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, water temperatures 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 models can be applied to other rivers or streams with daily, long-term flow and water temperature records

Abstract

Low streamflows can increase vulnerability to warming, impacting coldwater fish. Water managers need tools to quantify 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 to vary throughout the year. Using 21 years of air temperature and flow data, we modeled daily water temperatures in California's snowmelt-driven Scott River where agricultural diversions consume most summer surface flows. We used generalized additive models to test time-varying and nonlinear effects of flow on water temperatures. Models that represented seasonally varying flow effects with intermediate complexity outperformed simpler models assuming constant relationships between water temperature and flow. Cross-validation error of the selected model was ≤1.2 °C. Flow variation had stronger effects on water temperatures in April–July than in other months. We applied the model to predict effects of instream flow scenarios proposed by regulatory agencies. Relative to 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 delay onset of water temperatures >22 °C during some drought years. Testing the same modeling approach at nine additional sites showed similar accuracy and flow effects. These methods can be applied to streams with long-term flow and water temperature records to fill data gaps, identify periods of flow influence, and predict temperatures under flow management scenarios.

Plain Language Summary

Warm water temperatures threaten culturally and economically important salmon in Pacific Northwest rivers, causing chronic stress and direct mortality. Climate change and agricultural water use have reduced summer river 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 21 years of river flow and air temperature data from the Scott River, California, to create computer models that simulate water temperatures. 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 the Scott River model to simulate water temperatures under two alternative flow scenarios considered in local water management plans. Our simulations indicate that relative to current conditions, the higher flow scenario would lower the summers' highest temperatures and decrease the number of days that river temperatures 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 drive physical, chemical, and biological processes (Ouellet et al., 2020). Stream temperatures determine species ranges, 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., 2018). Channel geometry, including width/depth ratio, influences these effects (Dugdale et al., 2017).

The relationship between water temperature and flow varies through time. Seasonal changes in precipitation phase (i.e., snow and rain) 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 irrigation runoff can further alter temperature dynamics (Alger et al., 2021; Chandesris et al., 2019). Flow effects on water temperature are further mediated by seasonal changes to solar radiation received by the stream. Day length and solar angle, which affect topographic and riparian shading, remain consistent among years (Piotrowski & Napiorkowski, 2019; Yard et al., 2005). Other mediators of solar radiation including 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., 2018) and other aerosols follow 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, water managers need tools to predict stream temperature changes associated with climate change and flow management (Gibeau & Palen, 2020; Null et al., 2017). While process-based (i.e., deterministic) models simulating stream energy budgets 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 environmental drivers require fewer input variables so are easier to implement, but for scenario prediction they are generally not considered as reliable as process-based models (Arismendi et al., 2014; Benyahya et al., 2007a; Caissie, 2006). However, statistical 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 & 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., 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

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 (VanderKooi et al., 2011). The human population lives primarily on private land along watercourses including Scott Valley, where irrigated agriculture dominates land use, utilizing groundwater and surface water (Foglia et al., 2018). 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 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 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 groundwater withdrawals, especially since 1977 (Van Kirk and Naman, 2008). Climate change is expected to further reduce flows by decreasing snowpack and increasing irrigation demand (Persad et al., 2020).

Management flows have been proposed for the Scott River to protect Endangered Species Act-listed coho salmon (*Oncorhynchus kisutch*) and other coldwater salmonid fishes. These fishes' importance to local Native American tribes has led to contention over water management. River water temperatures in May–July are much cooler in high-flow years than low-flow years (Figure 2), and 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 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 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.

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 preparation

3.1.1 Water temperature and river flow

We obtained water temperature data from six sources (Table S1). For the Scott River site, we used Quartz Valley Indian Reservation (QVIR) (QVIR, 2016; Asarian et al., 2020) data, supplemented by U.S. Forest Service (USFS) (KNF, 2010, 2011) and U.S. Bureau of Reclamation (USBR) (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 & 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 T_{mean} and 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).

3.1.2 Air temperature

We retrieved daily mean air temperatures for each site from the 4-km resolution gridded PRISM dataset (Daly et al., 2008). Because stream temperatures are correlated with air temperature at multiple time scales, we initially explored many metrics (Piotrowski & Napiorkowski, 2019). 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 day *i*:

$$A_{2w} = \frac{A_i + (0.5 * A_{i-1})}{1.5} \quad (1)$$

To improve numerical stability, we standardized air temperature (°C) and flow (log10 m^3/s) by centering and scaling (i.e., subtracting the mean, 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

At each of the 10 sites, we developed 11 models of T_{max} and T_{mean} using combinations of river flow, air temperature, and day of year (D) as covariates, including interactions (Table 1). GAMs were developed in the mgcv R package version 1.8-36 using the bam function (Wood, 2017), fit using fast restricted maximum likelihood (fREML). We also re-fit using maximum likelihood (ML) solely to obtain Bayesian information criterion (BIC) scores. Model terms were either linear coefficients or smooth non-linear functions with wiggliness determined by a smoothing penalty (Pedersen et al., 2019; Wood, 2017). We used cyclic cubic regression splines ("cc") as the smoother for D and thin plate regression splines ("tp") as smoothers for other covariates. To improve prediction under new conditions and avoid overfitting (Jackson et al., 2018; Siegel & Volk, 2019), we limited smoothers for air temperature and flow to a maximum of three knots, except in the one-covariate model "GAM11" where air temperature was allowed six knots. D was allowed up to six knots, except in three-dimensional tensors where it was restricted to five knots.

Some models included interactions between D and other covariates (i.e., flow or air temperature) to allow that covariate's effect to vary seasonally. These interactions were either partially nonlinear or fully nonlinear. For partially nonlinear interactions, the linear slope of one variable (e.g., flow) varied as a smooth nonlinear function of D (Jackson et al., 2018, Siegel & Volk, 2019). Fully nonlinear relationships between two or more variables were specified as tensor product smooths or tensor product interactions (Wood, 2017).

