Elevation (m)	161.1	196.1	0	1,606.8
Stream slope (%)	0.04	0.05	0	0.65
Mean annual Precipitation (mm)	2,603.5	862.1	1162.5	6,602.4
Drainage area (km^2)	96.9	401.8	0.01	5,457.1
Riparian canopy cover (%)	67.2	26.3	0	99.0
Base-flow index	49.8	3.6	42	62
Lake (%)	0.1	0.7	0	18.0
Glacier (%)	0.003	0.03	0	0.74
Northing coordinate	1933830.9	59337.2	1838590.7	2078290

Description of Data Set

Data sets used in this analysis were made available by state, tribal, and federal natural resource departments throughout the region. All data were collected from digital temperature sensors with multiple daily recordings (minimum 10 recordings per day, but most were 48 recordings per day). Several temperature sensor models were likely used for data collection of new sites, but this information was not always included in information from data contributors. Data were screened by filtering for anomalies (values <0°C and >30°C, and >2.5°C change per hour) and visually inspecting thermographs to identify suspected erroneous records. Anomalies were likely due to dewatering and these records were removed prior to analyses. If sites had unique thermographs and or erroneous coordinates, clarification was sought to data contributors. If no clarification was given, sites were removed from the database. Some sensor sites were located on small tributaries that are not included in the National Stream Internet (NSI), which is the landscape network used for SSN modeling (described below). These sites were removed from the dataset. In total, the data set included 564 unique sensor sites.

For each site, AugST was calculated following NorWeST (mean of mean daily August temperature, limited to sites with data from at least 90% of days in August). Table 2 presents the range of covariates for sites where AugST was calculated.

Table 2. Descriptive statistics of environmental covariates at stream temperature monitoring locations (n = 564). Air temperature and stream flow were specific to WRIA areas and years of data collection, e.g. not unique to monitoring locations.

Covariate	Mean	Standard Deviation	Minimum	Maximum
August stream temperature (°C)	14.0	1.9	7.1	21.2
Elevation (m)	125.6	95.3	0	506.5
Stream slope (%)	0.03	0.04	0	0.26
Mean annual precipitation (mm)	2825.8	803.0	1170.2	5083.7
Drainage area (km^2)	202.8	521.3	1.3	5,114.1
Riparian canopy cover (%)	68.5	24.0	0	96.5
Base-flow index (%)	50.0	3.2	42	59
Lake (%)	0.2	0.9	0	13.5
Glacier (%)	0.002	0.01	0	0.08
Northing coordinate	1963721.9	61324.4	1842194.7	2053015.0
Air Temp °C	17.6	0.7	15.3	20.1
Stream flow (ft^3/s)	452.5	304.7	23.3	1652.3

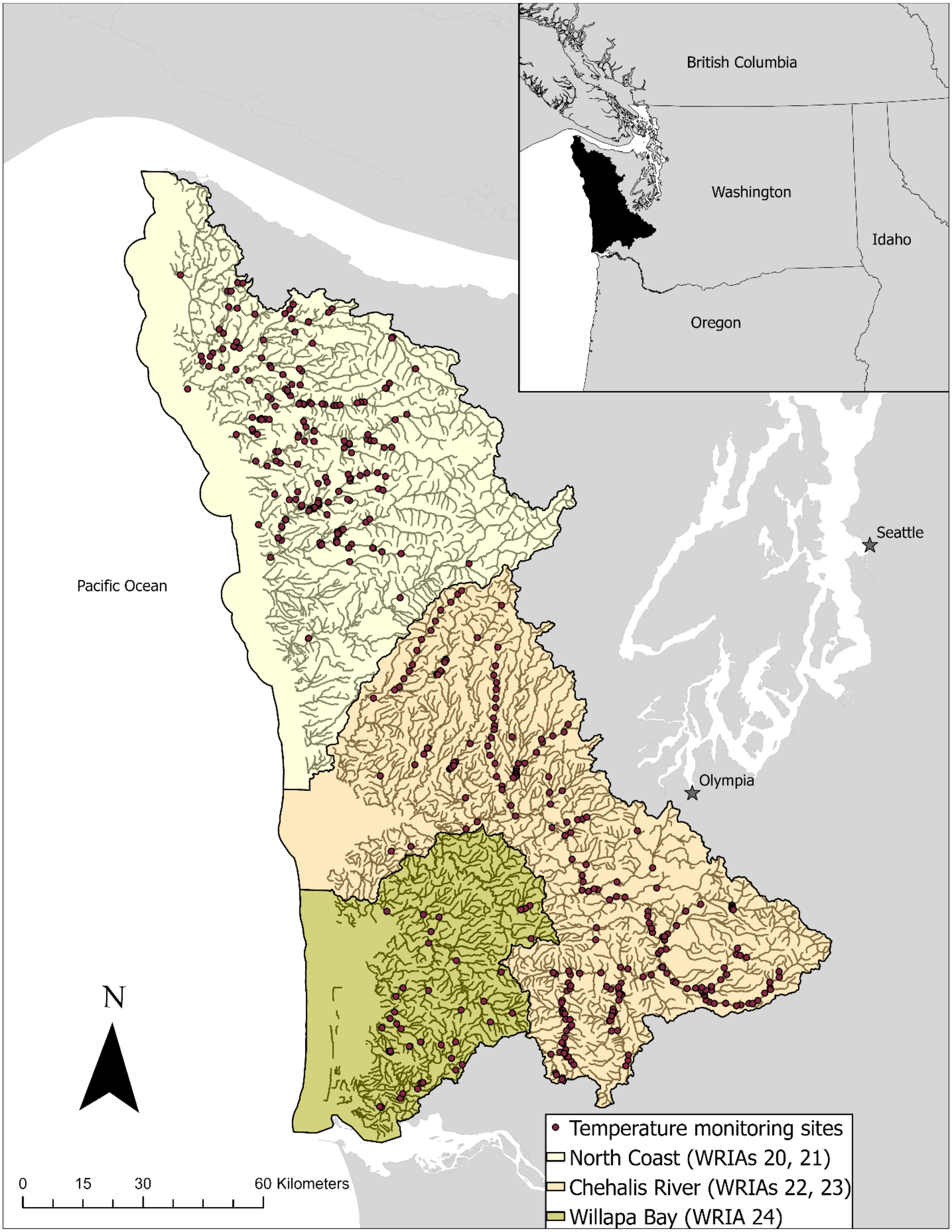

Figure 2. Temperature monitoring locations in streams of Washington Coast Salmon Recovery Region.

Spatial Autocorrelation in Stream Temperature Dataset

Spatial autocorrelation was expected to be present in the dataset because stream temperatures are influenced by passive downstream drift and terrestrial linkages, and the dataset was comprised of spatially clustered sensor sites. SSN models account for spatial correlation specific to river systems (e.g., flow connectivity and hydrological distances) which leads to unbiased parameter estimates and better predictive performance relative to non-spatial models when applied to correlated datasets. A spatial Torgegram is an empirical semivariogram and was developed to graphically represent spatial autocorrelation trends present in the stream temperature data for flow connected (e.g., water flows from an upstream site through a downstream site) and unconnected (e.g., sites do not share the same flow) site pairs as a function of increasing hydrologic distance (McGuire et al. 2014; Zimmerman and Ver Hoef 2017). The Torgegram revealed clear patterns of positive autocorrelation present in the dataset for flow connected and flow unconnected site pairs, as suggested by patterns of change in semivariance among site pairs in relation to the hydrological distances between them (Figure 3). This observation underscores the importance of applying an SSN model to the dataset. The changes in semivariance differed among flow connected and flow unconnected site pairs. For flow connected sites, there was a nearly linear increase in semivariance with distance to about 50 km, whereas semivariance of flow unconnected site pairs was generally smaller and exhibited a smaller rate of change over hydrological distance (Figure 3). Larger semivariance values of flow connected sites suggests greater overall spatial heterogeneity compared to flow unconnected sites (Figure 3). This observation is expected, as increased distances of flow connected sites reflects moving through the river network from high elevation small streams to low elevation large rivers and one would expect increasing variability of stream temperature correlated with landscape changes and processes of passive downstream drift.

