Modeling Seasonal Effects of River Flow on Water Temperatures in an Agriculturally Dominated California River

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Key Points:

- In this snowmelt and groundwater-influenced river, ~~cool~~ water temperatures ~~lasted longer~~stayed cool later into summer in high-flow years than low-flow years
- Statistical water temperature model predictions became more accurate when the influence of river flow was allowed to vary seasonally
- These accessible ~~methods~~models can be ~~used~~applied to ~~model any river~~other rivers or ~~stream~~streams with daily, long-term flow and water temperature ~~measurements~~records

Abstract

Low ~~summer river flows~~streamflows can increase vulnerability to warming, impacting coldwater fish. Water managers need tools to quantify ~~the complex linkages~~these impacts and predict future water temperatures. Contrary to most statistical models' assumptions, many seasonally changing factors (e.g., water sources and solar radiation) cause relationships between flow and water temperature~~, yet statistical models often assume a constant relationship between these variables. In California's snowmelt and groundwater-influenced Scott River where agricultural irrigation consumes most summer river flow, flow variation had stronger effects on water temperature in April–July than other months. Using 24~~ to vary throughout the year. Using 21 years of ~~daily~~ air temperature and flow data~~ as predictors~~, we ~~compared multiple statistical methods for modeling~~modeled daily ~~Scott River~~ water temperatures~~, including~~ in California's snowmelt-driven Scott River where agricultural diversions consume most summer surface flows. We used generalized additive models ~~with non-linear interactions between flow and day of the year.~~ to test time-varying and nonlinear effects of flow on water temperatures. Models ~~with~~that represented seasonally varying flow effects ~~performed better than those~~ with intermediate complexity outperformed simpler models assuming ~~a~~ constant ~~relationship~~relationships between water temperature and flow. Cross-validation ~~root mean squared errors~~error of the selected ~~models were ≤1 °C.~~ model was ≤1.2 °C. Flow variation had stronger effects on water temperatures in April–July than in other months. We applied the ~~models~~model to ~~several~~predict effects of instream flow scenarios ~~currently being considered~~proposed by ~~stakeholders and~~ regulatory agencies. Relative to historic conditions, the ~~most protective~~higher instream flow scenario would reduce ~~average~~ annual maximum temperature from 25.~~9~~2 °C to 24.~~6~~1 °C, reduce ~~average~~ annual ~~degree-days exceedance~~exceedances of 22 °C (a cumulative thermal stress metric) from ~~107~~106 to ~~54~~51 degree-days, and delay ~~the~~ onset of water temperatures ~~greater than~~ >22 °C during some drought years. ~~Withdrawal of river water after 1 June, including for groundwater management purposes, could contribute to~~Testing the same modeling approach at nine additional ~~exceedances of 22 °C.~~sites showed similar accuracy and flow effects. These methods can be applied to ~~model any stream~~streams with long-term flow and water temperature ~~measurements, with applications including scenario prediction and infilling~~records to fill data gaps, identify periods of flow influence, and predict temperatures under flow management scenarios.

Plain Language Summary

Warm water ~~threatens~~temperatures threaten culturally and economically important salmon in Pacific Northwest rivers, ~~including our Scott River study area,~~ causing chronic stress ~~or even~~and direct mortality. Climate change and agricultural water use have reduced summer river ~~flow~~flows in recent decades, intensifying water scarcity. Years with deep mountain snowpack and resulting high groundwater levels extend the high flow season and keep water temperatures cool through the end of July, whereas in drought years the river warms sooner. We used ~~24~~21 years of river flow and air temperature data from the Scott River, California, to create computer models that simulate water temperatures~~, provide a tool for assessing the effects of water management~~. Our models allow the effect of flow on water temperatures to vary by season (i.e., stronger cooling effects in spring and summer), improving accuracy of the simulated temperatures. We used ~~these models~~the Scott River model to simulate water temperatures under two alternative flow scenarios~~ being~~ considered in local water management plans. Our simulations indicate that relative to current conditions, the higher flow scenario would ~~reduce~~lower the ~~summer's hottest~~summers' highest temperatures~~. Diverting additional water from the river after 1 June could increase~~ and decrease the number of days ~~with warm~~that river temperatures ~~that are detrimental to fish~~exceed a biological threshold. Testing the same modeling approach at nine additional Klamath Basin sites showed similar accuracy and flow effects. Our model is freely available for public use.

1 Introduction

Water temperature in rivers and streams ~~affects everything from water chemistry~~drive physical, chemical, and ~~physics to inter-species interactions (Wenger et al., 2011), food webs (Power and Dietrich, 2002), and whole-community metabolism (Bernhardt et al., 2017). Effects on individual species include development (Steel et al., 2012), thermal tolerances (Dahlke et al., 2020), bioenergetics (Gibeau and Palen, 2020), and behavior (Sutton and Soto, 2012).~~

~~The net balance of surface and streambed heat fluxes determine stream temperatures. These energy fluxes include shortwave radiation (primarily from the visible light spectrum), longwave radiation (i.e., heat radiated from objects including clouds, land, and vegetation), latent heat (i.e., evaporation), sensible heat (i.e., convection of heat from air to water), conduction of heat between the water and stream bed, and advection (i.e., movement of water) (Caissie, 2006; Moore et al., 2005a; Webb et al., 2008; Dugdale et al., 2017). Humans affect stream temperatures through water diversions (Bartholow, 1991; Dymond J.,~~biological processes (Ouellet et al., 2020).~~1984; Folegot et al., 2018; Gibeau and Palen, 2020; Meier et al. 2003, Null et al.; 2017), discharge of industrial wastewater and sewage (Erickson and Stefan, 2000), reservoir impoundments (Webb and Walling, 1993; Chandesris et al., 2019), removal or enhancement of riparian vegetation (Johnson, 2004; Moore et al. 2005a, Wondzell et al., 2019), and alteration of channel and floodplain morphology (Gu and Li, 2002) including urbanization (Tan and Cherkauer, 2013).~~ Stream temperatures ~~have warmed in recent decades in response to rising air temperatures resulting from anthropogenic greenhouse gas emissions, a trend that is expected to continue (Isaak et al., 2017, 2018; Liu et al., 2020; Wanders et al., 2019).~~

determine species ~~River flow rates (i.e., discharge) can affect stream temperatures. Higher flows increase a stream's ability to store heat, reducing the temperature increase resulting from an equivalent amount of solar radiation (Brown, 1969; Meier et al., 2003; Sinokrot and Gulliver, 2000). Higher flow rates reduce daily temperature maximums and~~ ranges~~ (Folegot et al., 2018). Summer~~, with alterations to natural temperature regimes causing deleterious effects to native species (Wenger et al., 2011). Stream temperatures are widely altered by human activities (Webb et al., 2008). Maintaining ecological integrity is a major stream temperature management goal, yet models used to predict stream temperature response to management interventions either lack predictive power or are time-consuming to develop.

River flow rates (i.e., discharge) are a key driver of stream temperatures through multiple mechanisms. While stream temperatures are determined by surface and streambed energy fluxes and advected heat (Caissie, 2006; Moore et al., 2005), flows mediate these effects. Higher flows generally increase water volume and thus a stream's capacity to store heat, reducing daily temperature fluctuations (Brown, 1969; Folegot et al., 2018; Meier et al., 2003; Sinokrot &

Gulliver, 2000). Higher flows speed downstream transit of water, reducing the time that a parcel of water is exposed to ambient heating at a given location and increasing the influence of upstream conditions (Bartholow, 1991; Dymond J., 1984; Folegot et al., ~~typically negatively correlated with flow (Arora et al., 2016; Isaak et al., 2017; Luce et al., 2014; Mayer, 2012; McGrath et al., 2017; Moore, et al. 2005b; Neumann et al, 2003; Webb et al., 2003), with flow affecting daily maximum temperatures more strongly than daily mean temperatures~~2018). Channel geometry, including width/depth ratio, influences these effects (Dugdale et al., 2017).

~~(Asarian et al., 2020; Gu et al., 1998; Gu and Li, 2002). Stream temperature model fit often increases when flow is included as a predictor (Hilderbrand et al., 2014; Piotrowski and Napiorkowski, 2019; Rahmani et al., 2020; Sohrabi et al., 2017; van Vliet et al. 2011; Webb et al., 2003), although not always (Benyahya et al., 2008; Toffolon and Piccolroaz, 2015). Cooling effects of high flows are due to faster downstream transport of cold water (Bartholow, 1991; Dymond J., 1984; Folegot et al., 2018), greater depth and thermal mass which is more resistant to heating (Gu and Li, 2002; Meier et al., 2003; Sinokrot and Gulliver, 2000), and greater accretion of cool groundwater (Kelleher et al., 2012; Mayer, 2012; Isaak et al., 2017).~~

The relationship between water temperature and flow varies ~~seasonally. The source and flow paths of river water vary seasonally according to~~ through time. Seasonal changes in precipitation ~~form~~phase (i.e., snow and rain~~)(Siegel and Volk, 2019), groundwater dynamics of hillslope (Hahm et al., 2019) and alluvial (Foglia et al., 2013) aquifers, and irrigation management (i.e.,~~) affect water temperatures (Yan et al., 2021). The geographical source of water can shift seasonally, and can include tributaries, point sources, hillslopes, and alluvial aquifers, with each source having different temperatures and heating or cooling trajectories while en route to stream channels (Dugdale et al., 2017; Steel et al., 2017). Groundwater-surface water interactions and hyporheic exchange also affect temperatures (Hannah et al., 2009; Kurylyk et al., 2015). Water management, including reservoir releases, water withdrawals, and ~~subsequent return flows back to the river via surface or groundwater)(Tolley~~irrigation runoff can further alter temperature dynamics (Alger et al., 2021; Chandesris et al., 2019). Flow effects on water temperature are ~~also seasonally~~further mediated by ~~variables that affect the amount of~~seasonal changes to solar radiation ~~striking~~received by the ~~water, including~~stream. Day length~~,~~ and solar angle, which affect topographic and riparian shading, remain consistent among years (Piotrowski ~~and~~ & Napiorkowski, 2019; Yard et al., ~~2005), cloud cover (Dugdale et al., 2017), wildfire smoke (Asarian et al.,~~ 2005). Other mediators of solar radiation including ~~2020; David et al., 2018), and~~ leaf out and leaf fall of deciduous riparian vegetation, cloud cover (Dugdale et al., 2017), water vapor, dust (Theurer et al., 1984), wildfire smoke (Asarian et al., 2020; David et al., ~~(Dugdale et al., 2018). Some of these variables~~2018) and other aerosols follow ~~exactly the same seasonal trajectory each year while others fluctuate among years.~~ seasonal trajectories that vary among years. Despite time-varying changes in how flow dynamics influence stream temperature, many stream temperature models do not account for these seasonal variations in the relationship between flow and stream temperatures.

Given stream temperature's importance and vulnerability to human alterations~~ of river flow~~, water managers need ~~predictive~~ tools~~.~~ to predict stream temperature ~~models are often grouped into two categories: process-based~~changes associated with climate change and ~~statistical (Caissie, 2006).~~flow management (Gibeau & Palen, 2020; Null et al., 2017). While process-based (i.e., deterministic) models ~~simulate~~simulating stream energy budgets ~~using physically based equations representing energy fluxes such as shortwave radiation, longwave radiation,~~

~~latent heat, sensible heat, conduction and advection~~can have high predictive accuracy, their use is limited by extensive data input requirements (Brown, 1969; Caissie, 2006; Dugdale et al., 2017). Statistical models that use empirical relationships between stream temperature and ~~predictor variables, and typically~~environmental drivers require ~~many~~ fewer input variables ~~as data inputs than process-based models do,~~ so are ~~often much simpler to develop (Benyahya et al., 2007; Caissie, 2006; Gallice et al., 2015; Ouellet et al., 2020; Piotrowski and Napiorkowski, 2019). Mohseni et al.'s (1998) non-linear regression of stream temperature and air temperature has been widely replicated (Arismendi et al. 2014; Jones al. 2016) and adapted (Piotrowski and Napiorkowski, 2019; Santiago et al., 2017; Segura et al. 2015; van Vliet et al. 2011). Recent advances in statistical models of stream temperature include spatial stream network models (FitzGerald et al., 2021; Isaak et al., 2017), generalized additive models (GAM) (Arora et al., 2016; Jackson et al., 2018; Laanaya et al., 2017; Siegel and Volk, 2019; Yang and Moyer, 2020), Least Absolute Shrinkage and Selection Operator regression (St-Hilaire et al., 2018), functional data analysis (Boudreault et al., 2019), and machine learning (Rahmani et al., 2020; Zhu et al., 2018, 2020). Daily stream temperatures are highly correlated with adjacent days' temperatures. For measurements such as daily stream temperature that are not independent, it is best~~easier to ~~use a model that explicitly includes the correlation structure (Steel et al., 2013). For example, some stream temperature models include a first-order (AR-1) (Benyahya, 2007b; David et al., 2018; Letcher et al., 2016; Jackson et al., 2018; Sohrabi et al., 2017), second-order, periodic (~~implement, but for scenario prediction they are generally not considered as reliable as process-based models (Arismendi et al., 2014; Benyahya et al., 2007a~~, 2007b, 2008), or moving average autoregressive error structures (Yang and Moyer, 2020).~~

~~Process-based models account for the seasonal effects of flow by explicitly modeling energy fluxes, but it is infeasible to include all these individual fluxes in statistical model.~~; Caissie, 2006). However, statistical ~~models can represent the implicit aggregation of these fluxes by allowing the coefficients of hydroclimatic predictors to vary seasonally. One approach is to divide the year into multiple seasons and develop separate models for each (Mohseni et al., 1998, Sohrabi et al., 2017), but this may create abrupt changes at seasonal transitions. Recent approaches that allow smooth variation across seasons are time-varying coefficient models (Li et al., 2014), and GAMs that interact day of the year with predictor variables (Jackson et al., 2018; Siegel and Volk, 2019; Yang and Moyer, 2020~~modeling methods have evolved, improving prediction accuracy and temporal resolution (i.e., daily) (Ouellet et al., 2020; Piotrowski & Napiorkowski, 2019). Year-round daily temperature models are especially valuable because they match the time scales used in detailed biological studies and water quality regulations (Imholt et al., 2010; Railsback et al., 2015; USEPA, 2003).

Statistical stream temperature models have long relied on air temperature as the primary predictor (Mohseni et al., 1998), but year-round daily models should incorporate additional mechanisms to improve accuracy and reflect physical processes (Letcher et al., 2016). Statistical stream temperature models use air temperature to represent net radiative flux (Caissie 2006). Time lags between air temperatures and water temperature reflect heat exchange processes (Koch and Grünewald, 2010; Soto, 2016; Webb et al., 2003), while temporal autocorrelation acknowledges that stream temperature on a given day is in part a result of stream temperature the previous day (Benyahya et al., 2007a, 2007b, 2008; Yang & Moyer, 2020). Inclusion of flow can improve model accuracy (Piotrowski & Napiorkowski, 2019; Santiago et al., 2017; Sohrabi et al., 2017; van Vliet et al., 2011; Webb et al., ~~To test the hypothesis that statistical models with seasonally varying effects of river flow would perform better than models with a constant~~

~~relationship between stream temperature and flow, we modeled daily stream temperatures in the Scott River of Northern California where low flows and high temperatures are limiting factors for culturally and economically important coldwater fish. We compared multiple statistical approaches that: 1) include all days in a single model rather than dividing the year, 2) use interactions to allow the influence of predictors to vary smoothly by day of the year, 3) allow non-linear relationships, 4) have error structures that include temporal autocorrelation, and 5) are all implemented within the R software environment with simple, publicly accessible code. After model selection and validation which confirmed our hypothesis, we applied our final model to predict daily stream temperatures under flow scenarios being considered by local water managers. Results indicated that stream temperatures under these flow scenarios would be more favorable for coldwater fish than the historic flow scenario. Our accessible modeling approach could be widely replicated in other geographic areas to provide accurate stream temperature predictions to inform river management. Paired with air temperatures from a nearby weather station, our methods can be applied in any river or stream with long-term measurements of flow and stream temperature. Other potential applications include imputing missing measurements for analyses that require continuous temperature time series.~~

2003). The relationship between air and stream temperatures is nonlinear and differs among seasons (Arismendi et al., 2014, Caissie et al., 2001; Mohseni et al., 1998). Including time-varying effects could improve the predictive accuracy of stream temperature models across variable conditions.