All models except "GAM11", the simplest model structure tested, included an AR-1 autocorrelation error structure and a random effect for year. We initially fit each model without an autocorrelation term, and then re-fit with an autocorrelation term, assigning a rho value based on the initial model's lag-1 autocorrelation (Baayen et al., 2018; van Rij et al., 2019, 2020) (Text S3).

Since Mohseni et al.'s (1998) nonlinear logistic regression of weekly air temperature and stream temperature has been 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 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.

3.4 Model scenarios assessing management 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 model to scenarios representing differing air temperatures and flows (Table 2, Figure 3). We ran nine "quantile air temperature" scenarios representing combinations of three air temperature inputs (0.1, 0.5, and 0.9 quantiles) and three flow inputs (0.1, 0.5, and 0.9 quantiles) (Section 3.1.3) for each site. Replication is sparse for the co-occurrence of extreme quantiles of both air temperature and flow (e.g., mean 4.9 days of record per month and 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 site with flow ≤0.2 quantile and air temperature ≥0.8 quantile) (Figure 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 are aligned with extreme drought conditions in April and May (0.1 quantile) and high flows in August and September (0.5 to 0.9 quantile).

We also applied our selected model to "observed air temperature" scenarios that pair observed air temperatures for dates 1998–2020 with eight flow conditions for the Scott River: observed USGS flows, the five flows 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 were higher than the management flows (Table 2). Using observed air temperatures instead of quantile air temperatures provides more realistic predictions because air temperatures fluctuate from day to day (Figure 2a), instead of remaining near the same quantile like flow does during May–September recession. 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 T_{max} and summing all positive values. We chose 22 °C as an indicator of biological effects on juvenile salmonids, based on geographically proximal studies (Brewitt and Danner, 2014; Sutton et al., 2007; Sutton & Soto, 2012) (Text S4).

4 Results

4.1 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.

4.2 Model scenarios assessing management effects and timing of flow importance

Water temperature predictions under quantile air temperature scenarios on the Scott River using our selected model (GAM7) showed water temperatures responded to changes in flow across all quantiles of air temperature, consistent with measured data (Figure S2). Cooling effects of flow followed a seasonal pattern, rising in March to reach maximum effect size on 15 June (7.7 °C for T_{max} and 5.5 °C for T_{mean}), then diminishing to near zero by early September (Figure 7). Consistent with measured data (Figure S2), modeled annual maximum water temperatures occurred later in the season in high-flow conditions (i.e., late July or early August) than in low-flow conditions (i.e., early/mid-July) (Figure 7).

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, which paired observed air temperatures with eight flow scenarios, demonstrated how flow variation influences stream temperature timing and magnitude. The lowest flow scenario (0.1 quantile) had annual maximum temperatures 3.3 °C warmer than the highest flow scenario (0.9 quantile) (Figure 9a), and first reached 22 °C 48 days earlier (Figure 9c). The last day with temperatures >22 °C differed by only 2 days (Figure 9d). The observed scenario had the most interannual variation in annual maximum temperature (Figure 9a) and timing of exceedances of 22 °C (Figure 9c,d), because it included very low flows and very high flows. 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 reached 22 °C *earlier* than the observed flow scenario by 4 days for the CDFW flows and 13 days for USFS flows (Figure 9c and Figure S8) because these management flows are lower than observed flows in May and June (Figure 3). However, in the scenarios where the CDFW and USFS flows were replaced by observed USGS flows on dates when the observed flows 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 were reduced from 7 to 0 (Figure 9c) because CDFW flows were higher than observed flows in drought years. 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 9b) were similar to annual maximum temperature.

5 Discussion

At all 10 sites, models with seasonally varying flow effects substantially outperformed models with a constant relationship between stream temperature and flow, indicating that the influence of flow changes throughout the year. Models containing only air temperature performed particularly poorly because they did not include flow as a covariate, while models with a linear effect of flow 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.

5.1 Model selection and performance

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). 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). 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 rivers (Briggs et al., 2018; Isaak et al., 2017; Kelleher et al., 2012; Mayer, 2012; Nichols et al., 2014). 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). 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.

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).

5.4 Biological implications

Higher Scott River flows extend the period when cool water habitat is available (Figure 9), giving juvenile salmonids additional time to migrate downstream and reduce 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 daily with temperatures <22 °C even 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 hotter hours and then forage in the mainstem when temperatures are cooler (Brewitt and Danner, 2014; Sutton et al., 2007; Sutton & Soto, 2012). However, substantial portions of the Scott River and tributaries lack surface flow during summer, especially in dry years, reducing habitat connectivity.

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 to predict management outcomes.

Our modeling approach 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 developing a groundwater sustainability plan for the Scott Valley (Foglia et al., 2018). The current groundwater model does not simulate water temperatures (Tolley et al., 2019). Our model can be used to predict effects of flow on 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 were both predicted to cool 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 higher than typical observed flows in late summer and early fall, for March to early June they represent extreme drought conditions 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 9) reach 22 °C.

As with any statistical model, prediction accuracy 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. Streamflow depletion from groundwater pumping is greater in dry years than wet years (Foglia et al., 2013). Simulated total valley-wide streamflow depletion peaks around 150,000 m^3d^{-1} (60 ft^3/s) in July–August (Foglia et al., 2013), exceeding streamflow in dry years. Our model should be suitable for modeling 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 more uncertainty. Future application to scenarios with flows higher than observed should be 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

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 had a strong cooling effect on river temperatures during April through July at 10 sites in the Klamath Basin of California, corroborating similar findings from western North America.

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 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 delay onset of water temperatures >22 °C during some drought years.

These models contribute to an emerging body of work demonstrating the use of GAMs for predicting daily river temperatures. Our models are easy to implement and 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.

CRediT authorship contribution statement

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

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Data Availability Statement

All input and output data and codes are archived in the online repository HydroShare (Asarian 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?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/.