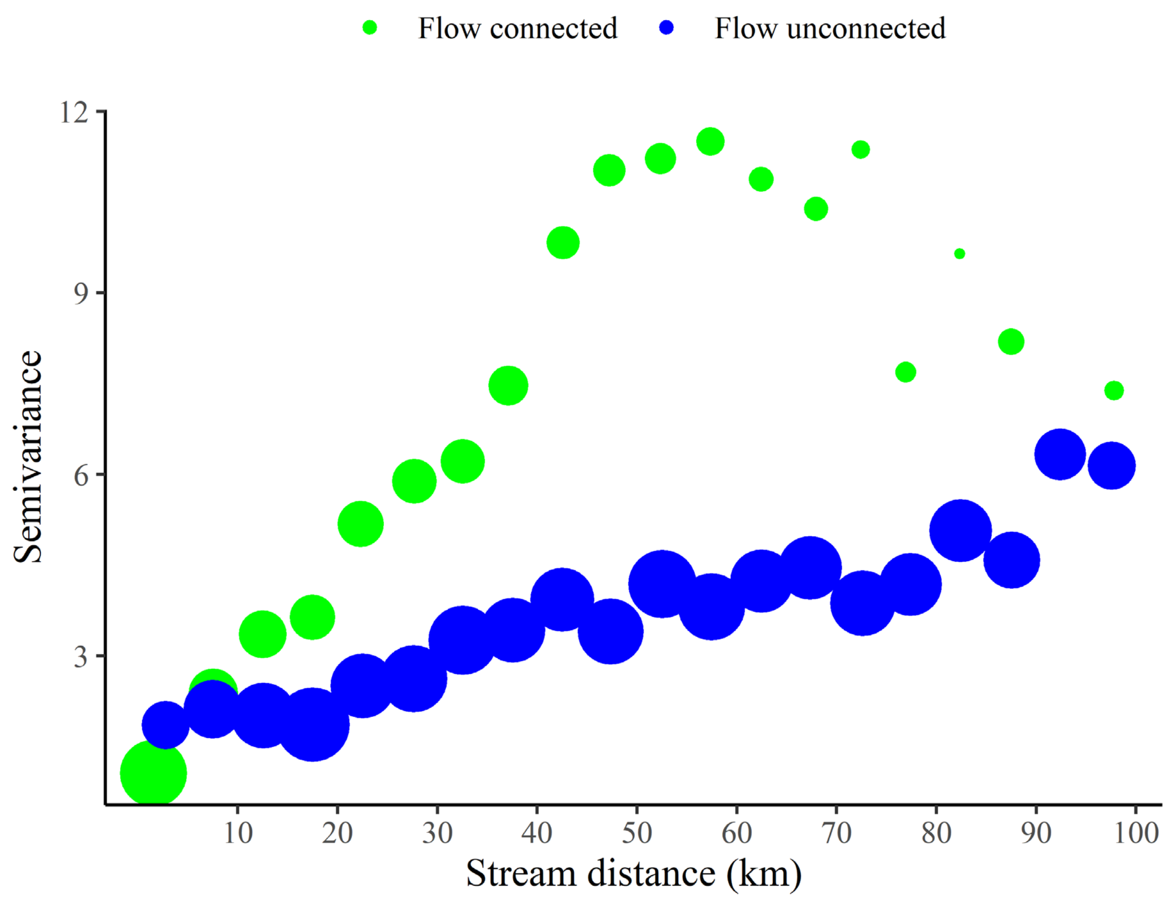

Figure 3. Empirical Torgegram describing similarity among stream temperature monitoring site pairs across increasing hydrological distances (km). Circles are proportional to the number of site pairs averaged for each semivariance value. Low semivariance values represent site pairs that are more similar and higher semivariance values represent site pairs that are less similar, translating to greater overall spatial variation.

Thermalscape Model Development

Thermalscape modeling steps (e.g., geospatial preprocessing, covariate selection and evaluation, and model fitting and evaluation) essentially followed the approach of Isaak et al. (2017) and is summarized here for this specific study. Briefly, geospatial preprocessing was conducted with STARS (Peterson and

Ver Hoef 2014) in ArcGIS 10.6.1, SSN objects were imported into R (R Development Core Team 2021), and the SSN package (Ver Hoef et al. 2014) was used to fit the data to spatial stream network models.

Appendix Table A.1 summarizes spatial and temporal covariates and rational for inclusion. Spatial covariate values are publicly available via the USFS NorWeST data repository (https://www.fs.usda.gov/rm/boise/AWAE/projects/NorWeST.html) and were geospatially linked to the location of each temperature monitoring site. Temporal covariates, mean August air temperature (AugAT) and mean August stream flow (AugQ), were included to account for annual variability in climate conditions as they can impact stream temperature (Figures 4 and 5). Year and subregion specific AugAT and AugQ values were assigned to all site-year-AugST observations. AugAT values were downloaded from the PRISM data explorer from the standard PRISM 4km time series data for a single location centrally located in each sub region (n = 3) at approximately similar elevations (100 m) (PRISM Climate Group 2004) (Table 3). AugQ values assigned to sites were the year specific average of mean August stream flow from stream gages within sub regions. Gages were characterized by stream records that spanned the study timeframe (1993-2021) and in locations without a dam or reservoir (Table 4, Figure 5).

Table 3. Locations selected for regionally representative mean August air temperature values to assign to all site-year-mean August stream temperature observations in each sub region.

WRIA	Latitude	Longitude
20, 21	47.952	-124.383
22, 23	46.741	-123.071
24	46.719	-123.584

Table 4. Stream flow gages used for calculating mean August stream flow values to assign to all site-year-mean August stream temperature observations in each sub region.

WRIA	Gage descriptor locations	USGS IDs
20, 21	Queets, Hoh, Calawah	12040500, 12041200, 12043000
22, 23	Chehalis mainstem (Doty, Grand Mound), Newaukum, Satsop	12020000, 12027500, 12025000, 12035000
24	Willapa, Naselle	12013500, 12010000

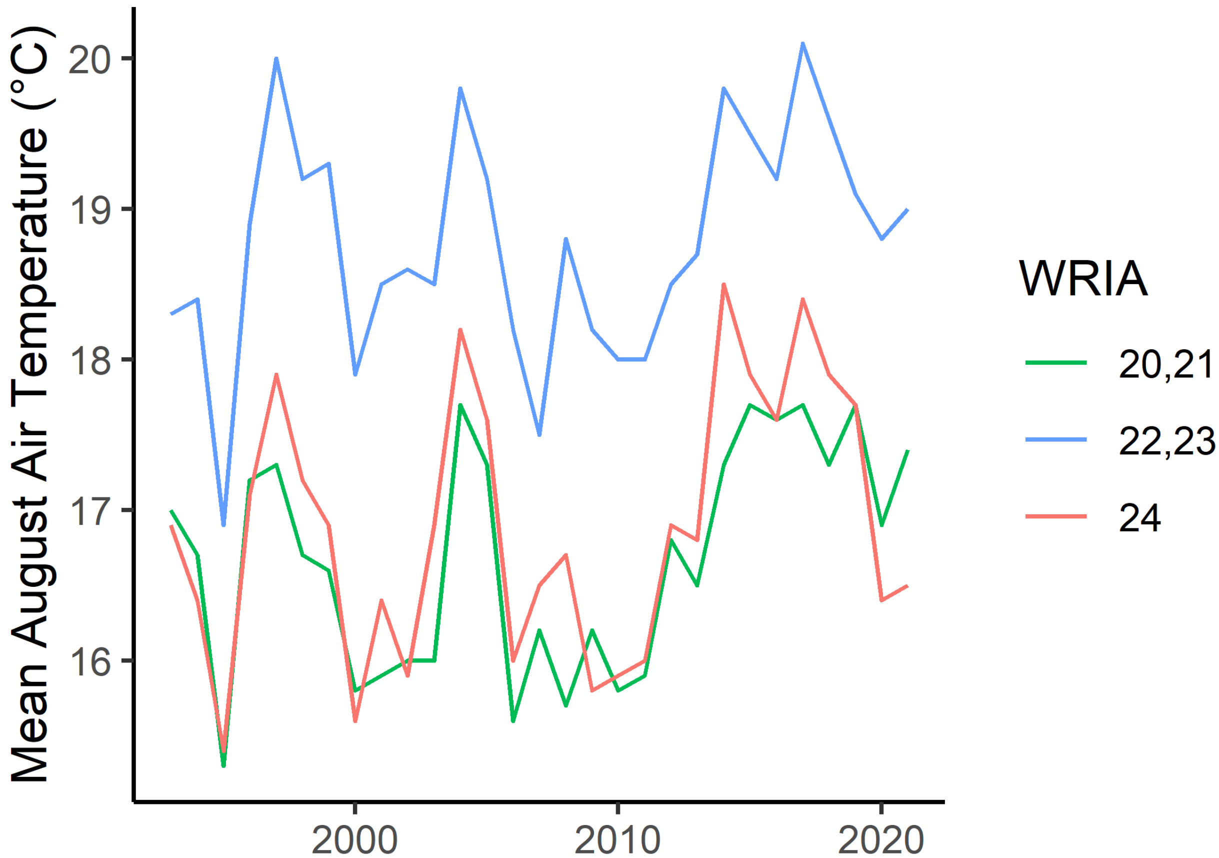

Figure 4. August air temperature trends (1993-2021) in sub regions of Washington Coast Salmon Recovery Region. WRIAs 20 and 21 = North Coast; WRIAs 22 and 23 = Chehalis Basin; and WRIA 24 = Willapa Bay. Data were sourced from the PRISM Climate Group (*https://prism.oregonstate.edu/*).