Several methods allow seasonal variation in the relationship between environmental covariates and stream temperatures. These methods not only improve model accuracy but also identify the times when effects are strongest. While time-varying covariate effects can be represented using separate models for each season (Mohseni et al., 1998; Sohrabi et al., 2017), this may cause unnatural, abrupt changes at seasonal transitions. Time-varying coefficients, including those used in generalized additive models (GAMs) (Pedersen et al., 2019; Wood, 2017) use continuous functions that avoid these abrupt changes (Li et al., 2014; Jackson et al., 2018; Siegel & Volk, 2019). While GAMs have been used in daily stream temperature modeling for single-site prediction (Boudreault et al., 2019; Coleman et al., 2021; Glover et al., 2020; Laanaya et al., 2017), spatiotemporal prediction (Jackson et al., 2018; Siegel & Volk, 2019), identifying extreme events (Georges et al., 2021), and trend assessment (Yang & Moyer, 2020), few studies have used GAMs to model seasonally varying flow effects or identify when stream temperatures are most affected by flow variation (Glover et al., 2020; Yang & Moyer, 2020). With flexible model structures and easy implementation, GAMs could be a powerful tool for predicting stream temperatures under flow management scenarios, but to our knowledge these models have not been previously used for this purpose.

Our objectives were to predict mean and maximum daily stream temperatures under management flow scenarios and new environmental conditions, and to identify periods when flow has the strongest influence on stream temperatures. We compared 11 GAM structures using flow, air temperature, and day of year as covariates that incorporated combinations of linear, nonlinear, and seasonally-varying effects. Our model selection and validation procedures included extrapolation tests evaluating predicted stream temperatures with flows and air temperatures outside the calibration range, designed to favor models that had enough complexity to represent the key patterns in the data, but not so complex that they overfit the data. We applied the top model to proposed management flow scenarios and extreme flow and air temperature conditions.

The models are intended to be used as a tool to inform water management, making the relatively simple model structure and coding of GAMs our choice of modeling technique. We focused our analyses on the Scott River of Northern California, where low flows and high temperatures are limiting factors for coldwater fish and water managers are considering implementing regulations to protect instream flows. To demonstrate wider applicability, we evaluated similar models in nine additional sites in the Klamath River Basin.

2 Study Area

~~The Scott River is a tributary of the Klamath River in Siskiyou County, California, USA (Figure 1).~~Our study area is the lower Klamath River Basin, California, USA, focusing on one large tributary—the Scott River (Figure 1). The Scott River study site is located at the outlet of Scott Valley, with a drainage area of 1,714 km^2. The other nine sites are near USGS gaging stations with drainage areas ranging from 58 km^2 to 31,300 km^2 (Figure 1, Table S1). The climate is Mediterranean with precipitation occurring primarily in winter and spring as rain at low elevations and snow at higher elevations~~. The mountainous headwaters are primarily National Forest, with elevations exceeding 2500m (Foglia~~ (VanderKooi et al., ~~2013~~2011). The human population lives primarily on private land ~~in the alluvial~~along watercourses including Scott Valley, where irrigated agriculture ~~is the dominant~~dominates land use, utilizing groundwater and surface water (Foglia et al., 2018). ~~Other land uses include timber harvest and mining. There are many water diversions but~~ The Scott River has no major dams or reservoirs~~.~~, but there are large dams on the Klamath River and two tributaries (Shasta and Trinity rivers), influencing some study sites.

The Scott Valley aquifer fills during the high flows of winter rainstorms and spring snowmelt-driven runoff. As runoff recedes through ~~the~~ summer, most surface water is diverted for irrigation and river water at the Scott Valley outlet becomes increasingly composed of groundwater from valley alluvium. Minimum flows occur in early September before rising due to fall rains (Figure ~~2~~2b). In late summer of drought years, portions of the Scott River have no surface flow (Tolley et al~~.~~., 2019). Summer and fall river flows have declined in recent decades (Kim and Jain, 2010; Asarian and Walker, 2016) due to a combination of climate change (Drake et al., 2000) and increased ~~withdrawal of~~ groundwater ~~for irrigation~~withdrawals, especially since 1977 (Van Kirk and Naman, 2008). Climate change is expected to further reduce ~~summer~~ flows by decreasing snowpack and increasing irrigation demand (Persad et al., 2020).~~ There are ongoing efforts to model interactions between groundwater and surface water (Foglia et al., 2013, 2018; Tolley et al., 2019). Pursuant to California's Sustainable Groundwater Management Act (SGMA), Siskiyou County is developing a groundwater sustainability plan for the valley.~~

Management flows have been proposed for the Scott River ~~has the Klamath Basin's largest population of~~to protect Endangered Species Act-listed coho salmon (*Oncorhynchus kisutch*) ~~population, despite currently impaired habitat (NMFS,~~and other coldwater salmonid fishes. ~~2014). High water temperatures are stressful to coho salmon, chinook salmon (*Oncorhynchus tshawytscha*) and steelhead (*Oncorhynchus mykiss*) (NCRWQCB, 2005).~~ These fishes' importance to local Native American tribes has led to contention over water management. ~~Government agencies, tribes,~~River water temperatures in May–July are much cooler in high-flow years than low-flow years (Figure 2), and ~~local organizations have studied Scott River stream temperatures for several decades (Asarian et al., 2020; KNF, 2010; Quigley et al., 2001; QVIR,~~

~~2016). The river is~~water extraction has contributed to the Scott River being listed as impaired for water temperature under the Clean Water Act~~,~~ (NCRWQCB, 2005). The U.S. Forest Service has a first-priority Schedule D water right for Scott River instream flow that varies by month and ~~California's North Coast Regional Water Quality Control Board developed Total Maximum Daily Loads (TMDLs) for water temperature~~ day from 30–200 ft^3/s (0.85–5.67 m^3/s) (Superior Court of Siskiyou County, 1980) (Figure 3b), but does not exercise its legal authority to curtail lower-priority water uses when flows drop below these levels. The California Department of Fish and ~~sediment (NCRWQCB, 2005).~~ Wildlife (CDFW) proposed interim Scott River instream flow targets that vary by month and day from 62–362 ft^3/s (10.3–1.75 m^3/s) (CDFW, 2017) (Figure 3b), but these have no legal force.

~~Our~~

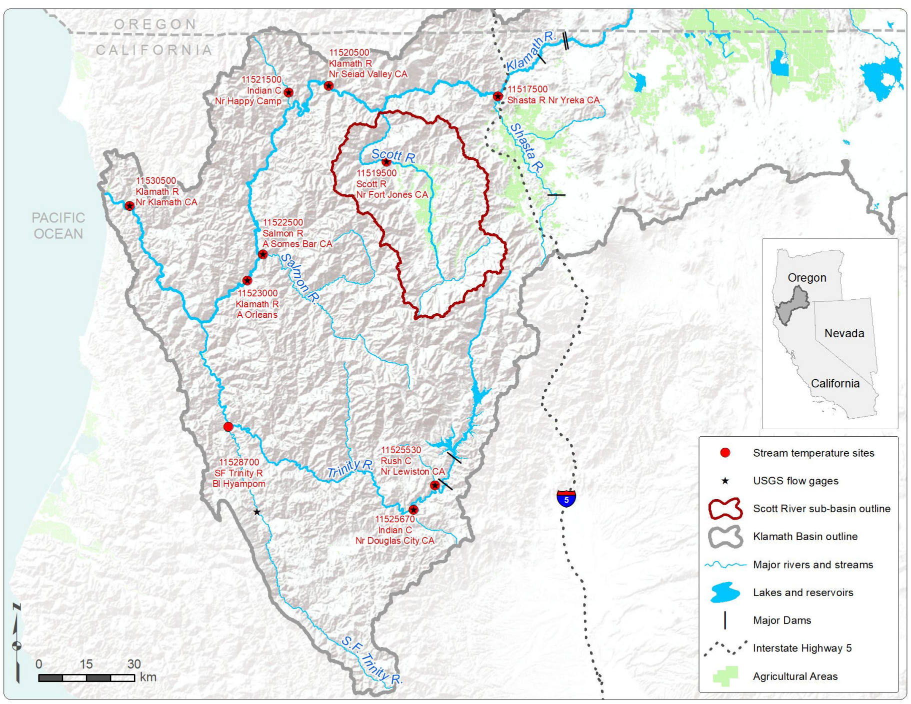
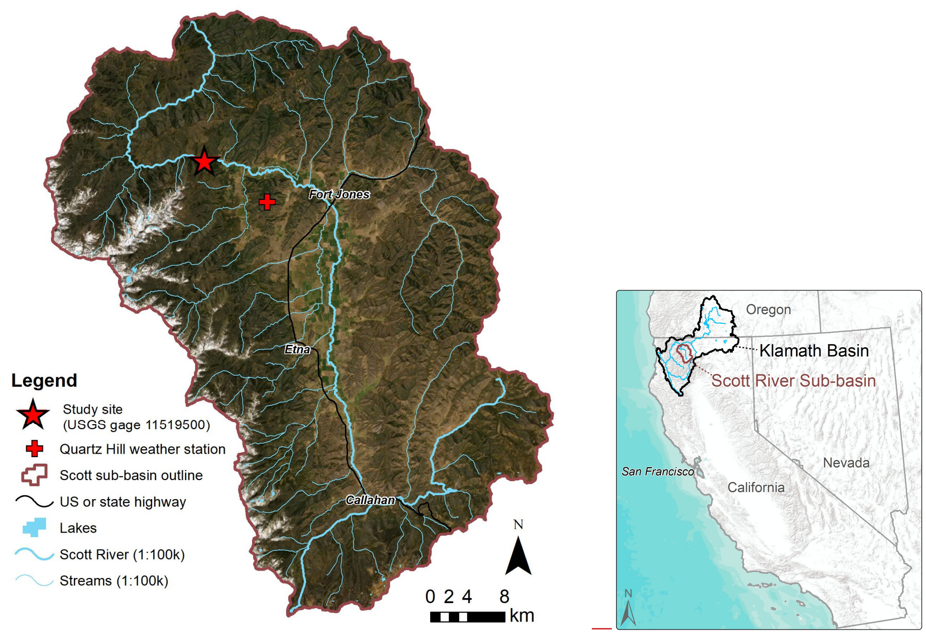
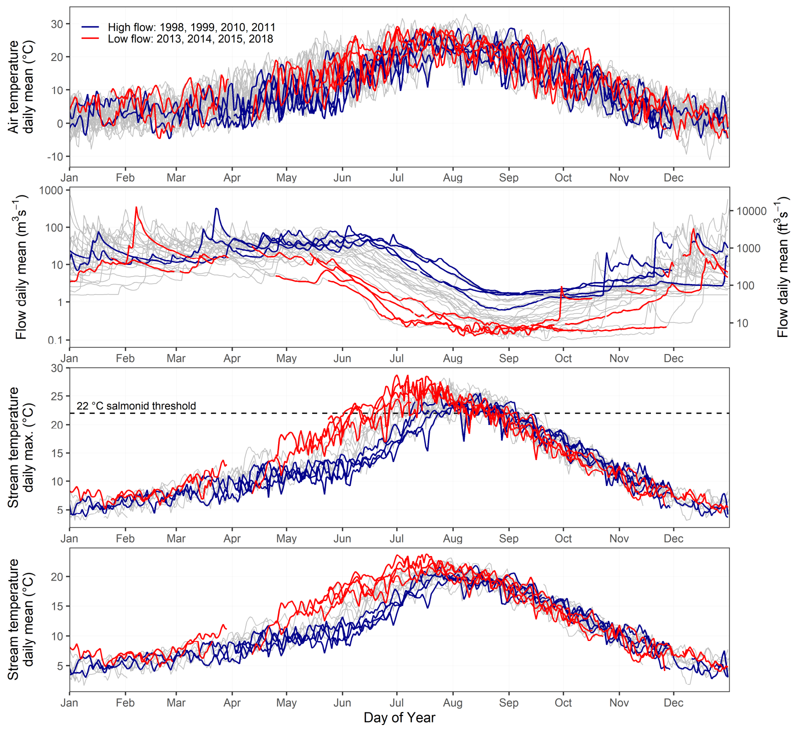


Figure 1. Klamath Basin study ~~site is located at the outlet of Scott Valley,~~sites with ~~a drainage area of 1,714 km^2 (Figure 1). Despite simulated total valley-wide streamflow depletion (i.e., decreased streamflow due to groundwater pumping) of approximately 150,000 m^{3}d^{-1} (60 ft^3/sec) in August (Foglia et al., 2013), the 10 kilometers of river directly upstream of our study site are primarily a gaining reach, receiving groundwater from the alluvial aquifer (Tolley et al., 2019).~~



~~**Figure 1.** Maps of study site and weather station within~~ the Scott River Watershed~~, the Klamath Basin, and California.~~ outlined in red. Source map credits: Esri ~~, Earthstar Geographics~~, NOAA, and USGS.


High flow: 1998, 1999, 2010, 2011
Low flow: 2013, 2014, 2015, 2018
Air temperature daily mean (°C)
Flow daily mean (m³s⁻¹)
Flow daily mean (ft³s⁻¹)
Stream temperature daily max. (°C)
22 °C salmonid threshold
Stream temperature daily mean (°C)
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Day of Year

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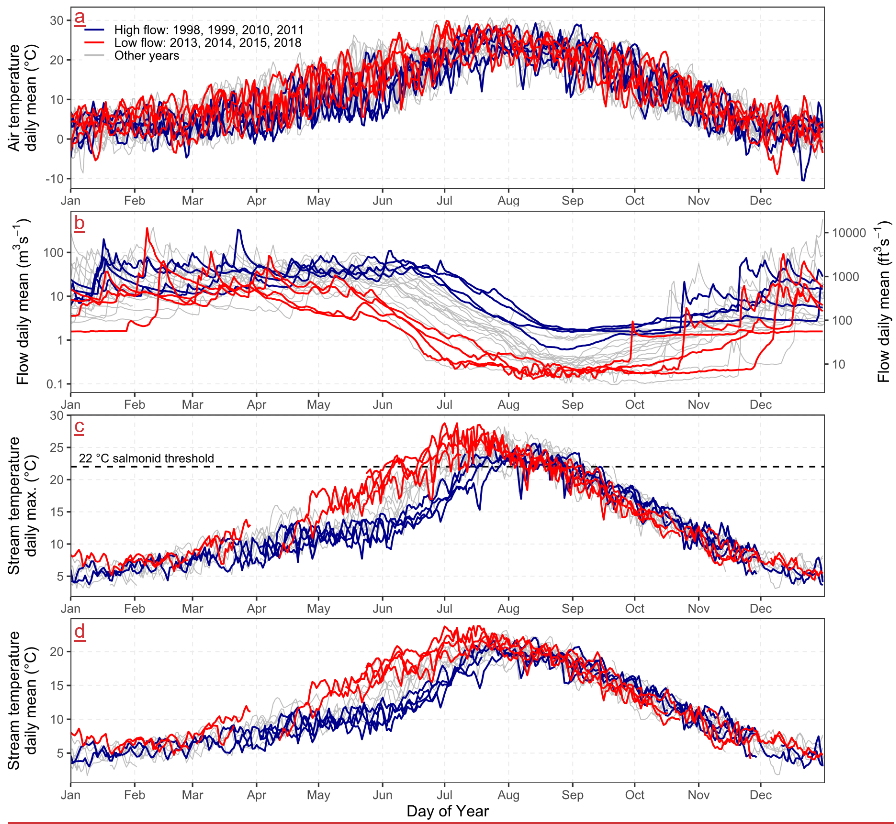

Figure 2. Time series of (a) daily mean air temperature, (b) daily mean flow, (c) daily maximum stream temperature (~~DMxST~~T_{max}), and (d) daily mean stream temperature (~~DMST) for the years 1995~~T_{mean}) at Scott River from 1998–2020.