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Figure 1. Klamath Basin study sites with the Scott River Watershed outlined in red. Source map credits: Esri , NOAA, and USGS.

Figure 2. Time series of (a) daily mean air temperature, (b) daily mean flow, (c) daily maximum stream temperature (T_{max}), and (d) daily mean stream temperature (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 are shown as gray lines.

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

Figure 5. 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.

Figure 7. Modeled Scott River T_{max} and T_{mean} under the 15 "quantile air temperature" scenarios representing combinations of three air temperature inputs (arranged in columns) and three quantile flow inputs and two management flow inputs (shown by color). Observed values for 1998–2020 are shown as gray lines. Selected data values are labeled on 15 June and the first day of March–October. Horizontal dashed line is the salmonid temperature threshold.

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 and (d) last day when T_{max} exceeded 22 °C in Scott River model scenarios pairing observed air temperatures with eight flow scenarios. Means of all years are shown with black points and grey "x" show individual years, offset for clarity.

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

		Daily maximum stream temperature (T_{max})						Daily mean stream temperature (T_{mean})					
Model Name	**Predictor variables**	**BIC**	**AR1**	**edf_F**	**edf_R**	**RMSE**	**R^2**	**BIC**	**AR1**	**edf_F**	**edf_R**	**RMSE**	**R^2**
GAM1: tensor Q-A_{2w}-D	te(Q, A_{2w}, D)	12830	0.526	23.6	18.1	1.06	0.973	8562	0.659	22.8	18.1	0.80	0.978
GAM2: tensors Q-D & A_{2w}-D	s(A_{2w}) + ti(A_{2w}, D) + te(Q, D)	12734	0.529	18.4	18.0	1.05	0.974	8492	0.667	17.1	18.0	0.80	0.979
GAM3: tensor Q-D & vary A_{2w}	s(D, by = A_{2w}) + s(A_{2w}) + te(Q, D)	12745	0.531	18.0	18.0	1.05	0.974	8482	0.672	16.3	18.0	0.80	0.978
GAM4: tensors Q-D & A_{2w}-Q	s(D, by = A_{2w}) + s(A_{2w}) + ti(A_{2w}, Q) + te(Q, D)	12717	0.531	17.2	17.9	1.05	0.974	8486	0.671	16.9	18.0	0.80	0.978
GAM5: tensor Q-D no vary A_{2w}	s(A2w) + te(Q, D)	12724	0.537	15.7	17.9	1.06	0.974	8456	0.679	15.6	17.9	0.80	0.978
GAM6: vary Q & A_{2w} linear	s(D, by = A_{2w}) + s(D, by = Q) + s(D)	12828	0.578	13.9	17.8	1.12	0.970	8594	0.728	10.9	17.3	0.89	0.973
GAM7: vary Q & A_{2w} (final)	s(D, by = A2w) + s(A_{2w}) + s(Q) + s(D, by = Q) + s(D)	12754	0.544	12.6	17.9	1.07	0.973	8538	0.695	11.8	17.6	0.84	0.976
GAM8: vary Q & no vary A_{2w}	s(A_{2w}) + s(Q) + s(D, by = Q) + s(D)	12736	0.552	12.3	17.8	1.08	0.973	8526	0.704	11.8	17.5	0.84	0.976
GAM9: A_{2w} no vary	s(A_{2w}) + s(Q) + s(D)	13105	0.673	8.4	17.6	1.32	0.959	8738	0.764	8.1	17.6	0.96	0.969
GAM10: A_{2w} no Q or vary	s(A_{2w}) + s(D)	13313	0.780	6.0	17.3	1.62	0.938	9150	0.840	6.0	16.6	1.20	0.952
GAM11: A7 only no AR1	s(A_7)	22668	N/A	5.8	0	2.40	0.865	20265	N/A	5.8	0	1.88	0.882

Note: Models are sorted by edf_F for T_{max}, from most complex (GAM1) to least complex (GAM11). Except GAM11, all models also include an AR1 autocorrelation structure and random effect of year. D = day of year from 1 (1 January) to 366 (31 December in leap year), Q = daily mean flow, see Section 3.1.2 for key to 'A' air temperature variables, 's()' is a nonlinear function, 's(D, by =)' is a linear interaction that varies smoothly by D, 'te()' is a fully nonlinear tensor product smooth of two or three variables, 'ti()' is a tensor product interaction, BIC = Bayesian information criterion score, AR1 = autocorrelation coefficient, 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 model scenarios representing combinations of air temperature and flow inputs, and organized into two scenario groups. The first group (15 scenarios) 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) were run only at Scott River and used “observed air temperature” inputs.

Scenario group	**Air temperature inputs**	**Flow inputs**							
		Lowest (0.1 quantile)	**Typical** (0.5 quantile)	**Highest** (0.9 quantile)	**USFS water right**	**CDFW flow criteria**	**Observed**	**Maximum of observed or USFS**	**Maximum of observed or CDFW**
Quantile air temperature	**Hottest** (0.9 quantile)	All sites	All sites	All sites	Scott only	Scott only			
	Typical (0.5 quantile)	All sites	All sites	All sites	Scott only	Scott only			
	Coolest (0.1 quantile)	All sites	All sites	All sites	Scott only	Scott only			
Observed air temperature	**Observed** (measured on date)	Scott only	Scott only	Scott only	Scott only	Scott only	Scott only	Scott only	Scott only

Figure 1.