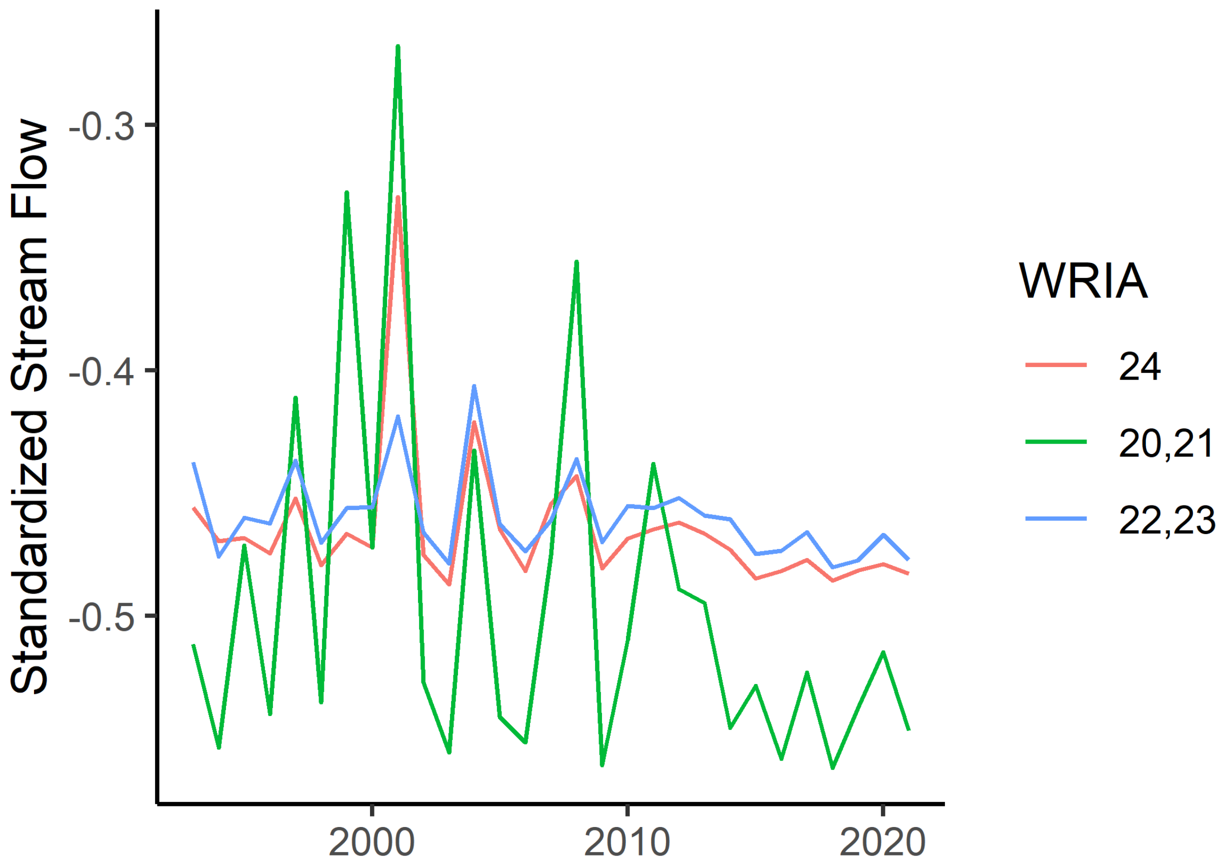

Figure 5. August stream flow trends (1993-2021) for WRIAs 20 and 21 (mean of USGS gages 12040500, 12041200, 1204300, WRIAs 22 and 23 (mean of USGS gages 12020000, 12027500, 12025000, 12035000), and WRIA 24 (mean of USGS gages 12013500, 12010000). Mean monthly stream flow values (ft^3/s) were standardized to a mean of 0 and standard deviation of 1 across the year and only August values are displayed.

To describe factors associated with AugST at the subregional vs full regional scale, three subregional SSN models were developed that comprised 1) WRIAs 20 and 21, 2) WRIAs 22 and 23, 3) WRIA 24, and one full regional model was developed representing all WRIAs (20-24), which are hereafter referred to as the North Coast (NC), Chehalis (CH), Willapa Bay (WB), and Washington Coast (WC) models, respectively.

The following model development process followed Isaak et al. (2017). Briefly, prior to fitting models, continuous covariates were standardized to mean = 0 and standard deviation = 1. Multicollinearity was addressed using variance inflation factors (VIFs). Variance inflation factor values for all covariates were generally below 3.0, which is an acceptable threshold (Zuur et al. 2010), with the exception of northing coordinate which was removed from the CH and WB models due to high VIF values (>15). No glacial covariate was included in the CH or WB models because there are no glaciers present in these sub regions. Furthermore, probable linear dependency was determined as expressed as a singular matrix for the slope covariate in the NC model and cumulative drainage area in the WB model and therefore removed from the respective analyses. Two random effects were included in the initial models: 1) "site" to account for repeat measurements at sites across years and 2) "year" to account for repeat measurements within years across sites. The spatial autocorrelation functions in the model included exponential Euclidean (EUC), exponential tail-down (TD), and exponential tail-up (TU) function with spatial weighting based on watershed area (Peterson and Ver Hoef 2010; Ver Hoef and Peterson 2010). A full mixture of spatial autocorrelation functions was included in the initial models to account for multiple patterns of spatial heterogeneity in the stream temperature dataset (e.g., Euclidean space and hydrologic distances and flow connection).

The first step of the model evaluation process was to fit the four models with all spatial and temporal covariates and full mixture of spatial autocorrelation functions and random effects. For each model, if <5% of the overall variance was explained by a spatial autocorrelation function or random effect, it was systematically removed, the model was refit, and models were compared using AIC. If the reduced model was within three points of other models, then the reduced model was used in the next steps; otherwise the autocovariance function or random effect were retained in the model. Second, to understand factors associated with variability in AugST at subregional and regional spatial scales, the relative importance of covariates was examined by comparing the magnitude and direction of standardized parameter estimates and their statistical significance for each model. Lastly, leave-one-out cross-validation (LOOCV) was used to evaluate the predictive performance of SSN models at sub-regional and regional spatial scales to 1) compute an r^2 for a linear model that regressed LOOCV predictions to observed stream temperature values, 2) compute mean absolute prediction error (MAPE) between observed and LOOCV prediction values (bias), and 3) compute the root mean square prediction error (RMSPE) as

$$RMSPE = \sqrt{\frac{\sum_{i=0}^{n}[\hat{y}(s_i) - y(s_i)]^2}{n}}$$

where $y(s_i)$ is the observed mean August value at site s_i, $\hat{y}(s_i)$ is the LOOCV prediction mean August value for s_i, and n is the total number of observed data values. Smaller RMSPE values reflect more accurate model predictions. Model performance statistics were compared (r^2, MAPE, RMSPE) across models and selected the model(s) with the best predictive ability to use for spatially continuous model predictions ("Thermalscapes") across the study area described below.

Current and Future Climate Change Scenarios

Inclusion of temporal covariates, AugQ and AugAT, provides the opportunity to model scenarios in stream temperature conditions. For example, the Thermalscape Model can be used to predict stream temperatures at nonmonitored locations under current conditions and to project region wide stream temperatures for future AugQ and AugAT values from downscaled climate projections of global climate models (GCMs).

To develop a stream temperature scenario representative of "current," or baseline, conditions the parameterized model was used with universal kriging (Ver Hoef et al. 2006) across the stream network based on mean values of Q and AugAT across the years present in the AugST dataset (1993-2021). To develop a stream temperature scenario representative of late century stream temperature conditions, the parameterized model was used with universal kriging across the stream network based on adjusted AugAT and AugQ values, and based on regionally specific projected changes (deltas) in AugAT and AugQ from current to late century (2080s). The AugAT deltas were downloaded from the National Climate Change Viewer (NCCV) (https://www.usgs.gov/tools/national-climate-change-viewer-nccv) which provides modeling results of the 5th Climate Model Intercomparison Program (CMIP5) from 20 global climate models (GCMs) in the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC). Mean delta AugAT values were sourced from 10 GCMs under Representative Concentration Pathway (RCP) 8.5 emissions scenario at the HUC level for Washington State. If a sub region was represented by more than one HUC, AugAT values were averaged so one delta value could be applied to each sub region. AugQ deltas were downloaded from the 2022 update of the Variable Infiltration Capacity (VIC) model (https://www.fs.usda.gov/rm/boise/AWAE/projects/VIC_streamflowmetrics/archived_modeled_stream_flow_metrics.shtml). AugQ deltas were sourced from VIC predictions at stream gage locations used to derive AugQ values for each sub region (see Table 4), and a mean delta was calculated for each sub region.

Adjustments were needed to delta values from the GCMs and VIC model because the baseline in the stream temperature dataset was centered later than the baseline of the GCMs and VIC model. The stream temperature dataset (1993-2021) was centered on data 12 years later relative to the GCM baseline (1981-2010), so the future AugAT delta used for climate scenarios was reduced proportionally to align with the baseline of the stream temperature data set. To account for the 12 years of the approximate 100-year period between the 1980s and 2080s, the AugAT delta was reduced by 12% for late century (2080s). The stream temperature dataset was centered on data 15.5 years later relative to the VIC model baseline (1977-2006). To account for the 15.5 years of the approximate 100-year period between the 1980s and 2080s, the AugQ delta was reduced by 15.5% for late century (2080s). Final baseline and adjusted delta values for each sub region are presented in Table 5.