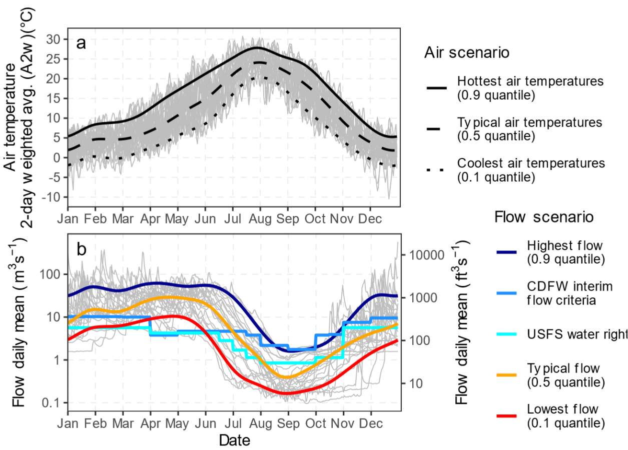

Figure 3. Inputs to Scott River "quantile air temperature" scenarios representing 15 combinations of (a) three air temperature inputs and (b) five flow inputs that vary by day. Observed values for 1998–2020~~. Colored~~ are shown as gray lines ~~are days in four example high-flow (red) and low-flow years (blue). Gray lines are other years~~.

3 Methods

At each of the 10 sites, we developed GAMs to predict daily mean stream temperature (T_{mean}) and daily maximum stream temperature (T_{max}) using flow, air temperature, and day of year as covariates. We compared models across a range of complexity, including those with seasonally varying flow effects, to models with a constant relationship between stream temperature and flow. We selected a final model based on the best overall performance averaged across the 10 sites. We then applied that model to flow management scenarios at one site– the Scott River.

3.1 Data sources and ~~data~~ preparation

3.1.1 Water temperature and river flow

~~Since 2007,~~We obtained water temperature data from six sources (Table S1). For the Scott River site, we used Quartz Valley Indian Reservation (QVIR) ~~Environmental Department has been using YSI (Yellow Springs, Ohio) 6600 multi-parameter datasondes to monitor Scott River water temperatures at the U.S. Geological Survey (USGS) gage 11519500 near the outlet of Scott Valley~~ (QVIR, 2016; Asarian et al., 2020) ~~(Figure 1). Temperature measurements are recorded every 30 minutes with a reported accuracy of ±0.15 °C. We combined QVIR's dataset with additional temperature data collected at the same site~~data, supplemented by ~~the~~ U.S. Forest Service (USFS) ~~in the years 1995–1998, 2003–2005, 2010–2016, and 2019~~ (KNF, 2010~~),~~, 2011) and U.S. Bureau of Reclamation (USBR) ~~for the years 1998–2000.~~(Smith et al., 2018) data. For the nine other sites, we used data from the U.S. Fish and Wildlife Service (USFWS) (Manhard et al., 2018; Romberger and Gwozdz, 2018), USFS (KNF, 2010, 2011), USBR, U.S. Geological Survey (USGS), and California Department of Water Resources (CDWR). Following compilation, we reviewed the data and removed any suspicious values (e.g., when there were calibration issues or probes appear to have been exposed to air). We then calculated ~~daily mean stream temperature (DMST)~~T_{mean} and ~~daily maximum stream temperature (DMxST).~~T_{max}. For days when data were available from multiple entities, we averaged values (Text S1). Data availability ranged from 3540–5684 days and 16–21 years per site. We paired daily temperatures at each site with daily average streamflow data from nearby USGS gages (Figure 1, Table S1).

~~Daily average streamflow for gage 11519500 were downloaded from the USGS National Water Information System.~~

3.1.2 Air temperature

We retrieved daily mean air ~~temperature data from USFS' Quartz Hill weather station located approximately 8 km southeast of the flow gage (Figure 1) are available as Global Historical Climatology Network - Daily station USR0000CQUA (Menne et al., 2012a, 2012b). We excluded all dates with a quality flag. For days lacking Quartz Hill measurements (0.5% of days with measured stream temperatures and 3.8% of the all days 1995–2020), we infilled missing values by linear regression with nearby weather stations or the~~temperatures for each site from the 4-km resolution gridded PRISM dataset (Daly et al., 2008~~) (Text S2).~~

). Because stream temperatures are correlated with air ~~temperatures~~temperature at multiple time scales~~. The optimal number of days to average for regression modeling varies (Webb et al., 2003). In addition to simple averages across varying numbers of days, other approaches include applying exponential weights (Koch and Grünewald, 2010;~~ , we initially explored many metrics (Piotrowski ~~and~~ & Napiorkowski, 2019~~; Soto, 2016) or including separate terms for air temperatures on the day of interest and preceding days (Siegel and Volk 2019). We tested five categories of air temperatures covariates in our models, where A_i is the~~). In these initial explorations at Scott River, we found that two-day weighted air temperature (A_{2w}) resulted in good model fits (Text S2), so we used A_{2w} for all models except one that used a seven-day average (A_7) to mimic Mohseni et al.'s (1998) widely-implemented model. A_{2w} is calculated as follows, where A is mean air temperature on ~~the~~ day *i*~~, using Equations (1), (2), (3), (4), and (5):~~

~~Single-day average A_1:~~

$$\cancel{A_1 = A_i} \qquad \cancel{(1)}$$

~~Multi-day averages $A_2 \ldots A_7$:~~

$$\cancel{A_2 = \frac{(A_i + A_{i-1})}{2}, \ldots, A_7 = \frac{(A_i + A_{i-2} \ldots A_{i-6})}{7}} \qquad \cancel{(2)}$$

~~Multi-day weighted averages A_{2w} and A_{3w}, with preceding days discounted by 50% per day:~~:

$$A_{2w} \cancel{= A_i + \frac{(0.5*A_{i-1})}{1.5} \text{ and } A_{3w} = \frac{(A_i + 0.5A_{i-1} + 0.25A_{i-2})}{1.75}} \; \cancel{(3} = \frac{A_i + (0.5*A_{i-1})}{1.5} \qquad (1)$$

~~Lagged averages A_{L3} and A_{L5}:~~

$$\cancel{A_{L3} = \frac{(A_{i-1} + A_{i-2} + A_{i-3})}{3} \quad \text{and} \quad A_{L5} = \frac{(A_{i-1} + A_{i-2} + A_{i-3} + A_{i-4} + A_{i-5})}{5} \qquad (4)}$$

~~Differences between lagged average and day *i*:~~

$$\cancel{A_{\Delta 3} = (A_i - A_{L3}) \quad \text{and} \quad A_{\Delta 5} = (A_i - A_{L5}) \qquad (5)}$$

To improve numerical stability, we standardized ~~each~~ air temperature (°C) and flow ~~predictor variable~~(log10 m^3/s) by centering and scaling (i.e., subtracting the mean~~) and scaling (i.e.,~~ , then dividing by the standard deviation).

3.1.3 Flow and air temperature quantiles

At each site, we used smooth additive quantile regression models (Cade and Noon, 2003; Fasiolo et al., 2020) to calculate the air temperature associated with three quantiles (0.1, 0.5, and 0.9, equivalent to 10%, 50%, 90% exceedance probabilities) for each day of the year (Figure 3a), using the qgam R package (Fasiolo et al., 2020) with a 12-knot cyclic cubic regression spline (“cc”). We refer to the 0.1, 0.5, and 0.9 air temperature quantiles as Coolest, Typical, and Hottest, respectively. We also derived three flow quantiles, with the 0.1 quantile representing Lowest flows, 0.5 quantile representing Typical flows, and the 0.9 quantile representing Highest flows (Figure 3b). These quantiles were used to generate model scenarios (Section 3.4).

We used similar quantile regression models at each site to categorize each date into one of nine categories based on combinations of flow quantiles (High is >0.67 quantile, Moderate is 0.33–0.67 quantile, Low is <0.33 quantile) and air temperature quantiles (Cool is <0.33 quantile, Moderate is 0.33–0.67 quantile, Warm is > 0.67 quantile). These categories were used to define cross-validation blocks (Section 3.3).

3.2 Model development and calibration

~~We~~ At each of the 10 sites, we developed ~~statistical~~11 models ~~to predict DMxST~~of T_{max} and ~~DMST~~T_{mean} using combinations of river flow ~~and~~, air temperature, and day of year (D) as ~~predictors~~ covariates, including interactions (Table 1). ~~We tested three classes of models: non-linear logistic regression, harmonic regression, and generalized additive models (GAM).~~ ~~Models~~GAMs were developed in ~~R version 4.02 (R Core Team 2020).~~

~~3.2.1 Generalized additive models (GAMs)~~

~~We focused our stream temperature modeling on GAMs because they offer powerful flexibility including non-linear smoothers (Pedersen et al., 2019; van Rij et al., 2019). We used the bam function in the~~ the mgcv R package version 1.8-~~31~~ 36 using the bam function (Wood, 2017~~) to develop GAM models,~~), fit using fast restricted maximum likelihood (fREML). ~~GAM~~We also re-fit using maximum likelihood (ML) solely to obtain Bayesian information criterion (BIC) scores. Model terms ~~can be~~were either linear coefficients or smooth non-linear functions ~~(Wood,~~

~~2017; Pedersen et al., 2019). The non-linear functions are smooth curves~~ with ~~the amount of~~ wiggliness ~~automatically~~ determined by a smoothing penalty~~.~~ (Pedersen et al., 2019; Wood, 2017). We used cyclic cubic regression splines ("cc") as the smoother for ~~day of the year~~ D and thin plate regression splines ("tp") as smoothers for other covariates. ~~To~~ To improve prediction under new conditions and avoid overfitting (Jackson et al., 2018; Siegel ~~and~~ & Volk, 2019~~)~~), we limited smoothers for ~~most variables~~air temperature and flow to a maximum of ~~3~~three knots, except ~~D which~~in the one-covariate model "GAM11" where air temperature was allowed six knots. D was allowed up to ~~5~~six knots, except in three-dimensional tensors where it was restricted to five knots.

~~We compared GAMs that~~ Some models included interactions between D and other covariates (i.e., flow or air temperature) to allow ~~the relationships between covariates and the response variable to~~ that covariate's effect to vary seasonally ~~to GAMs where those relationships are seasonally constant. Our GAM models represented interactions between variables as~~. These interactions were either partially non-linear or fully non-linear. For ~~a~~ partially non-linear ~~interaction~~interactions, the linear slope of one variable (e.g., flow) ~~changed~~varied as a smooth non-linear function of ~~another variable (i.e.,~~ D~~), an approach used by~~ (Jackson et al~~. (~~., 2018~~)~~ ~~and Siegel~~, Siegel &~~and~~ Volk ~~(2019) and specified in mgcv using the "by" option.~~, 2019). Fully non-linear relationships between two or more variables were specified as tensor product smooths ~~in mgcv using the syntax "te()" (Wood, 2017). If main effects were included as separate terms, then we used "ti()" to specify a~~or tensor product ~~interaction~~interactions (Wood, 2017).

All ~~our GAM~~ models ~~included a random effect for year and all but one ("~~except "GAM11~~,"~~ ~~Section 4.2)~~", the simplest model structure tested, included an AR-1 autocorrelation error structure~~. The bam function cannot automatically derive the AR-1 coefficient (rho), so it must be manually assigned. Following Baayen et al. (2018) and van Rij et al. (2019, 2020),~~ and a random effect for year. We initially fit each model without an autocorrelation term, and then re-~~ran the model~~fit with an autocorrelation term, assigning a rho value based on the initial model's lag-1 autocorrelation ~~from the residuals of the initial model.~~ (Baayen et al~~. (~~., 2018~~) and~~; van Rij et al~~. (~~., 2019~~) advise testing several rho values using model-comparison procedures, which in our case always confirmed the initial values were optimal.~~, 2020) (Text S3).

~~3.2.2 Harmonic regression~~

~~As an alternative to compare to GAMs, we use harmonic regression (also known as trigonometric or periodic regression) (Cox, 2006) with paired sine and cosine interaction terms that allow the slope of covariates to vary as a smooth cycle over the course of the year (Bodeker et al., 1998). For daily periodicity, we multiplied day of the year D by 2π/365 (Helsel et al., 2020). We developed these models using the lme function in the nlme R package version 3.1-148 (Pinheiro et al., 2020) with an AR-1 autocorrelation term and a random intercept for year, fit using maximum likelihood (ML). Harmonic regression of stream temperature is common (Kothandaraman, 1971; Johnson et al., 2020), but we are not aware of previous applications of harmonic interactions between D and other covariates for stream temperatures.~~

~~3.2.3 Non-linear logistic regression~~

Since Mohseni et al.'s (1998) non-linear logistic regression of weekly air temperature and stream temperature has been ~~so widely applied, we use it as a benchmark to compare our other model to. Many streams, including the Scott River (Manhard et al., 2018), exhibit hysteresis in which the relationship between stream temperature and air temperature differs between spring and fall (Mohseni et al., 1998). Following Jones et al.'s (2016) code using R's optim function, we modeled the ascending (weeks 1–30) and descending (weeks 31–52) limbs separately, fitting models using weekly averages and then apply them to daily data. These models do not include flow, autocorrelation, or random effects. We used 7-day average air temperatures to match the original method~~widely applied and adapted (Piotrowski & Napiorkowski, 2019), we included a GAM equivalent of it as a benchmark for comparison. A_7 is the only predictor in this "GAM11" model (i.e., no flow, autocorrelation, or random effects).

We reviewed residual plots and autocorrelation function plots to verify assumptions. We evaluated each model's concurvity using mgcv's concurvity function.