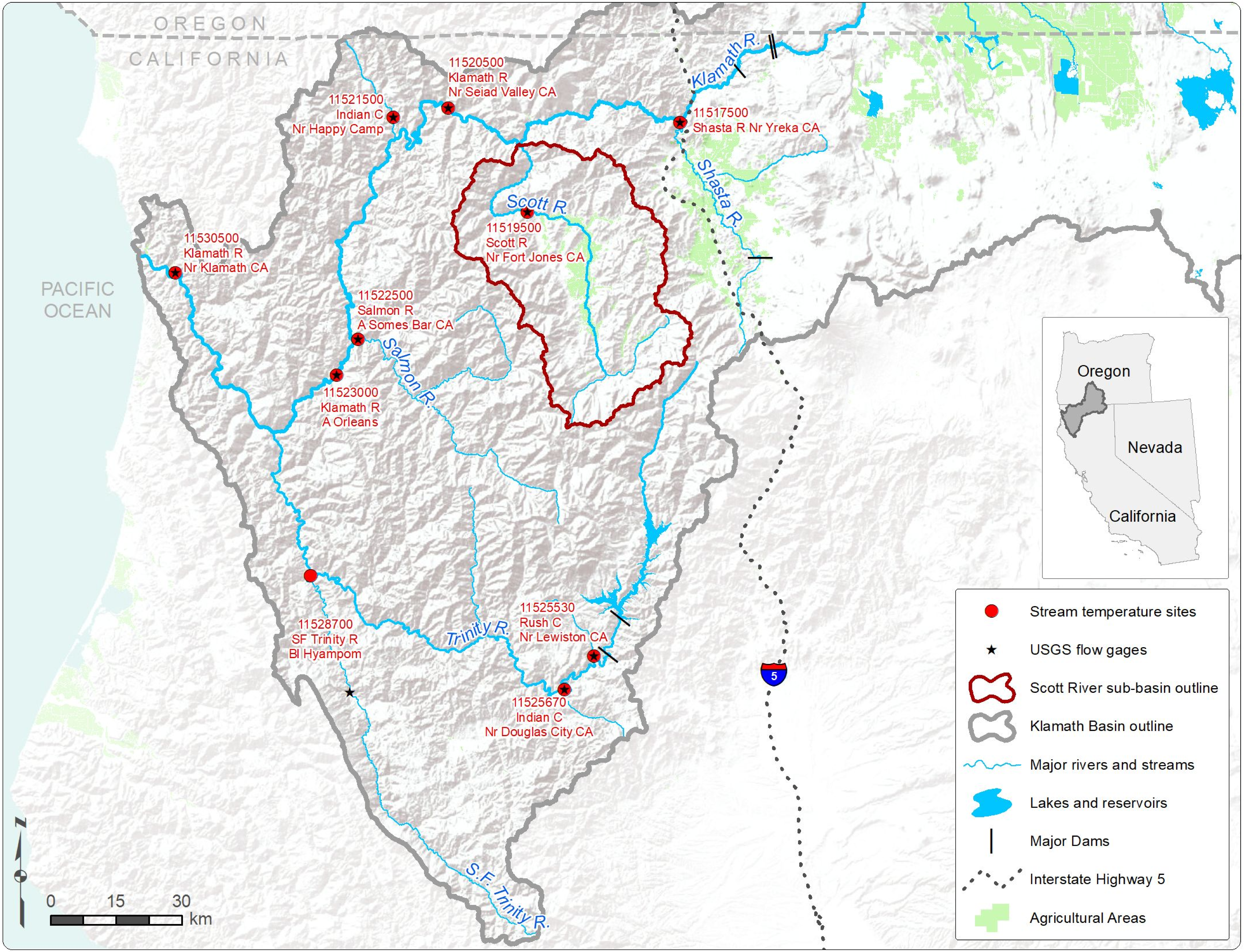
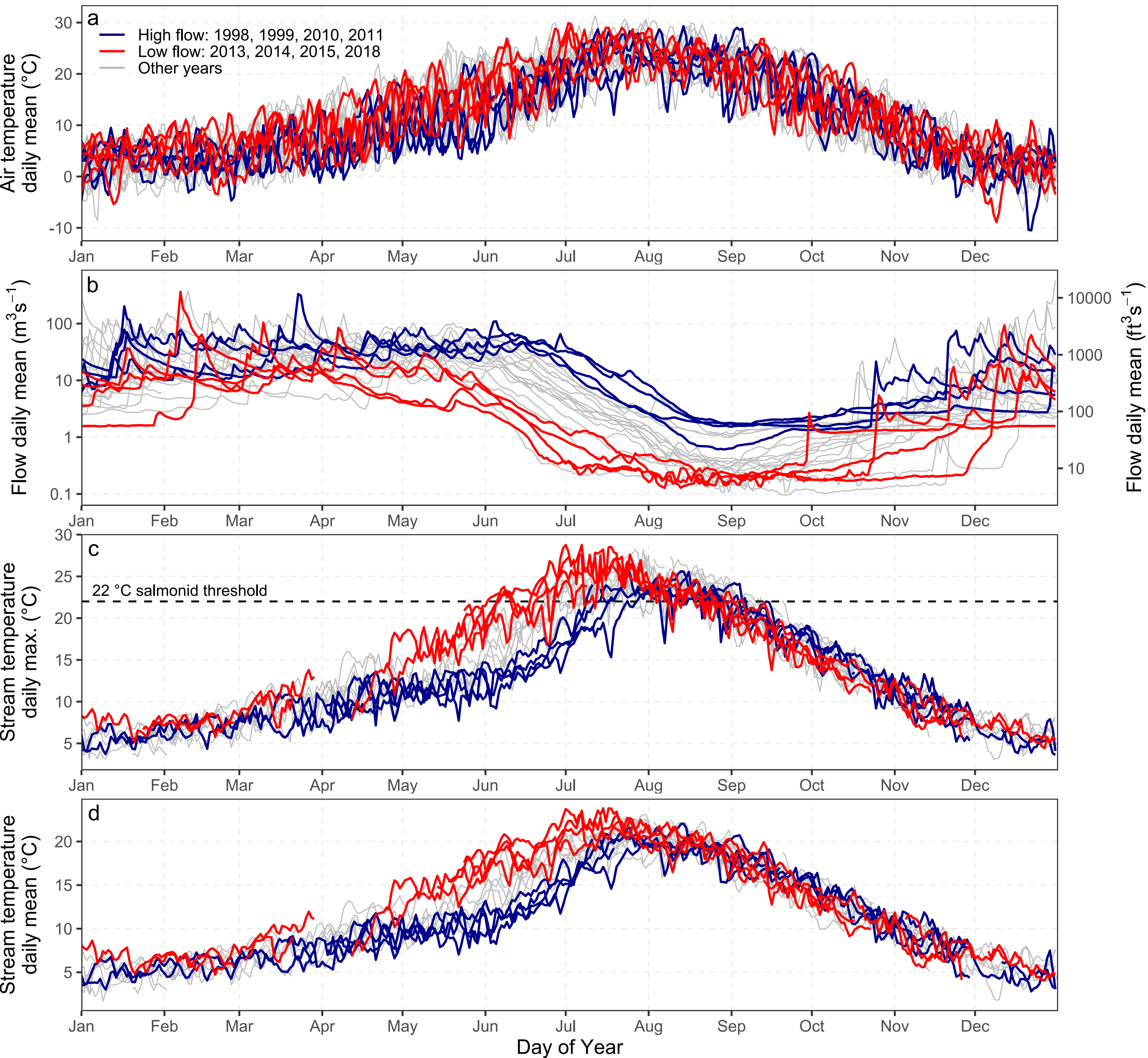