Table 5. Baseline and projected change (delta) in future August air temperature (AugAT) and stream flow (AugQ) (ft^3/s) used for the Washington Coast Thermalscape Model.

WRIA	Baseline AT	Delta AT	Future AT	Baseline Q	Delta Q (%)	Future Q
2021	16.7°C	+4.5°C	21.2°C	703.2	-37.2	441.8
2223	18.8°C	+4.6°C	23.4°C	167.3	-16.0	140.5
24	16.9°C	+4.5°C	21.4°C	45.6	-12.6	39.9

Results

Selection of Spatial Autocorrelation Structures and Random Effects

Best fitting combinations of spatial autocovariance structures varied by model (Table 6). For the WC model, all spatial autocorrelation structures and random effects were retained because they each accounted for at least 5% of the overall variance explained. Spatial autocovariance structures and random effects were evaluated for all subregional models because at least one component accounted for less than 5% of the overall variance explained. The final NC model included tail up and tail down spatial autocovariance structures and the year random effect. The final CH model included tail up and tail down spatial autocovariance structures and the site ID random effect. The final WB model included the tail down spatial autocovariance structure and the year random effect. Euclidean distance was removed from all final subregional models.

Table 6. Spatial autocovariance structures and random effects evaluated for model fit based on AIC. The presence of an “X” indicates that the respective variable was included in the model and “-“ indicates it was not. The final model selected for model performance evaluation is noted with an “X” in the last column.

Model	Tail-up	Tail-down	Euclidean	Site ID	Year	AIC	Selected for performance evaluation
WC	X	X	X	X	X	3291.2	X
NC	X	X	X	X	X	1812.1	-
NC	X	X	-	X	X	1808.1	-
NC	X	X	-	X	-	1983.1	-
NC	X	X	-	-	X	1807.7	X
CH	X	X	X	X	X	1129.7	-
CH	X	X	-	X	X	1126.7	-
CH	X	X	-	X	-	1140.4	-
CH	X	X	-	-	X	1123.9	X
WB	X	X	X	X	X	189.7	-
WB	X	X	-	X	X	185.7	-
WB	-	X	-	X	X	183.7	-
WB	-	X	-	-	X	183.2	X

Covariates Associated with Variability in AugST

The proportion of variation in AugST explained by spatial and temporal covariates ranged from 12-55% depending on region and scale (Table 7). The total proportion of variation in AugST explained by spatial autocorrelation (combination of tail up, tail-down, Euclidean) ranged from 31-71% depending on region and scale (Table 7). Covariates associated with variability in AugST varied by region and scale (Table 8). For the WC model, significant positive relationships (*$p<0.05$)* existed with AugAT, cumulative drainage area, and % lake, while significant negative relationships existed with stream flow, elevation, riparian canopy cover, and mean annual precipitation (Table 8, Figure 6). For the NC model, significant positive relationships existed with AugAT, cumulative drainage area, and lake %, and significant negative relationships existed with stream flow and elevation (Table 8, Figure 7). For the CH model, significant positive relationships existed with AugAT and cumulative drainage area, and significant negative relationships existed with stream flow, elevation, and mean annual precipitation (Table 8, Figure 8). For the WB model, significant positive relationships existed with AugAT and lake %, and significant negative relationships existed with elevation and riparian canopy cover (Table 8, Figure 9).

Table 7. Total variation explained by spatial and temporal covariates, spatial autocovariance structures, random effects, and nugget (or unexplained fine scale spatial variability) for the final version of each model.

Model	Spatial and Temporal covariates	Tail-up	Tail-down	Euclidean	Site ID	Year	Nugget
WC	0.12	0.44	0.10	0.17	0.05	0.08	0.04
NC	0.23	0.57	0.12	NA	NA	0.03	0.05
CH	0.31	0.30	0.34	NA	NA	0.01	0.04
WB	0.55	NA	0.31	NA	NA	0.13	0.01

Table 8. Covariates associated with August stream temperature. Significant relationships ($p < 0.05$) are noted with "+" (positive relationships) and "-" (negative relationships). NA's are noted for covariates that were not included due to multicollinearity or because they were not relevant for the sub region.

Model	Stream Flow (ft^3/s)	Air temperature (°C)	Elevation (m)	Riparian Canopy Cover (%)	Slope (m/m)	Mean annual precipitation (mm)	Cumulative drainage area (km^2)	Glacier (%)	Northing coordinate	Lake (%)	Base flow index
WC	-	+	-	-		-	+			+	
NC	-	+	-		NA*		+			+	
CH	-	+	-			-	+	NA	NA - VIF		
WB		+	-	-			NA*	NA	NA - VIF	+	

*Inclusion resulted in a singular matrix likely due to interdependencies among predictor variables not identified with VIFs. Therefore, it was not included in the final model.

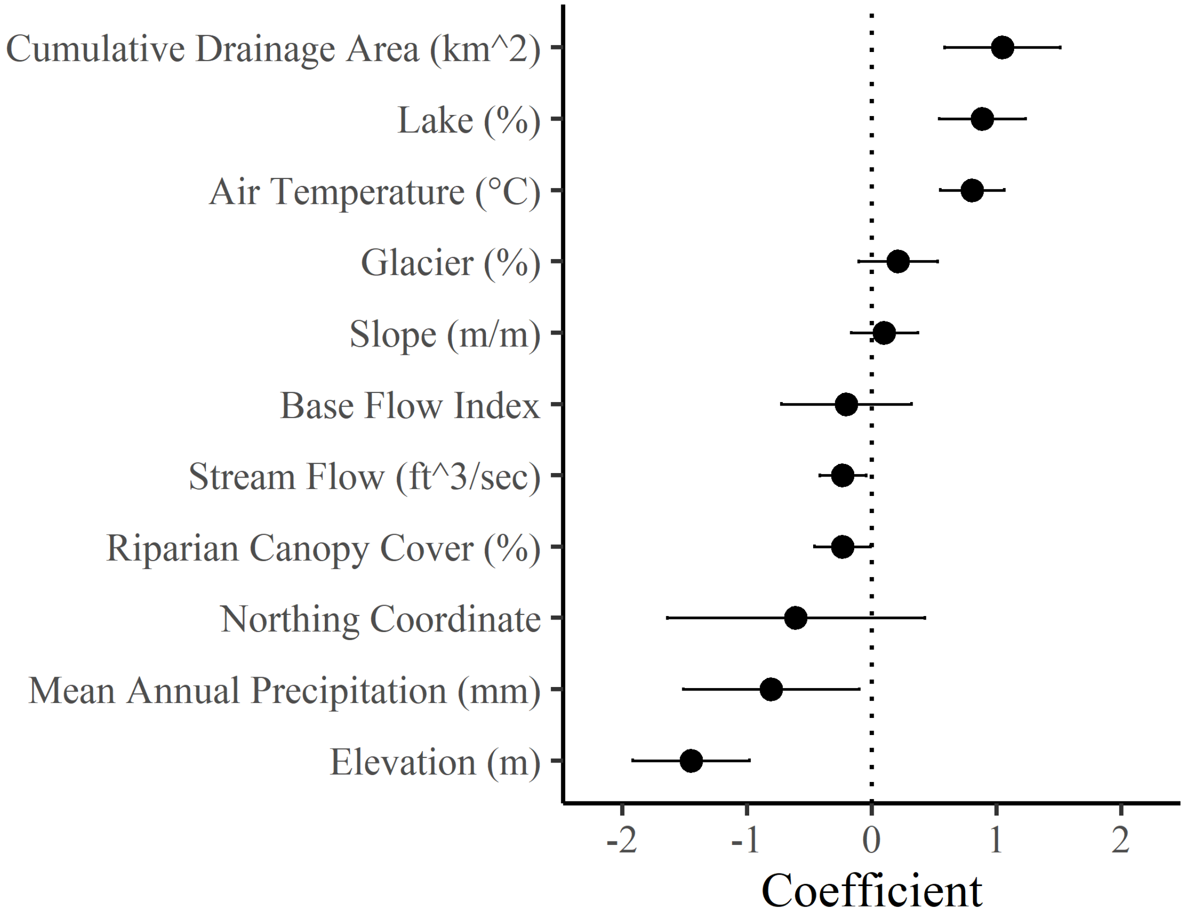

Figure 6. Covariate coefficient values (points) and 95% confidence intervals (CI, bars) for Washington Coast (WC) Thermalscape model. Statistically significant covariates (p < 0.05) are indicated by 95% CI that do not intercept 0. For positive coefficients, increasing value of the factor is associated with warmer temperatures. For negative coefficients, increasing value of the factor is associated with cooler temperatures.