3.3 Model selection and validation

~~We compared alternative model configurations (which variables and interactions are included, which are assigned random effects, etc.) to select a final model (Table 1). Initial exploration indicated that A_{2w} (2-day weighted air temperature) provided better model fits than other air temperature variables, so we used A_{2w} for most of our models. After final model selection, we developed a separate set of models to assess the sensitivity of model fits to using different air temperature variables (Figure S1). Rather than slavishly follow a pre-specified procedure such as forward-selection or backward selection, we took a more holistic approach to model selection. We selected a final model after considering multiple models using a variety of methods including Akaike information criterion (AIC), fREML (fast restricted maximum likelihood) scores for GAMs, goodness of fit metrics (root mean squared error [RMSE] and coefficient of termination [R^2]), and review of residual plots and auto correlation function plots. Concurvity, the non-linear equivalent of collinearity, is a potential concern for GAMs such as ours that contain smooths for time along with other time-varying covariates (Amodio et al., 2014; Wood, 2017), so we evaluated each GAM's concurvity using mgcv's concurvity function.~~

~~Prior to modeling, we randomly selected and excluded all data from 4 (17%) of the 24 years. These data were not used in model selection but instead were retained for out-of-sample validation.~~

~~We validated models using two methods. First, we used leave-one-year-out (LOYO) cross-validation, a version of k-fold variation in which we withhold a year, re-fit the model using the 19 remaining years, compare predictions for the withheld year against the measured data using goodness of fit metrics (RMSE and R^2), and then repeat the same process for each year. Second, for out-of-sample validation, we compared model predictions (calibrated with 20 years of data) against data from the four removed years using goodness of fit metrics (RMSE and R^2).~~

~~3.5~~We used cross-validation (CV) for model selection and validation because it is preferred over information theoretic approaches when prediction is paramount (Pedersen et al., 2019). We designed extrapolation CV tests to select models that performed well when applied to environmental conditions (i.e., flow and air temperature) outside the calibration range (Lute & Luce, 2017; Roberts et al., 2017). We split data into blocks based on quantiles of flow and air temperature (Section 3.1.3), withheld one block, and fit the model using the remaining block (Figure 4). We compared predictions for the withheld block against the measured data using root mean squared error (RMSE). These dual-variable differential split-sample tests (Klemeš, 1986) extrapolate not only into new combinations of flow and air temperature but also into new ranges of both individual variables.

We selected the final model by averaging all 40 RMSE values from extrapolation tests (10 sites × 2 extrapolation tests × 2 parameters [T_{max} and T_{mean}]) and choosing the model with lowest mean RMSE. We selected the same model structure for T_{max} and T_{mean} (rather than optimizing separately) so predictions for both metrics could be used together. We present BIC scores to compare our extrapolation-based model selection to more commonly applied model selection methods. To facilitate comparisons to previous studies, we also use leave-one-year-out (LOYO) CV where data were split into annual blocks and then treated similarly to the extrapolation tests (i.e., steps repeated for each year: year withheld, model refit using remaining data, and predictions compared to withheld data). We assessed the relative importance of individual model terms by comparing performance among models with and without individual predictors and/or interactions.

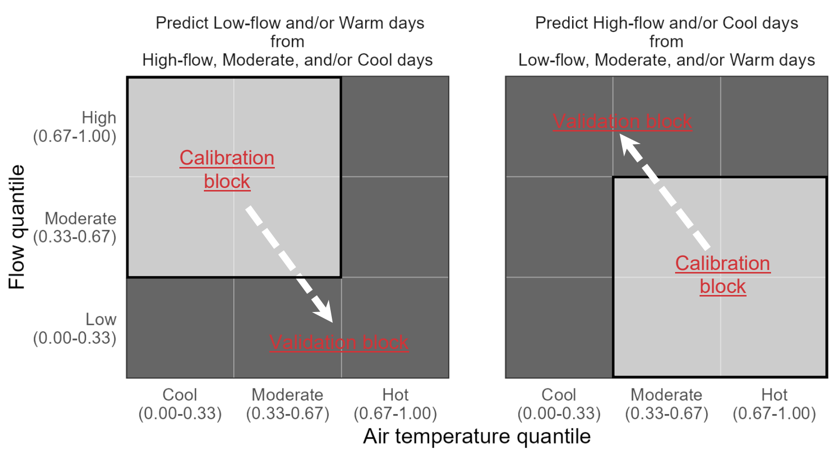

Figure 4. Configuration of data blocks used in extrapolation tests for model selection and validation.

3.4 Model ~~application to hydroclimatic and flow~~ scenarios assessing management ~~scenarios~~effects and timing of flow importance

3.4.1 All sites

To assess the seasonal response of stream temperatures to variation in flow and air temperatures, we applied our selected ~~GAM models to a group of 15~~model to scenarios representing differing air temperatures and flows (Table 2, Figure 3). We ran nine "quantile air temperature" scenarios representing combinations of ~~3 air temperature inputs and 5 flow inputs (Table 2, Figure 3). All~~ three air temperature inputs ~~were derived using non-parametric quantile regression (Cade and Noon, 2003; Muggeo et al., 2013) to calculate the air temperature associated with three quantiles~~ (0.~~05~~1, 0.~~50~~5, and 0.~~95, equivalent to 5%, 50%, 95% exceedance probabilities) for each day of the year (Figure 3a), using the quantregGrowth R package (Muggeo et al., 2013), with options described in Text S3. For air temperature, the~~ 9 quantiles) and three flow inputs (0.~~50 quantile represented typical conditions, the~~ 1, 0.~~05 quantile represented hottest conditions, and the~~ 5, and 0.~~95 quantile represented coolest conditions. Three of the five flow inputs were based on quantiles (0.05, 0.50, and 0.95) derived using similar methods as the air temperature inputs, with the 0.50 quantile representing typical conditions, the 0.05 quantile representing very low flow conditions, and the 0.95 quantile representing high flow conditions (Figure 3b). The remaining two of the five~~ 9 quantiles) (Section 3.1.3) for each site. Replication is sparse for the co-occurrence of extreme quantiles of both air temperature and flow ~~inputs are based on the USFS water right and California Department of Fish and Wildlife (CDFW) Interim Instream Flow Criteria. The USFS first-priority Scheduled D water right varies by~~ (e.g., mean 4.9 days of record per month and ~~day, from a high of 200 ft^3/sec (5.67 m^3/sec) in November through March to a low of 30 ft^3/sec (0.85 m^3/sec) in August and September (Superior Court of Siskiyou County, 1980) (Figure 3b). The CDFW criteria vary by~~ site with flow ≤0.1 quantile and air temperature ≥0.9 quantile); however, ample data are available in nearby quantiles (e.g., mean 19.1 days per month and ~~day, from a minimum of 62 ft^3/sec (1.75 m^3/sec) in September to a high of 362 ft^3/sec (10.3 m^3/sec) in February (CDFW, 2017~~site with flow ≤0.2 quantile and air temperature ≥0.8 quantile) (Figure ~~3b).~~S1).

3.4.2 Scott River

At Scott River only, six additional scenarios were run that paired the three quantile air temperatures with the USFS water right and CDFW flow criteria (Section 2) as flow inputs (Table 2, Figure 3). The CDFW and USFS flows ~~do not follow a particular flow quantile through the entire year, but instead~~ are aligned with extreme drought conditions in April and May (0.~~05~~1 quantile) and high flows in August and September (0.~~50~~5 to 0.~~95~~9 quantile).

~~To assess the realistic timing and magnitude of modeled exceedances of stream temperature thresholds,~~ We also applied our selected ~~GAM~~ model to ~~predict stream temperatures in a group of~~ "observed air temperature" scenarios that pair ~~the~~ observed ~~daily~~ air ~~temperature time series~~temperatures for ~~1995~~ dates 1998–2020 with eight flow conditions for the Scott River: observed USGS flows ~~in addition to the five flows used in the "quantile air temperature" scenarios (low, typical, high, USFS, and CDFW) as well as two additional scenarios in which the CDFW and USFS~~, the five flows ~~are used as minimums that are supplanted~~from the "quantile air temperature" scenarios (Lowest, Typical, Highest, USFS, and CDFW), and two additional scenarios in which the CDFW and USFS flows were replaced by observed USGS flows on dates when the observed flows ~~are~~were higher than the management flows (Table 2). ~~We expect that~~ Using observed air temperatures instead of quantile air temperatures provides more realistic ~~real-world~~ predictions because air temperatures fluctuate ~~erratically~~ from day to day (Figure ~~22~~2a), instead of ~~staying~~remaining near the same quantile like flow does during ~~the seasonal flow~~ May–September recession ~~each year from May through September.~~

. We summarized the results of each "observed air temperature" scenario by calculating: 1) annual maximum temperature, 2) first and last day each year in which water temperatures exceed 22 °C, and 3) the annual degree days exceedance of 22 °C, calculated by subtracting 22 from all ~~DMxST~~T_{max} and summing all positive values ~~by year~~. We chose 22 °C as an indicator of biological effects on juvenile salmonids ~~that rear in the mainstem Scott River or outmigrate downstream using the river as a migratory corridor. Given the potential for local genetic adaptation to thermal regimes (Zillig et al., 2021), we prioritized~~, based on geographically proximal studies ~~near the Scott River in selecting thresholds. When the Klamath River exceeds 22–23 °C, juvenile salmonids move to tributary confluences~~ (Brewitt & Danner, 2014; Sutton et al., 2007; Sutton ~~and~~ & Soto, 2012~~; Brewitt and Danner, 2014). Similar behavior was observed in the Shasta River (Nichols et al., 2014) and 22 °C was also used by McGrath et al~~)~~. (2017). The 22 °C threshold is not fully protective for coho salmon~~ (Text S4~~) but we chose it because our study site is a mainstem river where temperatures are expected to be higher than a cool tributary.~~).

Table 1. ~~Comparison~~List of Scott River GAMs and model training statistics.

		Daily maximum stream temperature (~~DMxST~~T_{max})						Daily mean stream temperature (~~DMST~~T_{mean})					
Model Name	**Predictor variables**	~~fREML~~**BIC**	~~AIC~~ **AR1**	~~AR1~~ **edf_F**	~~edf~~**edf_R**	**RMSE**	**R^2**	~~fREML~~**BIC**	~~AIC~~ **AR1**	~~AR1~~ **edf_F**	~~edf~~**edf_R**	**RMSE**	**R^2**
GAM1: tensor Q-A_{2w}-D	te(Q, A_{2w}, D)	~~5004~~12830	~~9901~~0.526	~~0.587~~23.6	~~46.5~~18.1	~~0.86~~1.06	0.~~982~~973	~~3354~~8562	0.659~~6607~~	~~0.747~~22.8	~~46.5~~18.1	0.~~77~~80	0.~~979~~978
GAM2: tensors Q-D & A_{2w}-D	s(A_{2w}) + ti(A_{2w}, D) + te(Q, D)	~~5036~~12734	~~9973~~0.529	~~0.603~~18.4	~~36.4~~18.0	~~0.88~~1.05	0.~~981~~974	~~3364~~8492	~~6639~~0.667	~~0.769~~17.1	~~35.6~~18.0	0.80	0.~~978~~979
GAM3: tensor Q-D & vary A_{2w}	s(D, by = A_{2w}) + s(A_{2w}) + te(Q, D)	~~5039~~12745	~~9978~~0.531	18.0~~.580~~	~~39.3~~18.0	~~0.86~~1.05	0.~~982~~974	~~3373~~8482	~~6649~~0.672	~~0.742~~16.3	~~39.1~~18.0	0.~~75~~80	0.~~980~~978
GAM4: tensors Q-D & A_{2w}-Q ~~*(final)*~~	s(D, by = A_{2w}) + s(A_{2w}) + ti(A_{2w}, Q) + te(Q, D)	~~5053~~12717	~~10022~~0.531	~~0.603~~17.2	~~36.3~~17.9	~~0.89~~1.05	0.~~981~~974	~~3401~~8486	~~6729~~0.671	~~0.763~~16.9	~~35.4~~18.0	0.80	0.978
GAM5: ~~tensors~~tensor Q-D ~~&~~no vary A_{2w} ~~-Qv2~~	s(A2w) + ~~ti(A_{2w}, Q) +~~ te(Q, D)	~~5095~~12724	~~10116~~0.537	~~0.608~~15.7	~~34.1~~17.9	~~0.90~~1.06	0.~~98~~974	~~3452~~8456	~~6840~~0.679	15.6~~0.764~~	~~33.2~~17.9	0.~~82~~80	0.~~977~~978
GAM6: ~~tensor Q-D no~~ vary Q & A_{2w} linear	s(D, by = A_{2w}) + ~~te(~~s(D, by = Q~~,~~) + s(D)	~~5105~~12828	~~10139~~0.578	~~0.611~~13.9	~~30.4~~17.8	~~0.90~~1.12	0.~~98~~970	~~3466~~8594	~~6873~~0.728	~~0.77~~10.9	~~28.6~~17.3	0.~~83~~89	0.~~976~~973
GAM7: ~~varying~~vary Q & A_{2w} (final)	s(D, by = A2w) + s(~~D~~A_{2w}) + s(Q) + s(D, by = Q) + s(D)	~~5160~~12754	~~10254~~0.544	12.6~~0.659~~	~~28.2~~17.9	1.07~~0.96~~	0.~~978~~973	~~3464~~8538	~~6871~~0.695	~~0.804~~11.8	~~27.5~~17.6	0.~~88~~84	0.~~973~~976
GAM8: ~~A_{2w}~~vary Q & no ~~*varying*~~vary A_{2w}	s(A_{2w}) + s(Q) + s(D, by = Q) + s(D)	~~5448~~12736	~~10855~~0.552	~~0.773~~12.3	~~23.1~~17.8	1.~~35~~08	0.~~956~~973	~~3626~~8526	~~7208~~0.704	~~0.834~~11.8	~~23.8~~17.5	~~1.08~~0.84	0.~~96~~976
GAM9: A_{2w} no ~~*Q or varying*~~vary	s(A_{2w}) + s(Q) + s(D)	~~5525~~13105	~~11010~~0.673	~~0.846~~8.4	~~22.3~~17.6	1.~~70~~32	0.~~931~~959	~~3749~~8738	0.764~~7459~~	~~0.875~~8.1	~~21~~17.6	0.96~~1.30~~	0.~~941~~969
~~GAM10: A_7 only with AR1~~	~~s(A_7)~~	~~6606~~	~~13186~~	~~0.886~~	~~21.3~~	~~2.75~~	~~0.817~~	~~5044~~	~~10062~~	~~0.905~~	~~21.2~~	~~2.29~~	~~0.819~~

~~*GAM11: A_7 only*~~GAM10: A_{2w} no ~~*AR1*~~Q or vary	s(~~A_7~~A_{2w}) + s(D)	~~10441~~13313	~~2082~~ ~~3~~0.780	~~N/A~~ 6.0	~~23.2~~ 17.3	~~2.21~~1.62	0.~~882~~938	~~9330~~9150	~~1860~~ ~~2~~0.840	~~N/A~~ 6.0	~~23.1~~16.6	1.~~74~~20	0.~~895~~952
~~*Harmonic12: varying Q & A_{2w}*~~	~~A_{2w} + A_{2w}:sin(Dn) + A_{2w}:cos(Dn) + Q + Q:sin(Dn) + Q:cos(Dn) + cos(Dn) + sin(Dn)~~	~~N/A~~	~~10368~~	~~0.73~~	~~N/A~~	~~1.04~~	~~0.969~~	~~N/A~~	~~6810~~	~~0.859~~	~~N/A~~	~~0.94~~	~~0.964~~
~~*Logistic13: Mohseni*~~ GAM11: A7 only no AR1	~~Logistic regression with A_7~~s(A_7)	~~N/A~~22668	N/A	~~N/A~~ 5.8	~~N/A~~ 0	2.~~34~~40	0.~~868~~865	~~N/A~~20265	N/A	~~N/A~~ 5.8	~~N/A~~0	1.~~84~~88	0.~~883~~882

Note: ~~GAM~~ Models are sorted by ~~fREML score~~edf_F for ~~DMxST.~~T_{max}, from most complex (GAM1) to least complex (GAM11). Except ~~'~~GAM11 ~~A_7 only no AR1'~~, all ~~GAM and LMM~~ models also include an AR1 autocorrelation structure and ~~a~~ random effect of year. ~~For models with italicized names, validation statistics are provided in Figures 4 (DMxST) and S5 (DMST).~~ D = day of year from 1 (1 January) to 366 (31 December in leap year), Q = daily mean flow ~~in units of m^3/s~~, see Section 3.1.~~1~~22 for key to 'A' air temperature variables, 's()' is a non-linear function, 's(D, by =)' is a linear interaction that varies smoothly by D, 'te()' is a fully non-linear tensor product smooth of two or three variables, 'ti()' is a tensor product interaction, ~~':' is linear interaction, n = 2π/365, fREML = fast restricted maximum likelihood score, AIC = Akaike~~BIC = Bayesian information criterion score, AR1 = autocorrelation coefficient, ~~edf~~edf_F = effective degrees of freedom (edf) for fixed effects, edf_R = edf for random effects, RMSE = root mean squared error~~,~~ of model training fit (not CV), and R^2 = coefficient of determination~~.~~ from model training fit (not CV).