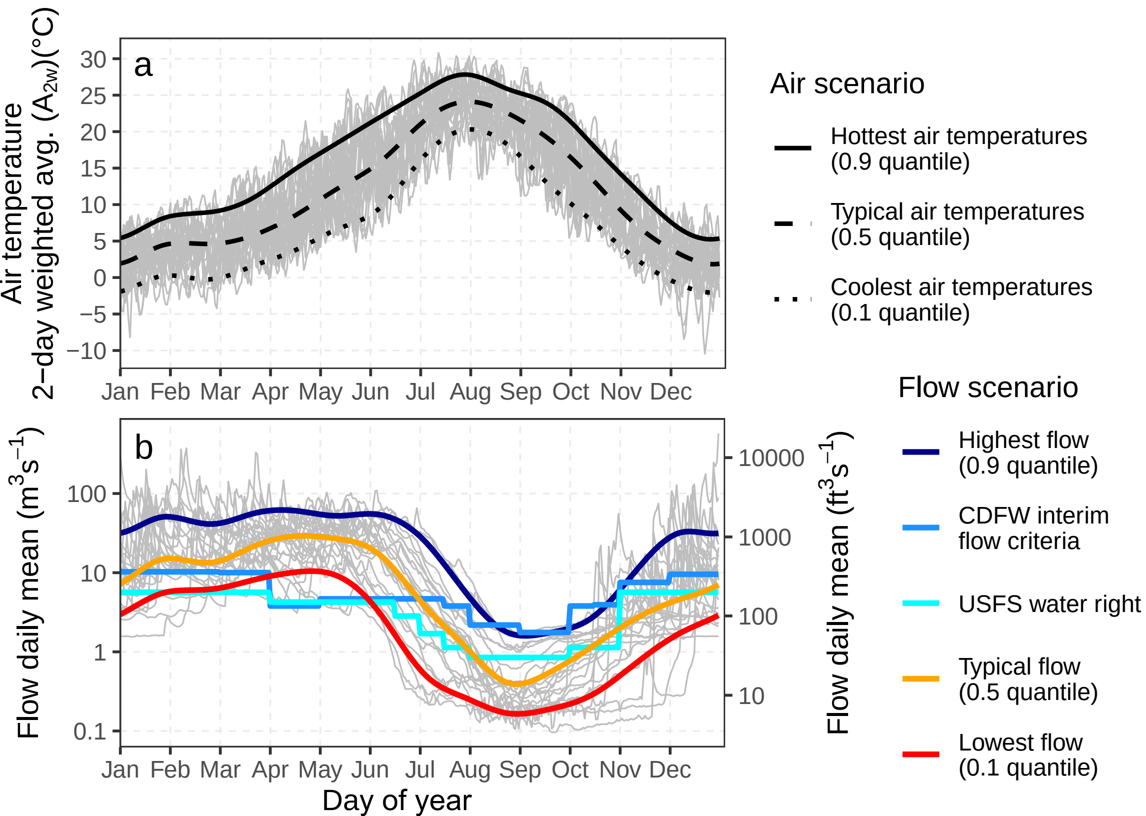