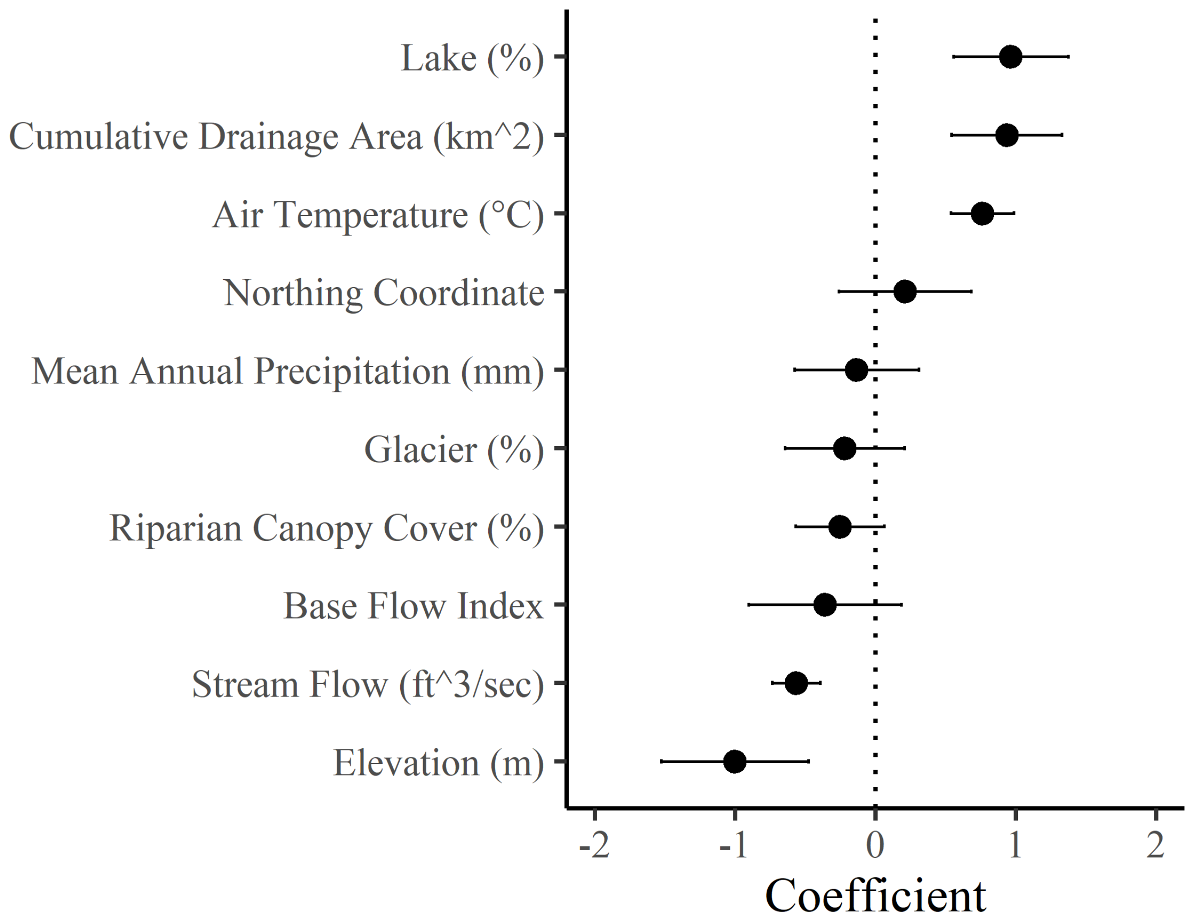

Figure 7. Covariate coefficient values (points) and 95% confidence (CI, bars) for North Coast (NC) Thermalscape model. Statistically significant covariates ($p < 0.05$) are indicated by 95% CI that do not intercept 0. For positive coefficients, increasing value of the factor is associated with warmer temperatures. For negative coefficients, increasing value of the factor is associated with cooler temperatures.

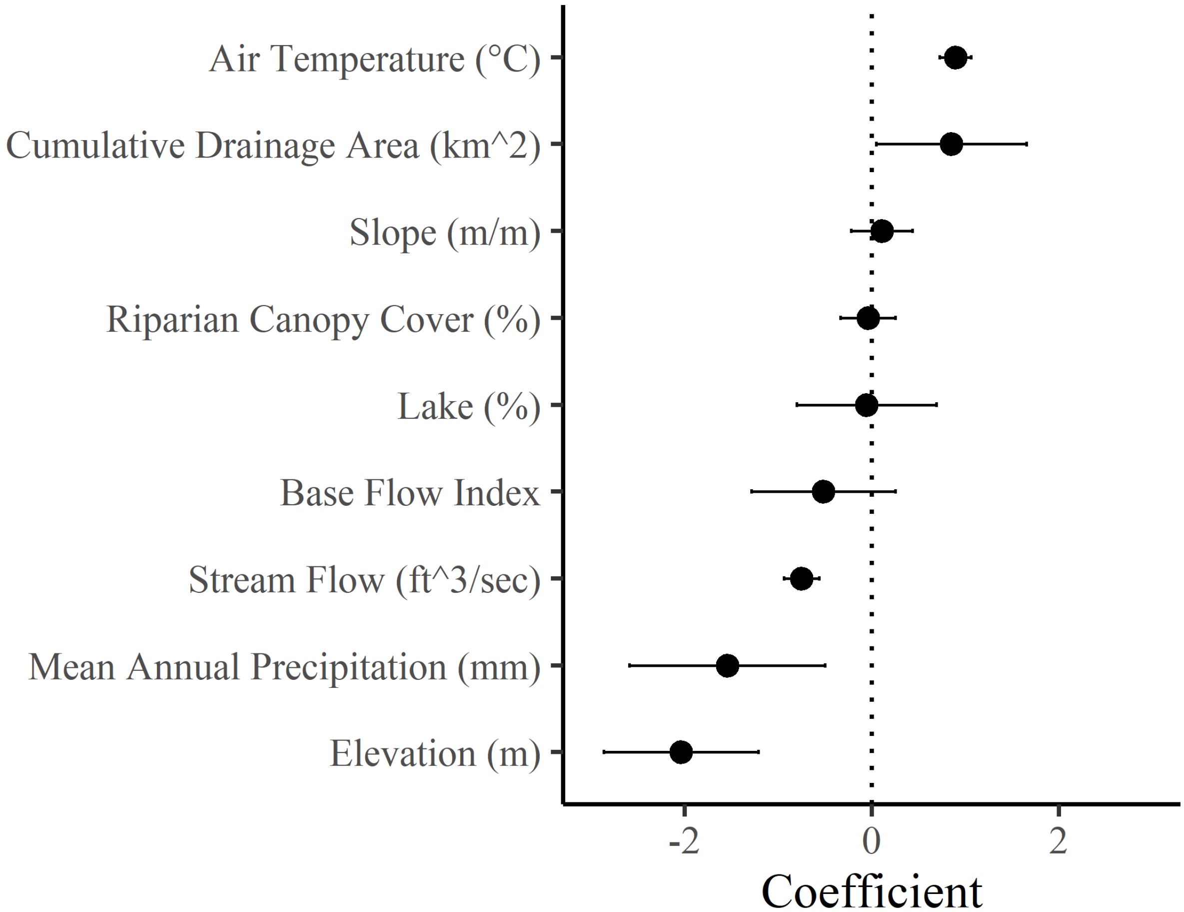

Figure 8. Covariate coefficient values (points) and 95% confidence interval (CI, bars) for the Chehalis (CH) Thermalscape model. Statistically significant covariates ($p < 0.05$) are indicated by 95% CI that do not intercept 0. For positive coefficients, increasing value of the factor is associated with warmer temperatures. For negative coefficients, increasing value of the factor is associated with cooler temperatures.