Table 2. Matrix showing~~ the 23 stream temperature~~ model scenarios representing combinations of air temperature and flow inputs, and organized into two scenario groups. The first group (15 scenarios~~ in Group 1 use~~) used "quantile air temperature" inputs (6 were only run only at Scott River while 9 were run at all Klamath Basin sites) and the second group (8 scenarios~~ in Group 2 use~~) were run only at Scott River and used "observed air temperature" inputs.

Scenario group	**Air temperature inputs**	**Flow inputs**								
		Lowest (0.~~05~~1 quantile)	**Typical** (0.~~50~~5 quantile)	**Highest** (0.~~95~~9 quantile)	**USFS ~~exact~~ water right**	**CDFW ~~exact~~flow criteria**	**Observed**	**Maximum of observed or USFS ~~as minimum~~**	**Maximum of observed or CDFW ~~as minimum~~**	~~**Observed**~~
Quantile air temperature	**Hottest** (0.~~95~~9 quantile)	~~Group 1~~All sites	~~Group 1~~ All sites	~~Group 1~~ All sites	~~Group 1~~Scott only	~~Group 1~~ Scott only				
	Typical (0.~~50~~5 quantile)	~~Group 1~~All sites	~~Group 1~~ All sites	~~Group 1~~ All sites	~~Group 1~~ Scott only	~~Group 1~~ Scott only				
	Coolest (0.~~05~~1 quantile)	~~Group 1~~ All sites	~~Group 1~~ All sites	~~Group 1~~ All sites	~~Group 1~~ Scott only	~~Group 1~~ Scott only				
Observed air temperature	~~Group 2~~**Observed** (measured on date)	~~Group 2~~ Scott only	~~Group 2~~ Scott only	~~Group 2~~ Scott only	~~Group 2~~ Scott only	~~Group 2~~Scott only	~~Group 2~~ Scott only	~~Group 2~~ Scott only	Scott only	

~~*Note:* USFS = USFS Schedule D first-priority water right (Superior Court of Siskiyou County, 1980), and CDFW = CDFW Interim Instream Flow Criteria (CDFW, 2017). See text for explanation of quantiles and flow minimums.~~

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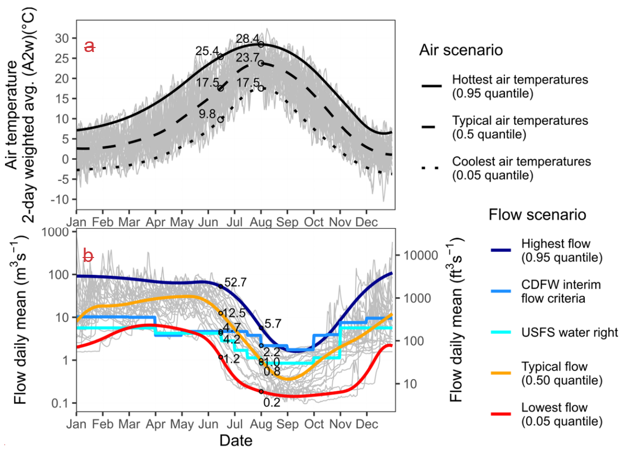


~~**Figure 3.** Inputs to Group 1 scenarios representing 15 combinations of (a) three air temperature inputs and (b) five flows inputs that vary by day. Observed values for 1995–2020 are shown as gray lines in both panels. Data values are labeled for 15 June and 1 August.~~

4 Results

4.1 ~~Measured water temperature, air temperature, and flow~~

~~From May–July, measured water temperatures were highly variable among years (Figure 2). For those months, the highest-flow years had DMxST averaging 6.8 °C cooler than during lowest-flow years, while DMST averaged 5.3 °C cooler. In contrast, from August through October inter-annual differences in water temperature much less pronounced. Annual maximum water temperatures occurred earlier in the season in low-flow years (i.e., early/mid-July) than in high-flow years (i.e., late July or early August). These observations inspired us to develop seasonally varying models.~~

~~4.2~~ Model selection and validation

In extrapolation CV of the 11 models (Table 1), GAM7 had the lowest all-site mean RMSE (T_{max} 1.13 °C, T_{mean} 1.00 °C), as well as the lowest RMSE for Scott River (T_{max} 1.20 °C, T_{mean} 1.00 °C), so was selected as our final model (Figure 5). GAM7 features nonlinear smoothers for day of year (D), two-day weighted air temperature (A_{2w}) , and flow (Q); a nonlinear smoother of D interacted with linear Q (i.e., linear slope of Q varies by D); and a nonlinear smoother of D interacted with linear A_{2w} (Table 1, Figure S3, Figure 6). GAM7 has intermediate complexity, with 12.6 effective degrees of freedom for fixed effects (edf_F) for Scott River T_{max}, compared to 23.6 for the most complex model (GAM1), and 5.8 for the least complex model (GAM11) (Table 1).

Extrapolation CV showed that at all sites, including Scott River, models with seasonally varying flow effects had much higher accuracy than models lacking that feature (Figure 5). For example, for T_{max}, all-site RMSE was 1.13–1.17 °C for models with seasonally-varying flow effects (GAM1–GAM8) and 1.66 °C for GAM9 that lacked seasonally varying flow. Models lacking flow (i.e., containing only D or A_{2w}) performed the worst, with all-site RMSE values of 1.72 °C and 2.21 °C for GAM10 and GAM11, respectively, for T_{max}. GAM7's combination of a nonlinear smoother for flow and a partially nonlinear interaction of flow and D represented flow effects well, given that the additional complexity of tensors (fully nonlinear interactions of flow and D) in GAM1–GAM5 did not substantially improve model performance at most sites. Models interacting flow and air temperature (i.e., GAM1 and GAM4) did not outperform GAM7 which lacked this interaction.

BIC scores (Figure S4) largely corroborate the extrapolation CV results identifying the importance of seasonally varying flow effects. Of eight models with seasonally varying flow effects, the most complex model (three-way tensor GAM1) had the worst overall (averaged across all sites) BIC score, but intermediate extrapolation CV RMSE. Averaging BIC ranks across sites, our extrapolation CV-selected model, GAM7, had the best BIC ranks for both T_{max} and T_{mean} (Figure S4); however, at many individual sites including Scott River, other models had better BIC scores (Figure S4, Table 1).

Scott River GAM7 LOYO CV predicted overall seasonal patterns in measured T_{max} for dates stratified into combinations of differing quantiles of air temperatures and flows. RMSE was higher for dates with low (<0.33 quantile) flows (Figure S2c). T_{max} Scott River GAM7 extrapolation CV prediction accuracy was only slightly lower than LOYO CV prediction accuracy when averaged over the entire year (i.e., RMSE 1.20 °C vs. 1.18 °C, Figure 5), but were biased low during May and June during high (>0.67 quantile) flows, having only been calibrated with data from the low-flow and moderate-flow quantile (Figure S5). Complete time series of Scott River measured and LOYO CV T_{max} and T_{mean} for all years are shown in Figures S6–S7.

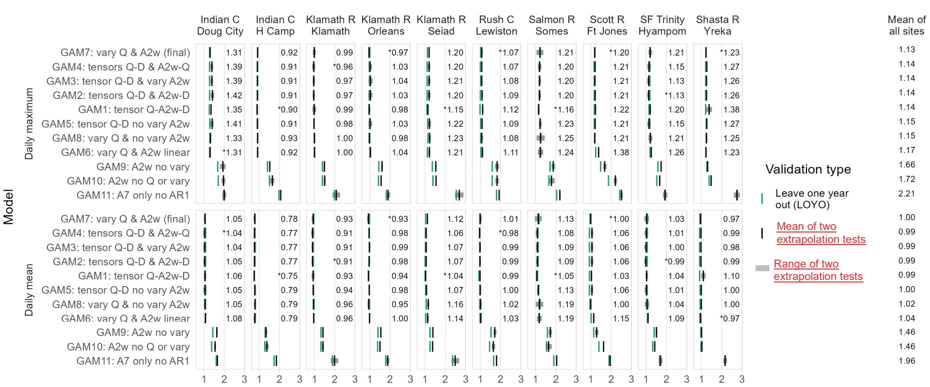


Figure 5. ~~The sensitivity analysis of model training statistics for models using various air temperature metrics indicated similar performance for most of the metrics, except the longest multi-day air temperature averages which had higher RMSE (Figure S1). For DMxST, RMSE~~

~~ranged from 0.88–0.90 °C for all air temperature metrics except the 3-day to 7-day averages which were 0.96–1.15 °C (Figure S1). For DMST, RMSE ranged from 0.79–0.82 °C for all air temperature metrics except the 4-day to 7-day averages which were 0.85–0.98 °C and the single-day average (0.87 °C) (Figure S1). Given the excellent performance of the 2-day weighted air temperature (A_{2w}) in predicting both DMxST and DMST (Figure S1), we use A_{2w} for all models except Logistic13 and the two GAM models that mimic it (Table 1).~~

~~Validation and training statistics indicate a wide range of performance (Table 1, Figure 4), with the tensor models (i.e., GAM1, GAM2, GAM3, GAM4, GAM5, GAM6) performing best while those models that used only~~ Summary of RMSE from extrapolation and LOYO CV tests at 10 Klamath Basin sites applying T_{max} (top panels) and T_{mean} (bottom panels) models to years (LOYO) or flow and air temperature combinations (extrapolation) not used in model calibration. Models are sorted by overall RMSE (i.e., mean of all 10 sites and both temperature metrics). Data labels for top eight models in individual site panels are means from extrapolation tests, with asterisk marking lowest RMSE in each panel. Labels at right edge of graph are all-site means for each model and parameter.

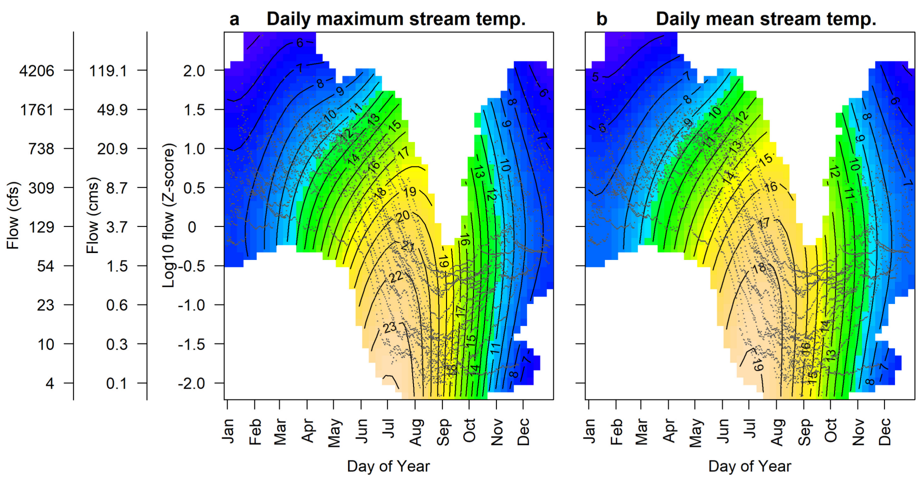
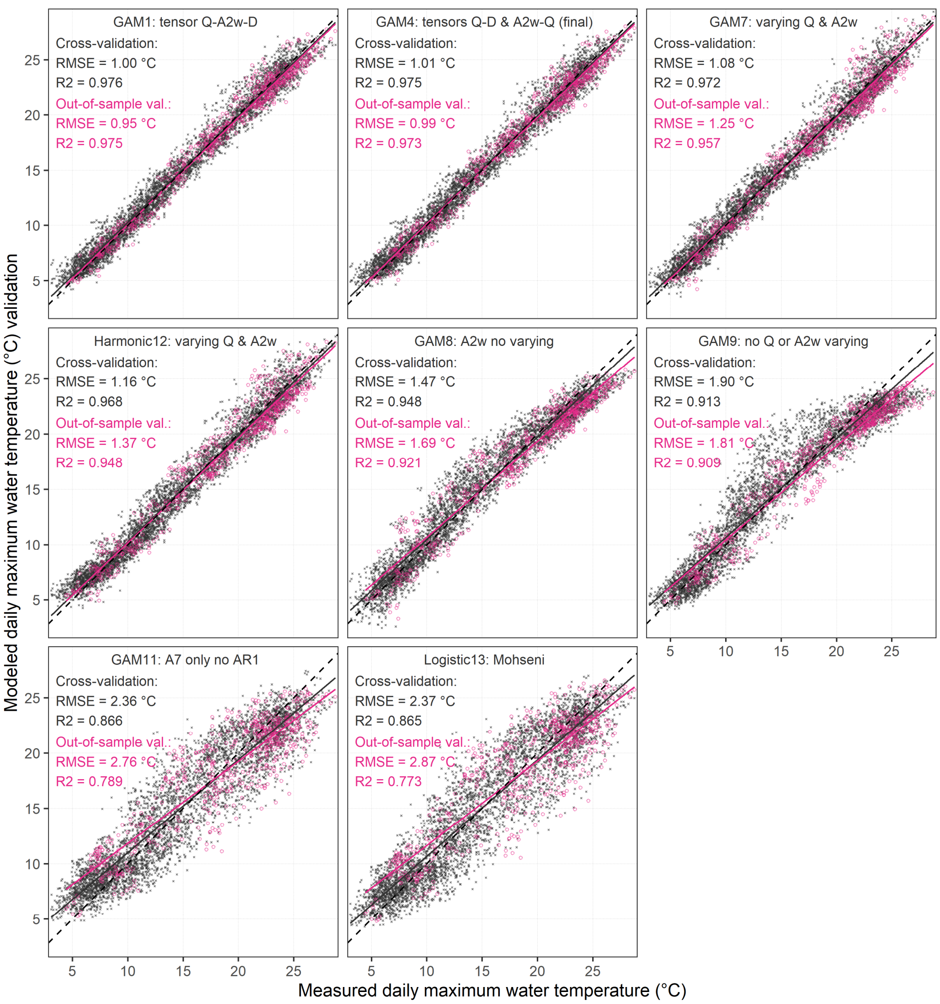


Figure 6. Effects of flow (Q) and day of year (D) on predicted values of (a) T_{max} and (b) T_{mean} in Scott River GAM7. Colors and labeled contour lines show predicted temperatures (°C). Underlying gray dots show calibration data.