OREGON
CALIFORNIA
PACIFIC OCEAN
11520500 Klamath R Nr Seiad Valley CA
11521500 Indian C Nr Happy Camp
11517500 Shasta R Nr Yreka CA
Klamath R.
Shasta R.
Scott R.
11519500 Scott R Nr Fort Jones CA
11530500 Klamath R Nr Klamath CA
11522500 Salmon R A Somes Bar CA
Salmon R.
11523000 Klamath R A Orleans
11528700 SF Trinity R Bl Hyampom
Trinity R.
11525530 Rush C Nr Lewiston CA
11525670 Indian C Nr Douglas City CA
S.F. Trinity R.
5
Oregon
Nevada
California
Stream temperature sites
USGS flow gages
Scott River sub-basin outline
Klamath Basin outline
Major rivers and streams
Lakes and reservoirs
Major Dams
Interstate Highway 5
Agricultural Areas
N
0 15 30
km

Figure 2.



a
High flow: 1998, 1999, 2010, 2011
Low flow: 2013, 2014, 2015, 2018
Other years
Air temperature daily mean (°C)
30
20
10
0
-10
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
b
Flow daily mean (m^3s^{-1})
100
10
1
0.1
Flow daily mean (ft^3s^{-1})
10000
1000
100
10
c
22 °C salmonid threshold
Stream temperature daily max. (°C)
30
25
20
15
10
5
d
Stream temperature daily mean (°C)
20
15
10
5
Day of Year

Figure 3.



a
Air temperature
2−day weighted avg. (A_{2w})(°C)
30
25
20
15
10
5
0
−5
−10
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Air scenario
Hottest air temperatures (0.9 quantile)
Typical air temperatures (0.5 quantile)
Coolest air temperatures (0.1 quantile)
b
Flow daily mean ($m^3 s^{-1}$)
100
10
1
0.1
Flow daily mean ($ft^3 s^{-1}$)
10000
1000
100
10
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Day of year
Flow scenario
Highest flow (0.9 quantile)
CDFW interim flow criteria
USFS water right
Typical flow (0.5 quantile)
Lowest flow (0.1 quantile)

Figure 4.