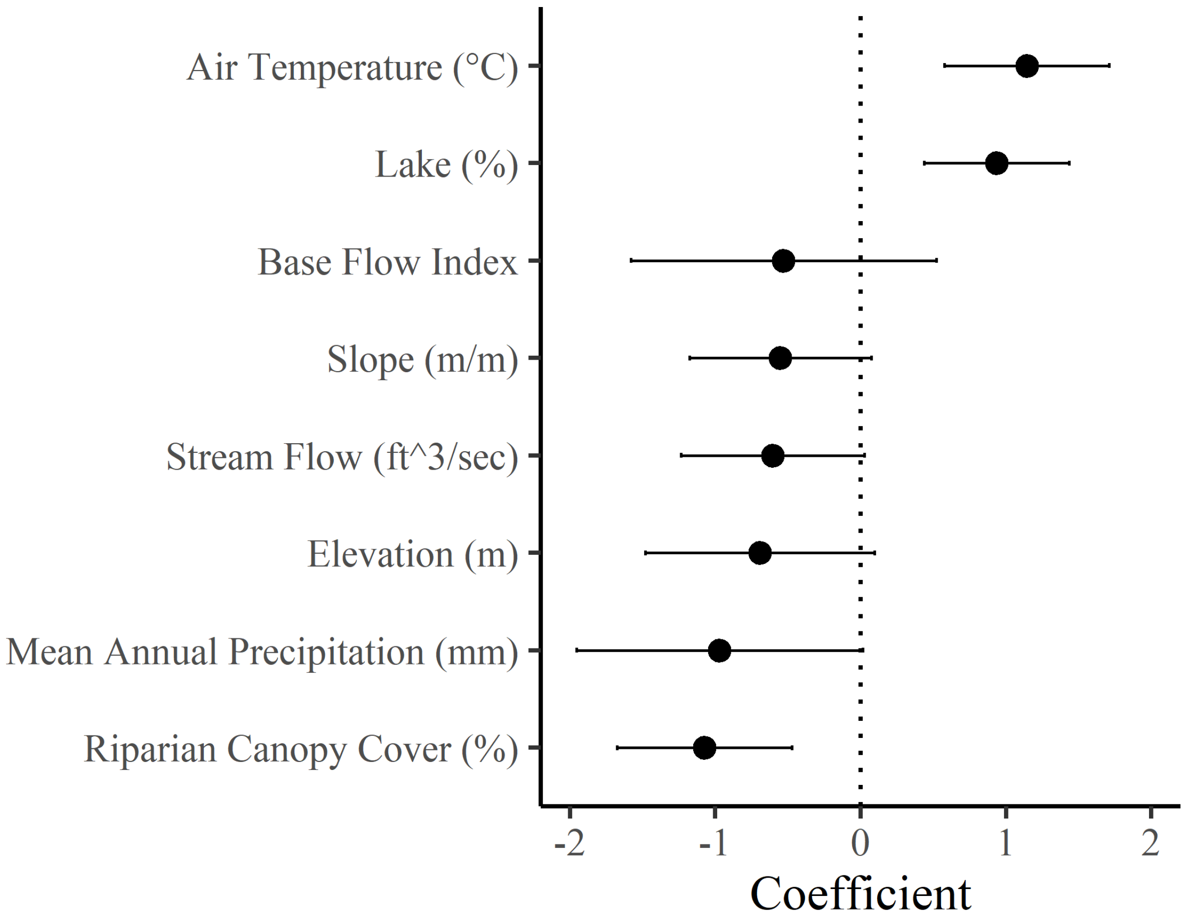

Figure 9. Covariate coefficient values (points) and 95% confidence (CI, bars) for the Willapa Bay (WB) Thermalscape model. Statistically significant covariates ($p < 0.05$) are indicated by 95% CI that do not intercept 0. For positive coefficients, increasing value of the factor is associated with warmer temperatures. For negative coefficients, increasing value of the factor is associated with cooler temperatures.

Model Selection and Evaluation

The WC, NC, and CH models displayed the highest predictive performance in terms of precision (RMSPE, r^2) and accuracy (MAPE) (Table 8). The WB model had lower predictive performance relative to the other models, likely due in part to lower sample size of sites informing the model (n = 39 sites) relative to the other models (n = 243 and 282 for CH and NC, respectively). The WC model was chosen for model prediction and Thermalscape development because it predicted stream temperatures with similar performance to the NC and CH models and better performance relative to the WB model (Table 8).

Table 8. Predictive performance statistics for all Thermalscape models. Root mean square predicted error (RMSPE) and r^2 provide an evaluation of precision and mean absolute prediction error provides an evaluation of accuracy.

Model	RMSPE (°C)	MAPE (°C)	r^2
WC	0.6	0.01	0.95
NC	0.6	0.00	0.96
CH	0.7	0.01	0.96
WB	1.6	0.13	0.68

Thermalscapes – Current and Future Climate Change Scenarios

The WC model was used to predict AugST for all 10,844 km of stream habitat of the Washington Coast Salmon Recovery Region under the current (baseline) and future (2080s) scenarios (Figures 10 and 11). Current maximum, minimum, and mean AugSTs across the Washington Coast Salmon Recovery Region were estimated at 25.0, 1.8, and 14.9°C, respectively. The cumulative length of the warmest river reaches (characterized by AugST $\geq$ 20°C) was approximately 17, 175, and 35 km in the NC, CH, and WB subregions, respectively (Figure 10). The coolest river reaches were predicted at high elevation streams draining the Olympic Mountains and Cascade Mountains in the NC and CH subregions in addition to southern tributaries in the WB subregion (Figure 10). Late century predictions (2080s) of maximum, minimum, and mean AugST across the Washington Coast were 25.8, 2.4, and 15.6°C, respectively. The cumulative lengths of the warmest river reaches (characterized by AugST $\geq$ 20°C) were projected to expand across subregions to approximately 31, 265, and 50 km in the NC, CH, and WB subregions, respectively (Figure 11). Warm river reaches were projected to expand into new river systems including Quillayute River, West Fork Satsop River, and North River in the NC, CH, and WB subregions, respectively (Figure 11). The coolest streams remained in high elevation streams draining the Olympic Mountains and Cascade Mountains in the NC and CH subregions in addition to southern tributaries in the WB subregion (Figure 11).

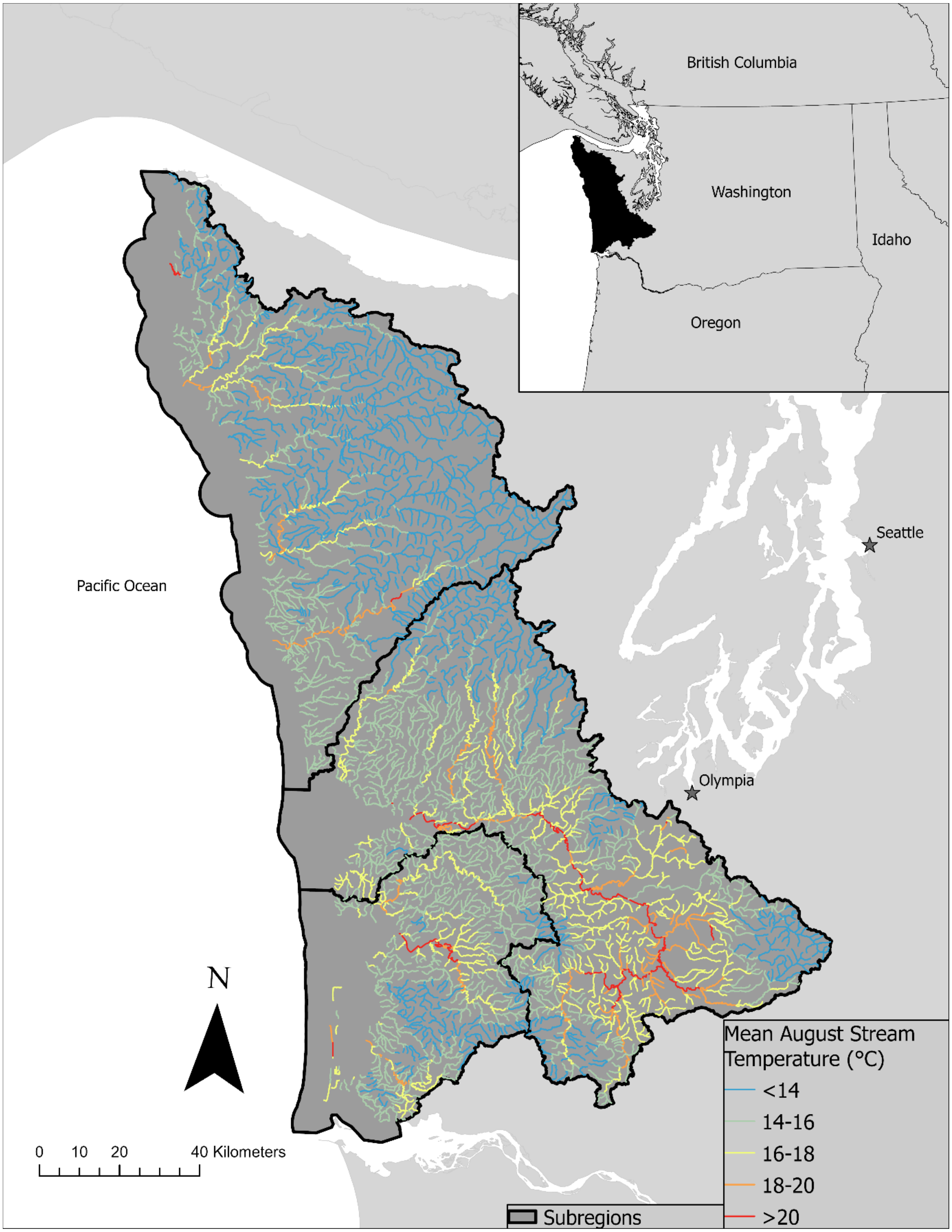

Figure 10. Mean August stream temperature (°C) predicted for current baseline (1993-2021) conditions by the Washington Coast region spatial stream network model.