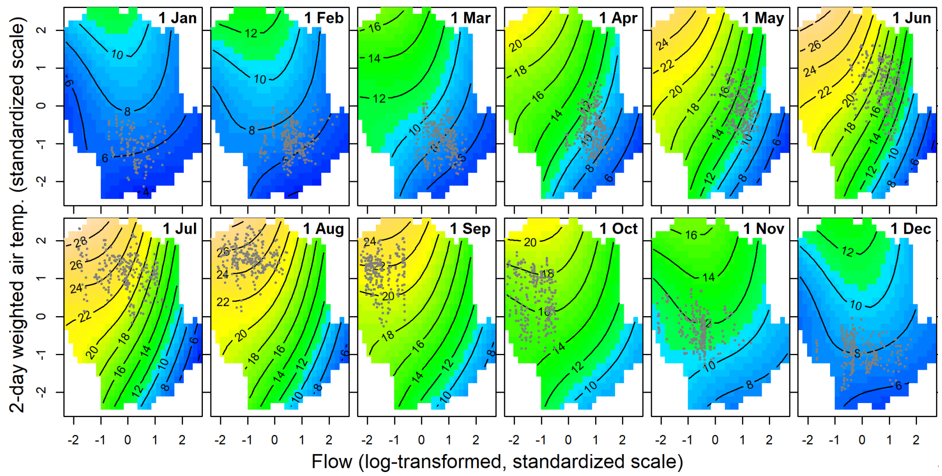
4.2 Model scenarios assessing management effects and timing of flow importance

Water temperature predictions under quantile air temperature ~~(e.g., Logistic13 and its GAM equivalent GAM11) performed~~scenarios on the ~~worst.~~

~~GAM4, chosen as~~Scott River using our selected model ~~for reasons discussed in Section 5.1, had a cross-validated RMSE of 1.01 °C for DMxST (Figure 4) and 0.93 °C for DMST (Figure S5), with similar values for out-of-sample validation. Similar to the measured data (Figure 2), in the May–July period the selected model predicts cool~~(GAM7) showed water temperatures ~~during high-flow years and warm water temperatures during low-flow years (~~responded to changes in flow across all quantiles of air temperature, consistent with measured data (Figure S2). ~~The effects plot for the selected models show that stream temperatures are relatively insensitive to flow from 1 December to 1 March, but that flow exerts a strong cooling influence from 1 April to 1 August (Figure 5, Figure S7). The complete time series of measured and modeled water temperature data for all years is available as Figure S3 and S4 for DMxST and DMST, respectively.~~



~~**Figure 4.** Comparison of measured DMxST to LOYO cross-validation predictions and out of sample validation predictions for 1995–2020. Solid lines are linear regression and dotted lines are the 1:1 (Y=X) lines.~~



Cooling effects of~~**Figure 5.** Effects plot showing predictions from selected model "GAM4: tensors Q-D & A2w-Q" that uses 2-day weighted air temperature (A_{2w}), flow (Q), and day of year (D) as predictors. Colors show predicted DMxST as function of Q and A_{2w}, with DMxST labeled contour lines spaced 2 °C apart. Panels represent the first day of each month. Gray dots show position of calibration points within 5 days of first of each month.~~

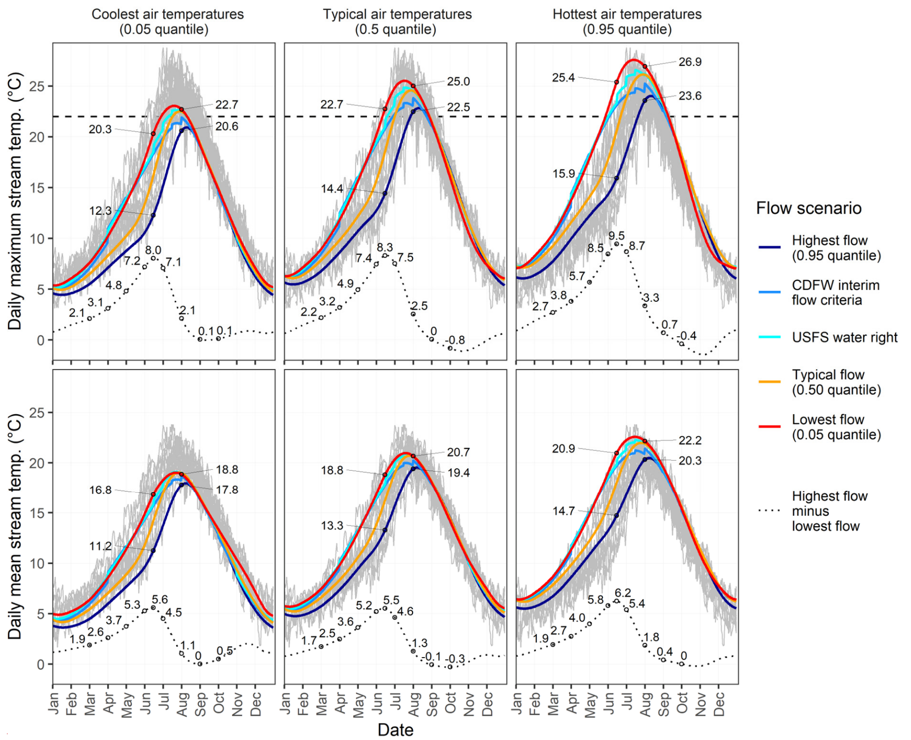
~~4.3 Model application to hydroclimatic and flow management scenarios~~

~~The "quantile air temperature" model scenarios show that flow and air temperature both had strong effects on water temperature (Figure 6). The cooling effect of high~~ flow followed a seasonal pattern, rising in March to reach ~~a peak~~maximum effect size on 15 June (~~up to 9.5 °C for DMxST and 6.2~~7.7 °C for ~~DMST~~T_{max} and 5.5 °C for T_{mean}), then diminishing to near zero by early September (Figure ~~6). Cooling effects of high flows were stronger when air temperatures were high than when air temperatures were low (e.g., 15 June difference in DMxST between highest-flow and lowest-flow scenarios is 9.5 °C with the hottest air temperatures and 8.0 °C with the coolest air temperatures). With less solar radiation (due to shorter days and lower solar angle) and lower air temperatures than earlier months, DMxST is almost always less than 22 °C by early September regardless of flow (gray lines in top panels of Figure 6).~~7). Consistent with ~~the~~ measured data (Figure ~~2~~S2), modeled annual maximum water temperatures occurred later in the season in high-flow ~~years~~conditions (i.e., late July or early August) than in low-flow ~~years~~conditions (i.e., early/mid-July) (Figure ~~6~~7).

~~In the~~Timing and magnitude of flow effects varied among the 10 Klamath Basin sites, but generally followed a similar seasonal trend of flow having the strongest cooling effects in April–July, less cooling effects in March and August, and warming effects in November through February (Figure 8). Cooling effects of flow were strongest at Scott River and weakest at Shasta River.

The Scott River "observed air temperature" scenarios, ~~we modeled DMxST pairing the~~which paired observed air ~~temperature time series for 1995–2020 with eight flow scenarios (Table 2, Figures 7 and S8). These scenarios provide an indication of the range (e.g., due to air temperatures) in daily water temperature associated with each~~temperatures with eight flow scenarios, demonstrated how flow variation influences stream temperature timing and magnitude. The lowest flow scenario~~. Compared to the lowest flow scenario (0.05 quantile), the highest flow scenario (0.95 quantile) has~~ (0.1 quantile) had annual maximum temperatures ~~that are~~ 3.~~7~~3 °C ~~cooler~~warmer than the highest flow scenario (0.9 quantile) (Figure ~~7a)~~9a), and ~~temperatures~~ first ~~reach~~reached 22 °C ~~51~~48 days ~~later~~earlier (Figure ~~7c); in contrast, there is only a 2-day difference in~~9c). The last day ~~of the year that has~~ with temperatures >22 °C differed by only 2 days (Figure ~~7d~~9d). The ~~scenario with~~ observed ~~flows has~~scenario had the most interannual variation in ~~the~~ annual maximum temperature (Figure ~~7a~~9a) and timing of exceedances of 22 °C (Figure ~~7c~~9c,d), because it ~~includes~~included very low flows ~~as well as~~and very high flows. ~~Water~~Predicted temperature responses to the CDFW and USFS flow scenarios are complex and depend on how the flows are implemented. If implemented as bypass flows, above which all additional water is diverted, then temperatures ~~reach~~reached 22 °C ~~17 days~~ *earlier* ~~with the exact USFS flows~~ than ~~with~~the observed ~~flows~~ flow scenario by 4 days for the CDFW flows and 13 days for USFS flows (Figure ~~7c~~9c and Figure S8) because ~~the USFS~~these management flows are ~~much~~ lower than ~~average~~ observed flows in May and June~~. In contrast~~ (Figure 3). However, in the ~~scenario in which~~scenarios where the CDFW and USFS flows ~~are treated as minimums (supplanted~~were replaced by observed USGS flows on ~~days~~dates when the observed flows ~~are higher), temperatures reach 22 °C on the same day as the observed flow scenario (Figure 7d). Due to high July and August flows in the CDFW scenarios, annual maximum water temperatures are 1.1–1.3 °C cooler in the CDFW scenarios than the observed flow scenario (Figure 7a). Relative to the observed flow scenario, the date that the CDFW as~~

~~minimum scenario first reaches 22 °C is only 3 days later average (2 July vs. 30 June), but~~ were higher than the management flows, then predicted temperatures reached 22 °C *later* than the observed scenario by 4 days with CDFW flows and 2 days with USFS flows. In addition, the number of years with exceedances of 22 °C prior to 23 June ~~20 are~~were reduced from ~~6~~7 to ~~2~~0 (Figure ~~7c~~9c) because ~~the~~ CDFW flows ~~are~~were higher ~~in~~than observed flows in drought years. ~~Patterns of inter-scenario~~Due to higher July and August flows, annual maximum water temperatures were 1.0–1.1 °C cooler in the CDFW scenarios than the observed flow scenario (Figure 9a). Differences in annual degree-days exceedance of 22 °C between scenarios (Figure ~~7b) are very~~9b) were similar to ~~those of~~ annual maximum temperature ~~(Figure 7a). While the CDFW flows and USFS flows are both predicted to improve (i.e., cool) summer temperatures relative to current conditions, these improvements would be greater with the higher CDFW flows~~.



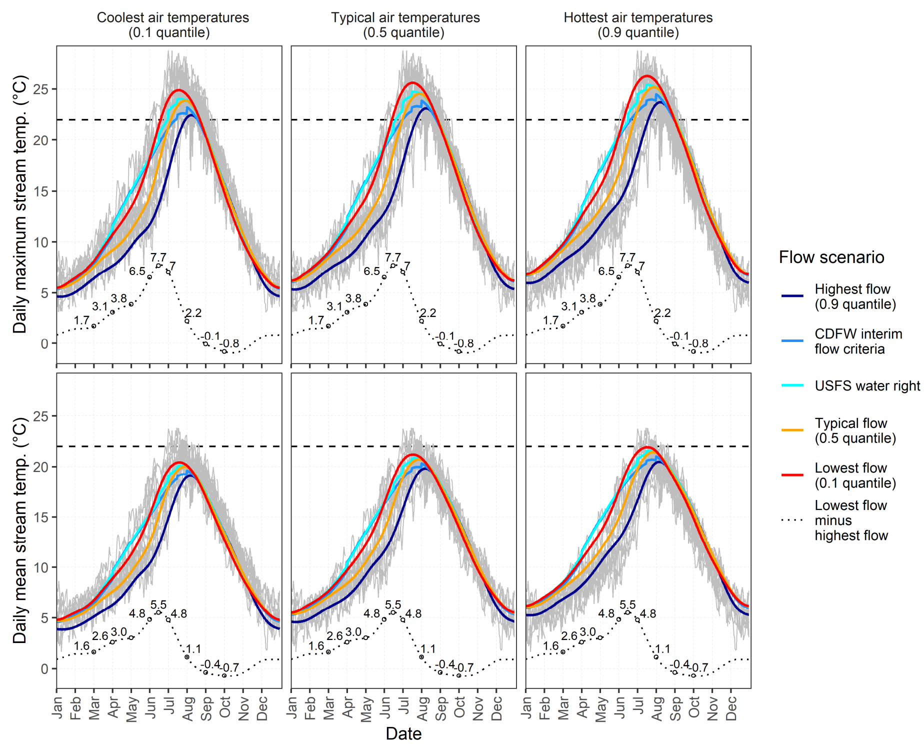
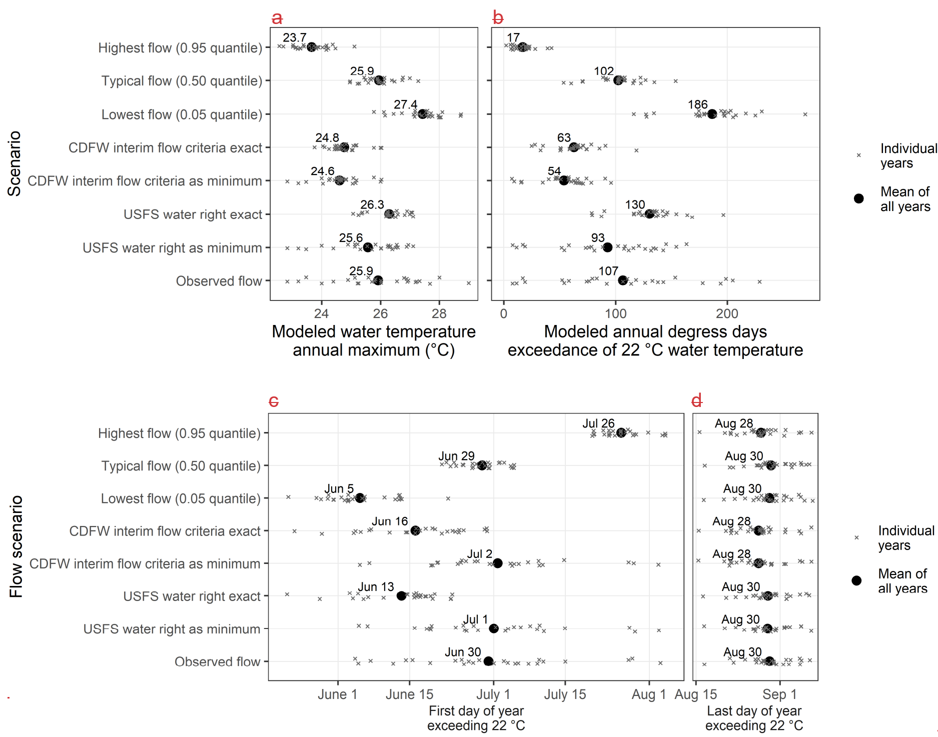


Figure ~~6. Predicted maximum~~**7.** Modeled Scott River T_{max} and ~~mean water temperatures~~T_{mean} under the 15 “quantile air temperature” scenarios representing combinations of ~~3~~three air temperature inputs (arranged in columns) and three quantile flow inputs and two management flow inputs (shown by color). Observed values for ~~1995~~1998–2020 are shown as gray lines. Selected data values are labeled on 15 June and the first day of ~~the months~~ March–October. Horizontal dashed line ~~at 22 °C DMxST~~ is the salmonid temperature threshold.



~~**Figure 7.**~~

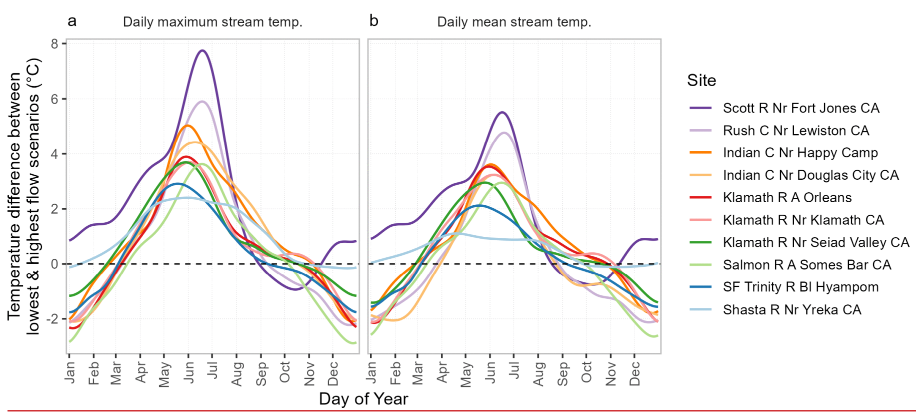


Figure 8. Modeled stream temperature differences between lowest flow (0.1 quantile) and highest flow (0.9 quantile) scenarios throughout the year for (a) T_{max} and (b) T_{mean} at 10 Klamath Basin sites estimated using GAM7.