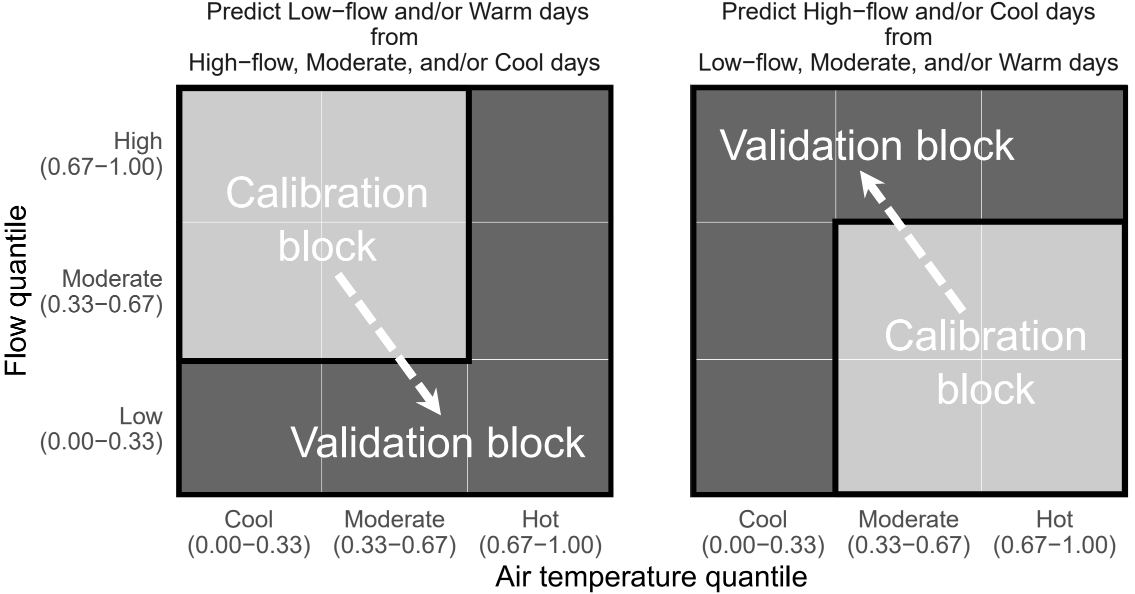
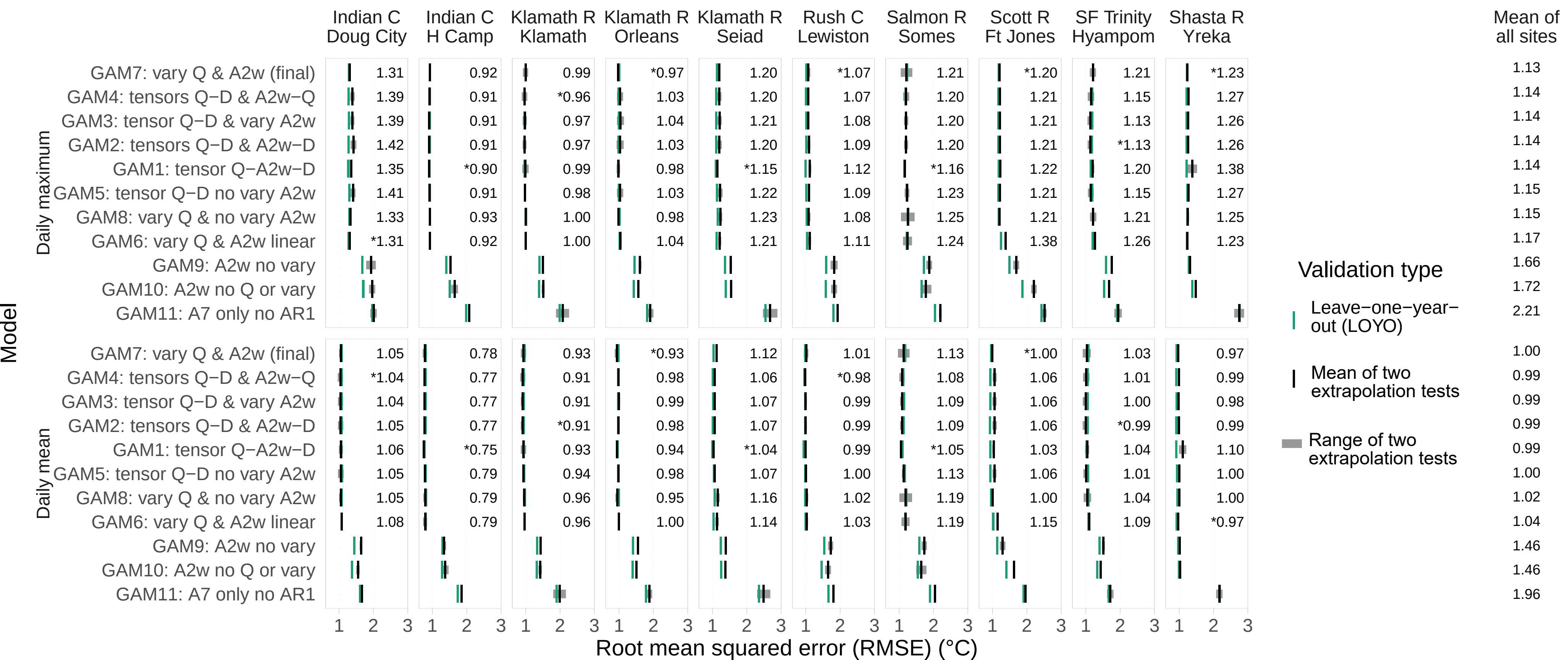
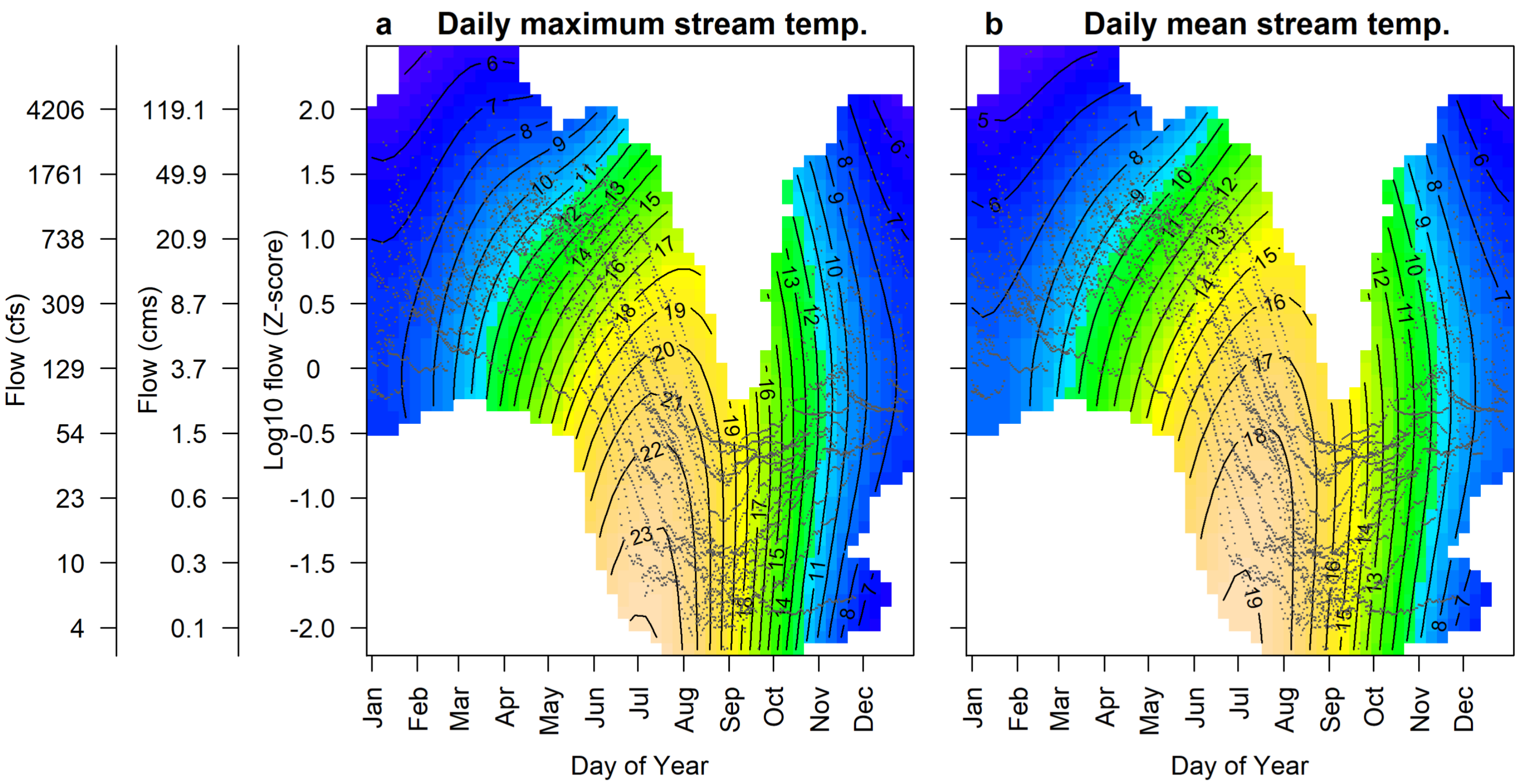