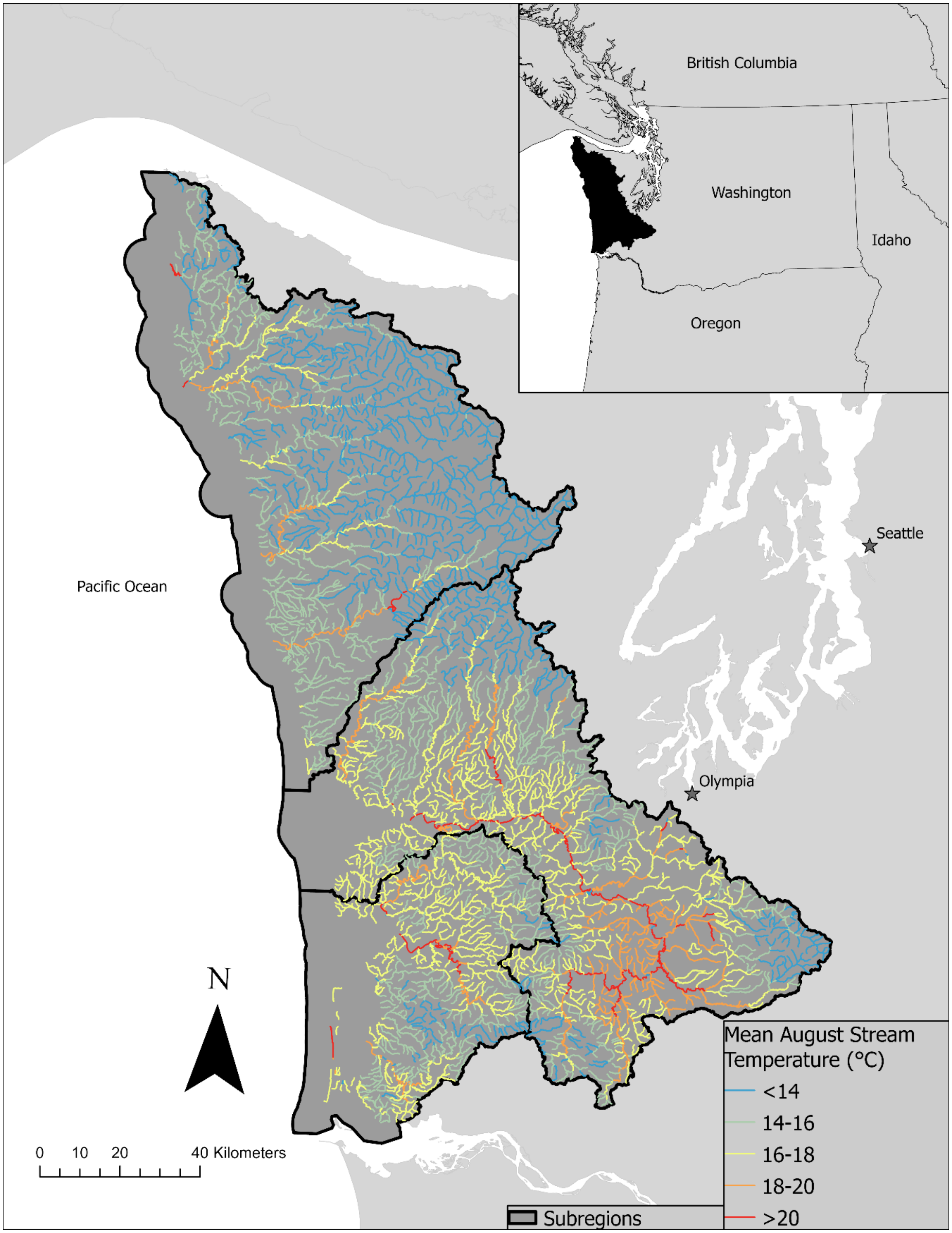

Figure 11. Mean August stream temperature (°C) projected for the 2080s by the Washington Coast region spatial stream network model.

Uncertainty in AugST predictions from the WC model, expressed as the standard error of predictions, averaged 1.4°C, although the magnitude of this uncertainty varied across the landscape (Figure 12). Relatively higher levels of uncertainty in AugST predictions were associated with locations with sparse or absent AugST data. For the NC sub region, these locations included, but were not limited to, the Copalis River, Moclips River, and Raft River in the southwest and the Sooes River in the north. Relatively high uncertainty in AugST predictions was also present in high elevation locations in the NC sub region including the upper North Fork Sol Duc River, Hoh River, South Fork Hoh River, Quinault River, and North Fork Quinault River. In addition, some high elevation river reaches draining the Olympic Mountains in the CH sub region were characterized by relatively high uncertainty in AugST predictions. Finally, the northern portions of the WB sub region, including the North River watershed, were characterized by high uncertainty in AugST predictions.

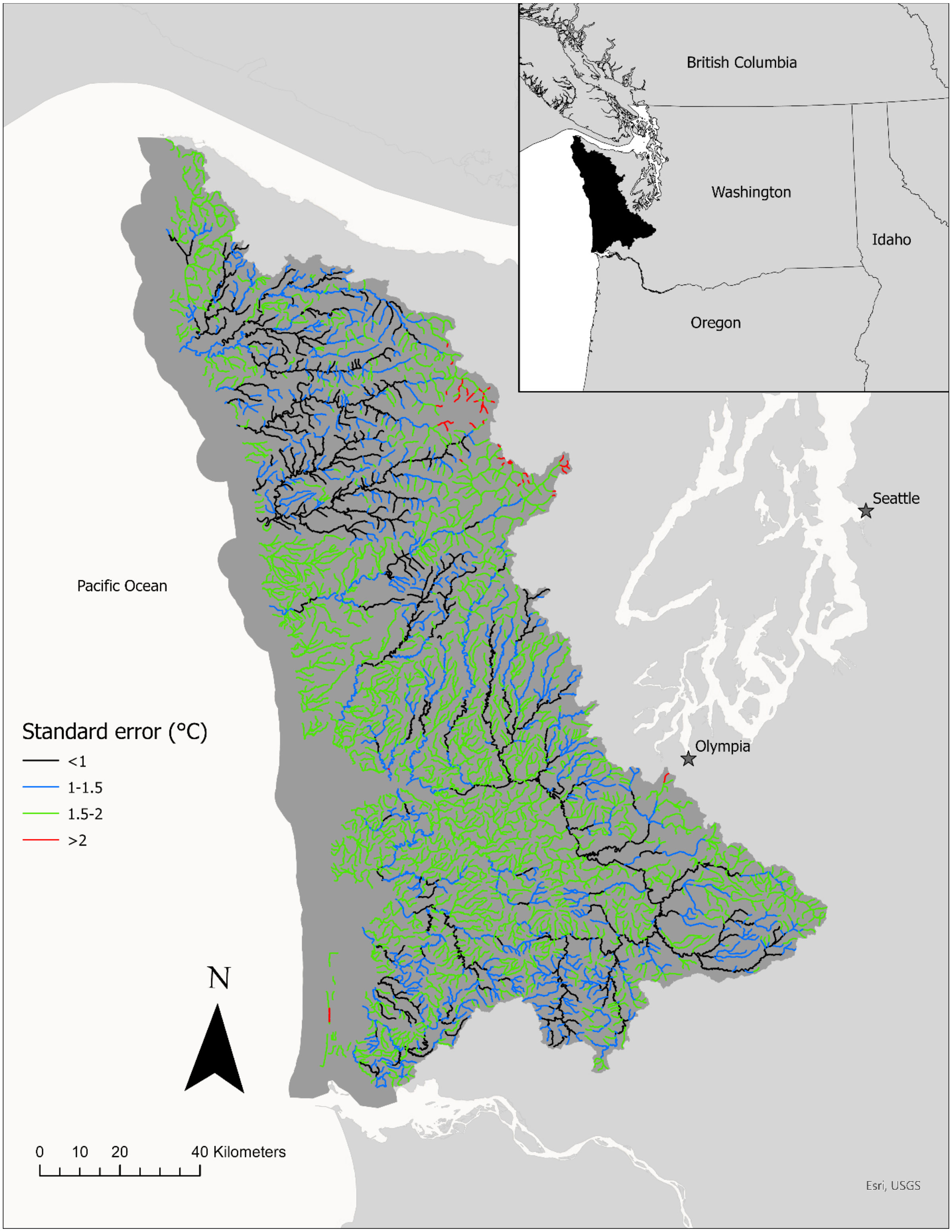

Figure 12. Standard error of mean August stream temperature predictions derived from the Washington Coast Region spatial stream network model.

Conclusions

This analysis provides a Washington Coast Thermalscape Model that characterizes spatial variability in August stream temperature and projects end-of-century stream temperatures across the Washington Coast Salmon Recovery Region. Analysis of predicted versus actual datasets demonstrated that the model covariates explained 95% of the variability in stream temperature with a high level of accuracy (MAPE = 0.01°C) and precision (RMSPE = 0.6°C). While similar stream temperature modeling efforts had previously been undertaken for the Washington Coast (Winkowski and Zimmerman 2019; Winkowski 2020), the current analysis is the first to evaluate AugST models between the subregional and regional scales. This analysis suggests a single model representing the entire Washington Coast has similar or better predictive performance for AugST compared to subregional models.