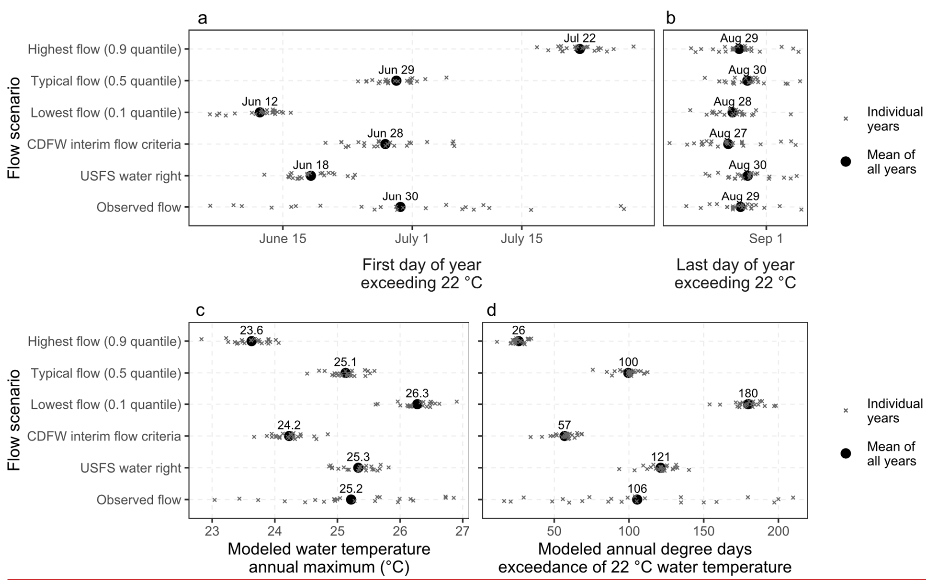


Figure 9. (a) Annual maximum stream temperature, (b) annual degree-days exceeding 22 °C, and (c) first ~~day~~ and (d) last day ~~each year~~ when ~~DMxST exceeds~~T_{max} exceeded 22 °C ~~predicted using a statistical~~in Scott River model scenarios pairing observed air temperatures ~~for 1995–2020~~ with ~~the same~~ eight flow ~~conditions~~scenarios. Means of all years are shown ~~in Figure S8. Points for~~with black points and grey “x” show individual years~~ are~~, offset ~~slightly~~ for clarity.~~ Data labels are the mean of all years.~~

5 Discussion

~~Consistent with our hypothesis~~At all 10 sites, models with seasonally varying flow effects ~~of flow~~substantially outperformed models with a constant relationship between stream temperature and flow.~~ High flows have a strong cooling effect on stream temperatures in April–July, but less influence during other months. The flexibility of GAMs, including non-linear and seasonally varying relationships between stream temperature and flow, produced more accurate predictions than harmonic regression models. Logistic regression of stream temperature with air temperature, based Mohseni et al.'s (1998) popular method,~~, indicating that the influence of flow changes throughout the year. Models containing only air temperature performed particularly poorly ~~in comparison to the GAMs~~ because ~~it~~they did not include flow as a ~~predictor. Our results confirm previous findings that summer stream temperatures are negatively correlated with~~ covariate, while models with a linear effect of flow ~~(Arora et al.,~~ had intermediate accuracy.

Flow had the strongest effect on water temperatures in April–July. The highest Scott River management flow evaluated would substantially decrease exceedances of 22 °C and reduce annual water temperature maximums. ~~2016; Isaak et al., 2017; Luce et al., 2014; Neumann et al, 2003), and that flow more strongly affects DMxST than DMST (Asarian et al., 2020; Gu et al., 1998; Gu and Li, 2002).~~

5.1 Model selection and ~~the importance of seasonally varying and non-linear relationships~~

~~After considering 13 models, we selected the GAM model with a two-day weighted air temperature (A_{2w}) whose slope varies by day of the year (D), a tensor product smooth of flow and day of the year (Q-D), and an A_{2w}-Q tensor product interaction (Table 1, Figure 4). We chose this model (GAM4 "tensors Q-D & A_{2w}-Q") based on a combination of model fit (low RMSE, high R^2, and low fREML score) and fewer effective degrees of freedom (edf) than other models with similar fit. This structure allowed modeled stream temperatures to respond flexibly to varying conditions in all three variables (D, A_{2w}, and Q). Although the three-way tensor GAM1 "tensor Q-D-A_{2w}" had the lowest fREML score, making it an appealing choice, it also had the highest edf, increasing the risk of being overfit. Indeed, when we experimented with applying GAM1 to model scenarios (not shown), the coolest air temperature scenarios (0.05 quantile) had mid-July temperatures that were higher in the typical flow (0.50 quantile) than either the lowest flow (0.05 quantile) or highest flow (0.95 quantile) scenario, which seemed implausible.~~

~~Comparing the relative~~ performance ~~of models with different smoothers and interactions provides insight into which are most important (Table 1, Figure 4, Figure S5). All models lacking seasonally varying flow effects (i.e., GAM8, GAM9, GAM10, GAM11, and Logistic13) performed worse than any model with seasonally varying flow effects, highlighting the importance of this feature. Modeled temperatures were biased high in April–June in models without seasonally varying flow effects, an issue that is diminished but still present in the Harmonic12 model that represents seasonal effects as perfectly symmetrical sine waves, and completely absent in the models that represents seasonal effects as flexible GAM smoothers (Figure S6). Models with tensors (i.e., GAM1, GAM2, GAM3, GAM4, GAM5, GAM6) had better fit than models with seasonally varying but linear relationships (e.g., GAM7), though the difference was not as great as the difference between seasonally constant models and seasonally varying models. For example, relative to the GAM7 model which is seasonally varying but linear, the GAM8 model with non-linear but seasonally constant relationships had a RMSE 0.4 C° lower (0.96 °C vs. 1.35 °C) for DMxST and 0.2 C° lower (0.88 °C vs. 1.08 °C) for DMST (Table 1). The selected model, GAM4, which has a fully non-linear tensor product smooth of D and Q, and a tensor product interaction of A_{2w} and Q, has improved (relative to GAM8) RMSE of 0.89 °C for DMxST and 0.80 °C DMST and improved rREML scores (Table 1). In addition, the results for GAM3 (seasonally varying A_{2w} and Q-D tensor product smooth) and GAM5 (A_{2w}-D tensor product interaction and Q-D tensor product smooth), suggests that most of the improvement between GAM7 and GAM4 comes from the Q-D tensor product smooth rather than from the D-varying A_{2w} or Q-A_{2w} tensor product interaction (Table 1).~~

~~The GAMs work well because they are able to represent the non-linear relationships and interactions between predictor variables present in our dataset. Heeding guidance from previous researchers we prevented overfitting by limiting the number of knots in the tensors (Jackson et al., 2018; Siegel and Volk, 2019). Our flexible approach takes maximal advantage of our multi-~~

~~decade daily calibration dataset featuring a range of environmental conditions (i.e., hot and cool air temperatures and high and low flows) over the 4696 days. Our validation results suggest that we have enough data to support our rather complex selected model GAM4. Future researchers modeling temperatures at other sites may not have as much data, so should exercise caution and may want to use the simpler GAM7 model.~~

~~5.3 Snow and groundwater mediate the effects of river flow~~ Model accuracy of our top model and similar model structures were high for both T_{max} and T_{mean}. For T_{mean}, our selected model's LOYO CV RMSE ranged from 0.80–1.17 °C at 10 sites (Figure 5), better than the 0.75–1.75 °C RMSE in Mohseni-based models at 14 sites within our study area (Manhard et al., 2018). In additional to outperforming other models applied within our study area, our selected T_{mean} model also had better LOYO CV RMSE than most single-station year-round daily statistical models from around the world (all-site average model validation RMSE for each analysis's best performing class of models: Ahmadi-Nedushan et al. [2007] 0.51 °C, Boudreault et al. [2019] 1.45 °C, Coleman et al. [2021] 1.3 °C, Koch and Grünewald [2010] 1.25 °C, Laanaya et al. [2017] 1.44 °C, Letcher et al. [2016] 1.16 °C, Sohrabi et al. [2017] 1.25 °C, van Vliet et al. [2011] 1.8 °C, and Soto et al. [2016] 1.20 °C). Our high model accuracy was achieved despite using PRISM air temperatures instead of local measurements—favoring ease of replicability.

GAMs were a useful modeling approach because they represented the nonlinear relationships and interactions between stream temperature and covariates. Our approach used >15-year calibration datasets spanning environmental conditions (i.e., hot and cool air temperatures and high and low flows). We prevented overfitting by restricting the number of knots in GAM smoothers (Section 3.2), basing model selection on extrapolation tests that evaluate prediction under expanded ranges of covariates (Section 3.3), and confirming that covariate responses and interactions matched scientific hypotheses regarding underlying physical processes (Section 5.3). Our selected model, GAM7, represented flow with two terms—a nonlinear smoother and a partially nonlinear interaction between flow and day of year—whose combined effects (Figure 6) provided enough flexibility for accurate predictions without overfitting. This two-term structure incrementally improves upon previous methods for representing flow effects, with GAM7's overall extrapolation CV RMSE 0.04 °C better than GAM6, the model with a simpler flow effects structure nearly identical to Glover et al. (2020). Consistent with warnings from Siegel & Volk (2019), tensors (fully nonlinear interactions) were too flexible and did not perform as well as GAM7 when applied to conditions differing from the calibration dataset (i.e., extrapolation tests), although tensor models still outperformed models without seasonally varying flow effects.

5.2 Magnitude and timing of flow effects on water temperature

Consistent with physical expectations, our results corroborate previous findings from northern temperate rivers that during seasons when air temperatures are typically high and flows are typically low (i.e., summer in our study area), lower flows are often temporally correlated with higher stream temperatures (Arora et al., 2016; Isaak et al., 2017; Luce et al., 2014; Neumann et al., 2003), and flow more strongly affects T_{max} than T_{mean} (Asarian et al., 2020; Gu and Li, 2002; Gu et al., 1998~~; Gu and Li, 2002~~). In our study streams, high flows had a strong cooling effect on stream temperatures in April–July, but less influence during other months. Multiple linear regression (MLR) models using monthly flow and air temperature at 239 Northwestern USA sites not regulated by dams (Isaak et al., 2018) and spatial stream network models for eight regions of the Western USA (FitzGerald et al., 2021) showed monthly timing and direction of flow effects on stream temperatures (Figures S9–S10) similar to our results (Figure 8b), with the exception of similar cooling in April and August whereas our models show weaker cooling in August than in April. Monthly MLR modeling in 17 sites in Canada's Frasier River Basin found flow-mediated cooling effects on summer water temperatures were stronger in July than August and weakest in September (Islam et al., 2019). In Poland, where inter-season flow differences are less pronounced than in our study area, high flows were correlated with cooler water temperatures in April–September, with the strongest relationships occurring in July–September at mountainous snowmelt-fed rivers (Wrzesiński and Graf, 2022). An Eastern USA river study using a daily year-round GAM found that water temperature decreased with increased flow from April through mid-October (Yang & Moyer, 2020). Previous studies evaluating year-round changes in the relationship between stream temperature and flow generally used monthly time steps. Our daily model provides a more nuanced understanding of seasonal dynamics by allowing this relationship to change smoothly at sub-monthly time scales, facilitating identification of changes within a month, as well as the rate of change.

Flow-induced cooling in snowmelt-dominated rivers is common. Process-based modeling of a Sierra Nevada river indicated early summer stream temperatures up to 16 °C cooler in a record wet year relative to a dry year (Null et al., 2013). In steep Alaskan streams, average summer stream temperatures were 3–5 °C cooler in high-snowpack years than low-snowpack years (Cline et al., 2021). In the conterminous USA, including flow as a covariate improved daily stream temperature predictions over air temperature only models in April–August, but only in snowmelt-dominated streams (Sohrabi et al., 2017). Stronger flow effects occurred in inland regions than coastal regions of the Western USA (Figure S10) (FitzGerald et al., 2021), consistent with a greater percent of precipitation falling as snow (Klos et al., 2014). Climate change studies have not parsed the separate influences of hydrology and air temperature on stream temperature, but in snowmelt-dominated areas of western North America, predictions for disproportionate spring and summer stream temperature warming are nearly ubiquitous and attributed to snowpack declines causing lower flows in those seasons (Caldwell et al., 2013; Crozier et al., 2020; Ficklin et al., 2014; Leach & Moore, 2019; Lee et al., 2020; Luo et al., 2013; Null et al., 2013).

5.3 Model correspondence to physical mechanisms

We used air temperature and flow as the major predictors in our model, recognizing that these predictors represent many processes that collectively determine stream temperatures. Air temperature is not the most important component of stream heat budgets (Johnson, 2004; Dugdale et al., 2017), but it has high predictive power because it is correlated with net radiative flux, a key driver of stream heat budgets (Caissie 2006). Air temperature data resulted in high model accuracy in our study, and are widely attainable unlike radiative fluxes.

The effects of flow on stream temperature vary throughout the year in response to the physical mechanisms affecting stream energy balances. High flows speed downstream transit of water and provide increased thermal mass that resists heating (or cooling). While flow has strong effects on water temperature in April–July in our study area, its effects are substantially weaker—though still present—in August. High flow can exert a dominant influence on water temperature, but this influence wanes as flow recedes, leading to progressively greater influence of solar radiation and air temperature. The relationship between flow and water temperature in our top-preforming model is nonlinear and varies with day. Marginal effects of decreasing flow diminish as flow approaches 0 m^3/s (Figure 6). At Scott River, August flows were much lower than July (Figure 2, Figure 6), and by 15 August were always below 2.6 m^3/s (92 ft^3/s). These low August flows have shallow water depth, low thermal mass, and slow transit times resulting in residence time sufficient for water to heat up to equilibrium temperature (Bogan et al., 2003; Nichols et al., 2014; Tague et al., 2007). During hot, dry conditions such occurs in our study area during summer, evaporative cooling limits how high stream temperatures can rise even when flows are extremely low (Mohseni & Stefan, 1999; Mohseni et al., 1998; Shaw et al., 2017). ~~Flow magnitude and seasonality at our study site is~~Wildfire smoke could also reduce warming of August stream temperatures (David et al., 2018). Widespread fire is more likely during drought conditions (Westerling, 2016), suggesting potential for smoke to confound low flow effects on temperature by decreasing solar radiation. We did not include smoke in our models because the data are difficult to process and we wanted easily replicable methods, but smoke effects on stream temperatures peaked in August in our study area (Asarian et al., 2020). With less solar radiation and cooler air temperatures than earlier months, T_{max} is almost always less than 22 °C at Scott River by early September regardless of flow (Figure 7). In October–November, a period of hydrologic transition when precipitation ends seasonal baseflow recession, flows had little influence over stream temperature (Figure 8), but Scott River and two other sites had weak, modal flow-temperature relationships (i.e., highest water temperatures at moderate flows) (Text S5).