The Washington Coast Thermalscape Model discerns factors varying in time and space that are associated with variability in AugST. The temporal covariates included in the model, air temperature and stream flow, consistently explained variation of AugST across all model versions, although stream flow was not statistically significant for the WB model (p = 0.05). AugST was positively correlated with air temperature and negatively correlated with stream flow. These observations suggest stream temperatures in the Washington Coast Salmon Recovery Region will be susceptible to changes in air temperatures and stream flows as projected by climate change scenarios.

Multiple spatial (landscape) covariates were important predictors of AugST, including elevation, cumulative drainage area, riparian canopy cover, mean annual precipitation, and lakes. Elevation was consistently negatively correlated with AugST at the regional and sub-regional spatial scales. High elevation locations are closer to groundwater sources and associated with cooler air temperatures and greater snow and precipitation accumulations leading to cooler stream temperatures (Smith and Lavis 1975; Isaak and Hubert 2001). Cumulative drainage area was positively associated with AugST across regional and sub-regional models (except for WB, where cumulative drainage area was removed due to multicollinearity). Stream temperatures tend to increase as a function of distance from source and stream order as water flows downstream (Caissie 2006). Mean annual precipitation was negatively associated with AugST in the regional (WC) and Chehalis Basin (CH) models. Streams located in areas with high annual precipitation values tend to be cooler because wetter landscapes lead to higher water yields and more groundwater (Isaak and Hubert 2001). In the CH subregion, cooler stream temperatures were associated with relatively higher mean annual precipitation in the northern portion of the basin which drains the southern slopes of the Olympic Mountains. Much of the rest of the CH subregion is characterized by relatively low annual precipitation, and this is also true relative to the entire Washington Coast Salmon Recovery Region. Although mean annual precipitation was not a significant covariate in the WB model, cooler stream temperatures were associated with areas of relatively high precipitation in the Nemah, Cannon, and South Fork Willapa rivers. At the regional scale, mean annual precipitation is highest in the NC subregion and lowest in most of the CH subregion and the northern portions of the WB subregion. The presence of an upstream lake was associated with warmer stream temperature in the regional, NC models, and WB models. This observation included warm stream temperatures at the outlets of Lake Quinault and Lake Ozette in the NC sub-region. This association was also expected, as lakes absorb heat and contribute to warming in downstream stream sections (Mellina et al. 2002; Dripps and Granger 2013). In WB, some of the river reaches with lake % values >0 were in the lower mainstem Willapa River, and upon closer examination, these locations were characterized by large sloughs connected to the mainstem. Finally, riparian canopy cover was negatively associated with stream temperatures in the WB subregional model and WC full regional model. This association suggests that after accounting for all other covariates, areas with higher riparian canopy cover tend to have cooler temperatures relative to areas with lower riparian canopy cover, an expected relationship as riparian canopy provides shading effects that buffers water from direct solar radiation (Dan Moore et al. 2005; Nussle et al. 2015; Dugdale et al. 2018).

Uncertainties regarding the stream temperature projections provided in this report should also be noted. In particular, the global climate models used to derive downscaled predictions of temperature and precipitation are continually being updated, and the emissions scenarios are approximate representations of dynamic international policies. As a result, these inputs to the Thermalscape Model should be tracked and updated over time. Uncertainty in stream temperature predictions varied among watersheds and was higher in areas that lacked field monitoring data. Identifying these areas serves as a guide for prioritizing future stream temperature monitoring activities in the Washington Coast Salmon Recovery Region. Of note, additional stream temperature data from southern watersheds in the NC subregion, northern watersheds in the WB subregion, and high elevation streams in general would improve the Thermalscape Model predictions for these areas.

Quantifying the expected spatial autocorrelation trends in the dataset led to unbiased parameter estimation and high predictive performance of the Thermalscape model. Stream temperature is subject to passive downstream diffusion along a river network, meaning flow connected stream temperature sites in proximity to one another are more similar compared to those separated by large hydrologic distances. This corresponds to the spatial autocorrelation trends in the dataset where flow connected relationships showed some of the strongest patterns of spatial autocorrelation, explaining 44% of the variation in AugST in the final WC Thermalscape Model. Spatial patterns of stream temperature can also be associated with terrestrial influences in climate, geology, or landcover which may be better accounted for by Euclidean distance. Indeed, 17% of variation of AugST in the final WC Thermalscape Model was explained by Euclidean distance, suggesting regional level terrestrial linkages are influencing variability in summer stream temperatures. The variability explained by the spatial autocorrelation functions also represents variation not accounted for by the covariates, suggesting development of additional (better or more comprehensive) sets of geospatial covariates could be an important avenue of future research. For example, other landscape covariates not included in the model could account for some of the variation explained by Euclidean distances. Finally, visual analysis of the Torgegram suggests the highest levels of similarities in AugST among site pairs were observed at hydrological distances < 5 km. This observation suggests an efficient network for monitoring summer stream temperatures in our study area should be designed with sites spaced by hydrological distances of at least 5 km.

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Appendix

Table A 1. Covariates used in OPTM. Expected influence on temperature is described in context of summer stream temperatures. Values for all covariates were collected from NorWeST Western Washington prediction points but data source is also listed (table modified from Isaak et al. 2017).

Covariate	Definition	Expected Influence on Temperature	References	Data Source
Spatial covariates				
Elevation	Elevation (m) at the temperature sensor site.	Higher elevation locations characterized by cooler air temperatures, greater snow and precipitation accumulations, and closer to groundwater sources leading to colder temperatures.	Smith and Lavis (1975); Isaak and Hubert (2001); Isaak et al. (2017); (Caissie 2006)	30-m resolution digital elevation model associated with NHDPlus (USEPA and USGS, 2010)
Stream slope (%)	Slope of the stream reach at the temperature sensor site.	Stream reaches with higher slopes should have higher flow velocities which reduces equilibration with warmer air temperature conditions resulting in cooler temperatures.	Pool and Berman (2001); Caissie (2006); Isaak et al. (2017)	NHDPlus Value Added Attribute (http://www.horizon-systems.com/NHDPlus/NHDPlusV2_home.php)
Annual Precipitation (mm)	Mean annual precipitation in watershed upstream of temperature sensor site.	Locations with higher precipitation yields are characterized by more ground water resulting in colder stream temperatures.	Poole and Berman (2001); Isaak and Hubert (2001); Caissie (2006)	NHDPlus Value Added Attribute (http://www.horizon-systems.com/NHDPlus/NHDPlusV2_home.php)
Drainage Area (km^2)	Drainage area of watershed upstream of temperature sensor site.	Drainage area is a proxy of stream size and larger streams are farther from groundwater sources and less shaded by riparian vegetation leading	Caissie (2006)	NHDPlus Value Added Attribute (http://www.horizon-systems.com/NHDPlus/NHDPlusV2_home.php)

		to warmer temperatures.		
Riparian Canopy Cover (%)	Canopy cover associated with stream reach surrounding temperature sensor site	Streams with more canopy cover are associated with more shade and therefore buffered from solar radiation resulting in colder stream temperatures.	Isaak and Hubert (2001); Isaak et al. (2010); Isaak et al. (2017b); Seixas et al. (2018)	1 km average canopy cover from NLCD 2011 USFS Tree Canopy Cartographic layer (https://www.mrlc.gov/nlcd11_data.php)
Base-flow index (%)	Ratio of base flow to total flow associated with the reach at temperature sensor site.	Indication of groundwater contributions to stream; higher values indicate greater base flows relative to peak flows suggesting larger groundwater influence and colder stream temperatures.	Mayer (2012); Chang and Psaris (2013)	Wolock (2003), http://ks.water.usgs.gov/pubs/abstracts/of.03-263.htm
Lake (%)	Percentage of watershed upstream of a temperature sensor site composed of lake or reservoir surfaces.	Water transit time in lakes is slower and water absorbs heat from solar influence resulting in increasing downstream temperatures.	Webb et al. (2008)	NHDPlus Value Added Attribute (http://www.horizon-systems.com/NHDPlus/NHDPlusV2_home.php)
Glacier	Proportion of watershed upstream from temperature sensor site composed of glacial surfaces.	Cool glacier meltwater should cool stream temperatures	Isaak et al. (2017)	http://glaciers.research.pdx.edu/Downloads
Northing Coordinate	Albers Equal Area Northing coordinate at sensor site	Cooler stream temperatures should be further north due to cooler	Ward (1985); Meisner et al. (1988)	Generated from GIS software

		air and groundwater temperatures		
Temporal covariates				
Air temperature (℃)	Mean August air temperature assigned to same year of mean August. stream temperature	Years with warmer air temperature would create conditions for warmer stream temperatures.	Caissie (2006), Isaak et al. (2012), Isaak et al. (2017)	PRISM Climate Group (http://www.prism.oregonstate.edu/)
Stream flow (m^3/s)	Mean August stream flow. Values assigned to same year of mean August stream temperature.	Years with higher stream flows would create conditions for cooler stream temperatures.	Isaak et al. (2012)	United States Geological Survey (http://waterdata.usgs.gov)