Groundwater contributes to the relationship between flow and stream temperature at our Scott River site, as it does in many ~~driven by a mix of valley groundwater dynamics and snowmelt-driven mountain runoff (Foglia et al., 2013; Van Kirk and Naman, 2008). Groundwater contributes to the relationship between flow and stream temperature at our study site, as it does in many other~~ rivers (Briggs et al., 2018; Isaak et al., 2017; Kelleher et al., 2012; Mayer, 2012; Nichols et al., 2014~~; Isaak et al., 2017~~). Thermal infrared imagery, field measurements (NCRWQCB, 2005), and a groundwater model (Tolley et al., 2019) confirm that the 10 km of river directly upstream of our study site are a gaining reach where valley constriction forces substantial groundwater into the Scott River, a common phenomenon at the outlet of alluvial valleys (Stanford and Ward, 1992). Scott River flows are driven by a mix of valley groundwater dynamics and snowmelt-driven mountain runoff (Foglia et al., 2013; Van Kirk and Naman, 2008). ~~2019) all confirm that substantial groundwater is forced into the Scott River where the valley constricts upstream of our site, a common phenomenon at the outlet of alluvial valleys (Stanford and Ward, 1992). Process-based model scenarios predicted a doubling of groundwater-derived flow would cool peak summer Scott River temperatures~~As mountain runoff recedes and tributaries are almost fully diverted for irrigation, the relative contribution of groundwater to surface flow at the valley outlet increases over the summer and becomes dominant (NCRWQCB, 2005). Sediments underlying the river and its tributaries have high hydraulic conductivity, so groundwater and surface water are strongly connected (Tolley et al., 2019). During the May–September recession period when temperatures are of greatest biological concern, flows are related to aquifer levels, and the relative proportions of valley outlet flow derived from mountain runoff and groundwater are well-predicted by flow and day of year. Thus, even though these two sources have different temperatures and our model does not explicitly differentiate them, the model performs well because the interaction of flow and day of year implicitly characterizes these dynamics adequately. Scenarios from a short-term process-based surface water model predicted doubling groundwater-derived flow would cool 30 July 2003 Scott River T_{max} by 2 °C, and a 50% reduction of groundwater-derived flow would warm temperatures by 2 °C (NCRWQCB, 2005). For comparison, applying our model to scenarios doubling or halving the 3.03 m^3/s (107 ft^3/s) gaged flow for that same date predicts T_{max} 1.0 °C cooler or 0.7 °C warmer, respectively.

~~The timing and magnitude of flow-induced cooling indicated by our models are similar to other snowmelt-dominated rivers. A process-based model of a Sierra Nevada river indicated early summer stream temperatures up to 16 °C cooler in an extreme wet year relative to a dry year (Null et al., 2013). Relative to a statistical model with only air temperature, including flow as a predictor improved stream temperature predictions in April through August in Idaho streams (Sohrabi et al. 2017). Most studies predicting climate change effects do not parse the separate contributions of hydrology and air temperature on stream temperature, but in snow-dominated areas of the western North America, predictions of disproportionate stream temperature warming expected in the summer and/or spring are nearly ubiquitous and attributed to earlier runoff timing from declining snowpack (Caldwell et al.,~~ Statistical models typically require many fewer variables as data inputs than process-based models do, so are often much simpler to develop (Caissie, 2006; Ouellet et al., 2020); however, this ease has tradeoffs. For example, our model does not differentiate between specific sources of inflows, which may have quite different temperature influences, nor how alternative management scenarios would spatially and temporally alter those inflows. If fundamental characteristics of valley hydrology (i.e., management or climate) changed dramatically, model accuracy could suffer. Similarly, applying the model to covariate combinations beyond those used in calibration will degrade predictive accuracy (Section 5.5). To avoid overly complex models that overfit calibration data, we used extrapolation tests to favor selection of simpler more generalizable models. Our model does not incorporate longer-term (e.g., annual to decadal) variation in air temperature that affects groundwater temperatures and precipitation phase (e.g., snow or rain), so may underestimate responses relative to predictions from integrated process-based models (Leach & Moore 2019).

~~2013; Crozier et al., 2020; Ficklin et al., 2014; Lee et al., 2020; Leach and Moore, 2019; Luo et al., 2013; Null et al., 2013).~~

5.4 Biological implications

~~The prolonged snowmelt-driven flow recession in high-flow years keeps~~Higher Scott River ~~temperatures cooler longer into the summer than in low-flow years, extending~~flows extend the period when cool water habitat is available ~~for fish (i.e., temperatures less than 22 °C)(~~(Figure ~~7). These cooler water temperatures give~~9), giving juvenile salmonids additional time to migrate downstream and reduce ~~overall~~ thermal stress for fish that rear in the Scott River through the entire summer. Climate change will likely continue to reduce snowpack and summer flows (Persad et al., 2020), increasing duration of detrimentally warm temperatures. Mean diel range in June–August exceeds 5 °C, providing hours ~~every day when~~daily with temperatures ~~are less than~~ ≤22 °C even ~~if DMxST~~when T_{max} exceeds 22 °C. Salmonids can potentially persist by using thermal refugia where cool tributaries, groundwater, or hyporheic flow enters the river during ~~the~~ hotter ~~parts of the day~~hours and then ~~moving into~~forage in the mainstem ~~to feed~~ when temperatures are cooler (Brewitt & Danner, 2014; Sutton et al., 2007; Sutton ~~and~~ & Soto, 2012~~; Brewitt and Danner, 2014~~). However, substantial portions of the Scott River and tributaries lack surface flow during summer, especially in dry years, reducing habitat connectivity ~~between thermal refugia and mainstem habitats~~.

5.5 Applications and management implications

These models can be used not only to identify the seasonally varying influence of flow, but also to predict future stream temperatures based on managed flow recommendations~~.~~ and to impute missing data. Instream flow management frameworks are evolving (Mierau et al., 2017; Poff et al., 2017; Yarnell et al., 2020) and accurate stream temperature models provide a valuable tool ~~for use in those processes.~~ to predict management outcomes.

Our modeling approach ~~is relatively easy to implement, especially in comparison to a process-based models, which we hope will~~could facilitate water managers' ability to include stream temperature as a management target~~.~~ in areas that do not currently have operational process-based models. For example, Siskiyou County is ~~currently~~ developing a groundwater sustainability plan for the Scott Valley (Foglia et al., 2018). The current groundwater model ~~(Tolley et al., 2019)~~ does not simulate water temperatures (Tolley et al., 2019). ~~, so our temperature~~ Our model ~~could~~can be ~~a~~ used to ~~assess the~~predict effects of ~~groundwater management on groundwater-dependent ecosystems. Our results quantify the effect of~~ flow on ~~stream~~Scott River temperatures, including the CDFW and USFS flow thresholds under consideration, and could inform state agencies' development of new flow objectives. The CDFW and USFS flows ~~are~~were both predicted to ~~improve (i.e.,~~ cool~~) summer~~ maximum annual temperatures relative to current conditions, but improvements would be greater with the higher CDFW flows~~.~~ (Figure 9). We caution that while the CDFW and USFS flows are ~~relatively high compared to~~higher than typical observed flows in late summer and early fall, for March to early June they represent extreme drought conditions ~~(Figure 2b), which has two implications. First, in dry years temperatures reach 22 °C in early or mid-June in the observed flow scenario, which is only delayed in a small number of years in the scenarios with CDFW and USFS flows as minimums. Second, if river flows were diverted down to the CDFW and USFS flows in May and June, then the 22 °C threshold would be reached an average of approximately two weeks earlier than occurred with the observed flows (Figure 7c).~~that could cause earlier exceedances of 22 °C (Figure 2b). Surface water diversions for in lieu recharge (switching irrigation source from groundwater to surface water) or managed aquifer recharge (Dahlke et al., 2018; Foglia et al., 2013) should not use the CDFW and USFS flows to guide maximum diversion rates, but instead be tailored to reduce deleterious effects on instream habitat including temperatures, such as ceasing diversions by 1 June, the first date when measured (Figure 2) and modeled temperatures (Figure ~~7~~9) reach 22 °C.

As with any ~~regression~~statistical model, prediction accuracy ~~is likely to~~will degrade when applied to conditions more extreme than those present in the calibration dataset. Our selected model interacts day of year with flow and air temperature, so extrapolation caution applies not just to the range of individual variables but also their combined distributions. Our calibration dataset includes a wide range of hydrologic conditions, but no years without surface water diversions or groundwater pumping because those activities occur every year. ~~Groundwater modeling efforts suggest that s~~Streamflow depletion from groundwater pumping ~~would be~~ is greater in dry years than wet years~~, because in dry years pumping starts earlier, cumulative amounts pumped are greater, and the aquifer is drawn down lower~~ (Foglia et al., 2013~~; Tolley et al., 2019~~). Simulated total valley-wide streamflow depletion peaks around 150,000 m^{3}d^{-1} (60 ft^3/~~sec~~s) in July~~ and ~~ August (Foglia et al., 2013), exceeding streamflow in dry years. Our model should be suitable for modeling ~~stream temperatures in~~ dry years for scenarios with reduced pumping and/or diversions, which would presumably have flows similar to existing wet years (and hence are within the range of calibration flows); however, in wet years such scenarios would likely exceed the range of calibration flows and therefore be subject to ~~considerably higher levels of~~more uncertainty. ~~Any~~ Future application ~~of our model~~ to scenarios with flows higher than observed should be~~ done carefully and~~ interpreted with appropriate caveats.

Flow records are typically less available than water temperature records, so may constrain where our modeling approach can be applied. However, if site-specific flows were not available, data from a nearby site could be used if they were likely to be highly correlated (i.e., similar watershed characteristics). We did not systematically explore that issue, but the one site (South Fork Trinity River) where we used flows from an upstream station had prediction accuracy similar to the other nine sites (Figure 5). In addition, although our modeling approach should work well with records shorter than the >15-year datasets we used, we recommend further research to determine the minimum required period of record.

These models can also be used to fill gaps in stream temperature data records needed for other analyses (Glover et al., 2020). Their high accuracy suggests they would compare well with imputation methods used in recent daily year-round stream temperature analyses (Isaak et al., 2020; Johnson et al., 2021).

6 Conclusions

~~Statistical models indicate~~ Long-term daily stream temperature datasets enabled development of generalized additive models (GAMs) that include nonlinear and seasonally varying effects of flow and air temperature on stream temperature. Cross-validation indicated these models had higher accuracy than models that did not account for seasonally variable effects of flow, providing evidence that flow is important in controlling stream temperatures and that the influence of flow is variable through time. Results from these models indicated that high river flow ~~has~~had a strong cooling effect on river temperatures during April through July ~~in California's Scott River,~~ at 10 sites in the Klamath Basin of California, corroborating similar ~~to previous~~ findings from ~~process-based models in many snow-dominated rivers in~~ western North America. ~~A 24-year dataset of daily streams temperatures allowed us to develop a generalized additive model using tensor product smooths and interactions~~

Results from extrapolation cross-validation tests show that our selected model is robust in estimating stream temperatures under environmental conditions moderately outside of the range of conditions used to train the model (although see cautions in Section 5.5). We applied the model to instream flow management scenarios proposed by regulatory agencies at our focal study site, the Scott River, finding that these scenarios would improve stream temperatures. Relative to ~~represent the non-linear and seasonally varying effects of flow and air temperature on stream temperature. Our model also includes the correlation structures inherent in the data, namely daily temporal autocorrelation~~historic conditions, the higher instream flow scenario would reduce annual maximum temperature from 25.2 °C to 24.1 °C, reduce annual exceedances of 22 °C (a cumulative thermal stress metric) from 106 to 51 degree-days, and ~~random effects for annual variation. Validation indicated excellent model performance, with average errors ≤1 °C. This project contributes~~delay onset of water temperatures >22 °C during some drought years.

These models contribute to an emerging body of work demonstrating the ~~benefits~~use of ~~generalized additive models (~~GAMs~~)~~ for ~~modeling~~predicting daily river temperatures. ~~Given the flexibility of GAMs, there is a risk of overfitting data, but this risk can be minimized by restricting the number of knots in GAM smoothers, confirming that smoother shape matches scientific hypotheses regarding the underlying physical processes,~~Our models are easy to implement and ~~considering whether sample size is adequate for the complexity of the model~~improve prediction accuracy of stream temperature responses to flow changes over models without seasonally variable effects of flow, providing tools that managers can use to select flow solutions most likely to protect species and ecosystems. The models are implemented in the R software environment with publicly accessible code. Testing at 10 streams in our study region indicated that models with seasonally variable flow effects had high prediction accuracy across all streams, suggesting that these models have broad applicability over a range of stream types. Our selected model, GAM7, incrementally improves upon previous methods for representing flow effects. Model applications include those explored here (i.e., scenario prediction and identifying periods of flow importance), as well as filling gaps in temperature time series. We suggest that GAM7, as well as similar model structures (i.e., GAM6, GAM8) will perform well across a range of streams. Model validation procedures, including extrapolation-based methods when models are applied to new data, should be conducted to test model accuracy at new sites and for datasets of variable periods of record.

~~These models identify the specific periods of the year when flow has greatest influence on stream temperatures, and can be used to evaluate the thermal effects of alternative flow management scenarios and prescriptions. The models are implemented in the R software environment with publicly accessible code, and could be applied to model year-round daily temperature in any stream with long-term measurements of flow and water temperature, provided that air temperatures are available from a nearby weather station.~~

CRediT authorship contribution statement

J. ~~Eli Asarian:~~E.A.: Conceptualization, Data curation, Methodology, Formal analysis, Visualization, Writing – original draft, Writing – review & editing. ~~Crystal Robinson:~~C.R.: Conceptualization, Investigation, Data curation, Funding acquisition, Project administration, Writing - review & editing. L.G.: Writing - review & editing.

Acknowledgments

The Klamath Tribal Water Quality Consortium (Karuk Tribe, Yurok Tribe, Hoopa Valley Tribe, Quartz Valley Indian Reservation, and Resighini Rancheria) supported ~~Eli Asarian~~J.E.A. and L.G. using funds provided by the U.S. Environmental Protection Agency, Region 9. Maija Meneks (KNF) and Callie McConnell (USFS Corvallis) provided the USFS water temperature data. Isaiah Williams, Alex Case, Sean Ryan and Marla Bennett (QVIR) assisted with data collection. ~~Edward Jones (USGS) provided code for non-linear regression. Laurel Genzoli reviewed a draft of~~Taylor Daley (USFWS Arcata) provided USFWS water temperature data. Daniel Isaak and Sara John provided data from Isaak et al. (2018) and FitzGerald et al. (2021), respectively. WRR editors and reviewers provided comments that substantially improved this manuscript.

Data Availability Statement

All input and output data and ~~code~~codes are archived in the online repository HydroShare (Asarian ~~and Robinson, 2021~~et al., 2022, http://www.hydroshare.org/resource/a6653e2919964f9b840ec0340d86e11c). USBR and USGS stream temperature data (Smith et al., 2018) are also available at~~:~~ https://or.water.usgs.gov/cgi-bin/grapher/graph_setup.pl?~~basin_id=all&~~site_id=11519500~~.~~ and https://cdec.water.ca.gov/dynamicapp/staMeta?station_id=RCL. CDWR stream temperature data are also available are available at https://wdl.water.ca.gov/WaterDataLibrary/StationDetails.aspx?Station=F3410000. Gridded PRISM air temperature data (Daly et al., 2008) are also available at: https://prism.oregonstate.edu/explorer/.~~ GHCN-D air temperature data (Menne et al., 2012a, 2012b) are also available at http://doi.org/10.7289/V5D21VHZ.~~

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