Predict Low−flow and/or Warm days
from
High−flow, Moderate, and/or Cool days
Predict High−flow and/or Cool days
from
Low−flow, Moderate, and/or Warm days
Calibration block
Validation block
Validation block
Calibration block
Flow quantile
High (0.67−1.00)
Moderate (0.33−0.67)
Low (0.00−0.33)
Cool (0.00−0.33)
Moderate (0.33−0.67)
Hot (0.67−1.00)
Cool (0.00−0.33)
Moderate (0.33−0.67)
Hot (0.67−1.00)
Air temperature quantile

Figure 5.



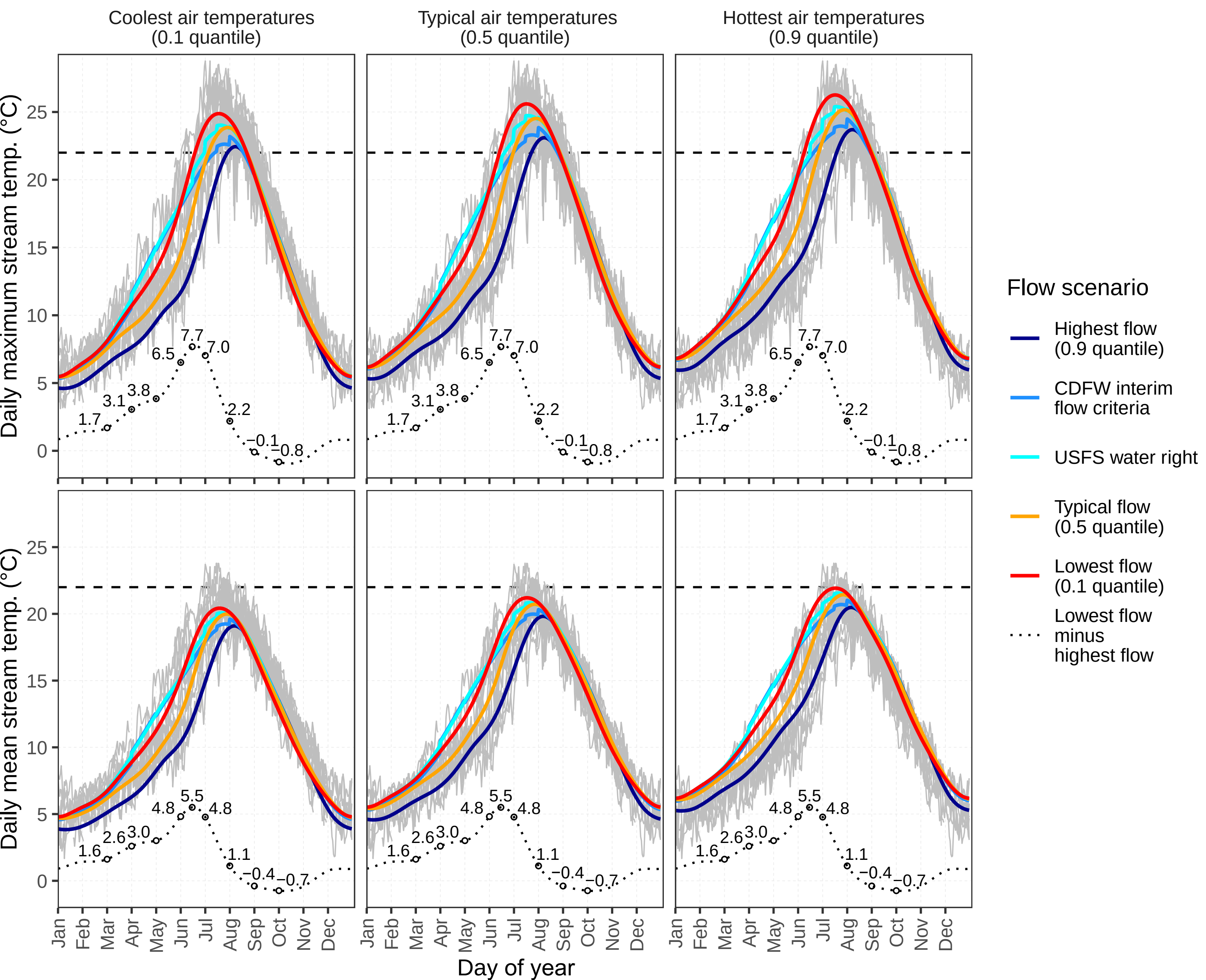
Indian C Doug City
Indian C H Camp
Klamath R Klamath
Klamath R Orleans
Klamath R Seiad
Rush C Lewiston
Salmon R Somes
Scott R Ft Jones
SF Trinity Hyampom
Shasta R Yreka
Mean of all sites
Daily maximum
GAM7: vary Q & A2w (final) 1.31 0.92 0.99 *0.97 1.20 *1.07 1.21 *1.20 1.21 *1.23 1.13
GAM4: tensors Q−D & A2w−Q 1.39 0.91 *0.96 1.03 1.20 1.07 1.20 1.21 1.15 1.27 1.14
GAM3: tensor Q−D & vary A2w 1.39 0.91 0.97 1.04 1.21 1.08 1.20 1.21 1.13 1.26 1.14
GAM2: tensors Q−D & A2w−D 1.42 0.91 0.97 1.03 1.20 1.09 1.20 1.21 *1.13 1.26 1.14
GAM1: tensor Q−A2w−D 1.35 *0.90 0.99 0.98 *1.15 1.12 *1.16 1.22 1.20 1.38 1.14
GAM5: tensor Q−D no vary A2w 1.41 0.91 0.98 1.03 1.22 1.09 1.23 1.21 1.15 1.27 1.15
GAM8: vary Q & no vary A2w 1.33 0.93 1.00 0.98 1.23 1.08 1.25 1.21 1.21 1.25 1.15
GAM6: vary Q & A2w linear *1.31 0.92 1.00 1.04 1.21 1.11 1.24 1.38 1.26 1.23 1.17
GAM9: A2w no vary 1.66
GAM10: A2w no Q or vary 1.72
GAM11: A7 only no AR1 2.21
Daily mean
GAM7: vary Q & A2w (final) 1.05 0.78 0.93 *0.93 1.12 1.01 1.13 *1.00 1.03 0.97 1.00
GAM4: tensors Q−D & A2w−Q *1.04 0.77 0.91 0.98 1.06 *0.98 1.08 1.06 1.01 0.99 0.99
GAM3: tensor Q−D & vary A2w 1.04 0.77 0.91 0.99 1.07 0.99 1.09 1.06 1.00 0.98 0.99
GAM2: tensors Q−D & A2w−D 1.05 0.77 *0.91 0.98 1.07 0.99 1.09 1.06 *0.99 0.99 0.99
GAM1: tensor Q−A2w−D 1.06 *0.75 0.93 0.94 *1.04 0.99 *1.05 1.03 1.04 1.10 0.99
GAM5: tensor Q−D no vary A2w 1.05 0.79 0.94 0.98 1.07 1.00 1.13 1.06 1.01 1.00 1.00
GAM8: vary Q & no vary A2w 1.05 0.79 0.96 0.95 1.16 1.02 1.19 1.00 1.04 1.00 1.02
GAM6: vary Q & A2w linear 1.08 0.79 0.96 1.00 1.14 1.03 1.19 1.15 1.09 *0.97 1.04
GAM9: A2w no vary 1.46
GAM10: A2w no Q or vary 1.46
GAM11: A7 only no AR1 1.96
Model
1 2 3
Root mean squared error (RMSE) (°C)
Validation type
Leave−one−year−out (LOYO)
Mean of two extrapolation tests
Range of two extrapolation tests

Figure 6.



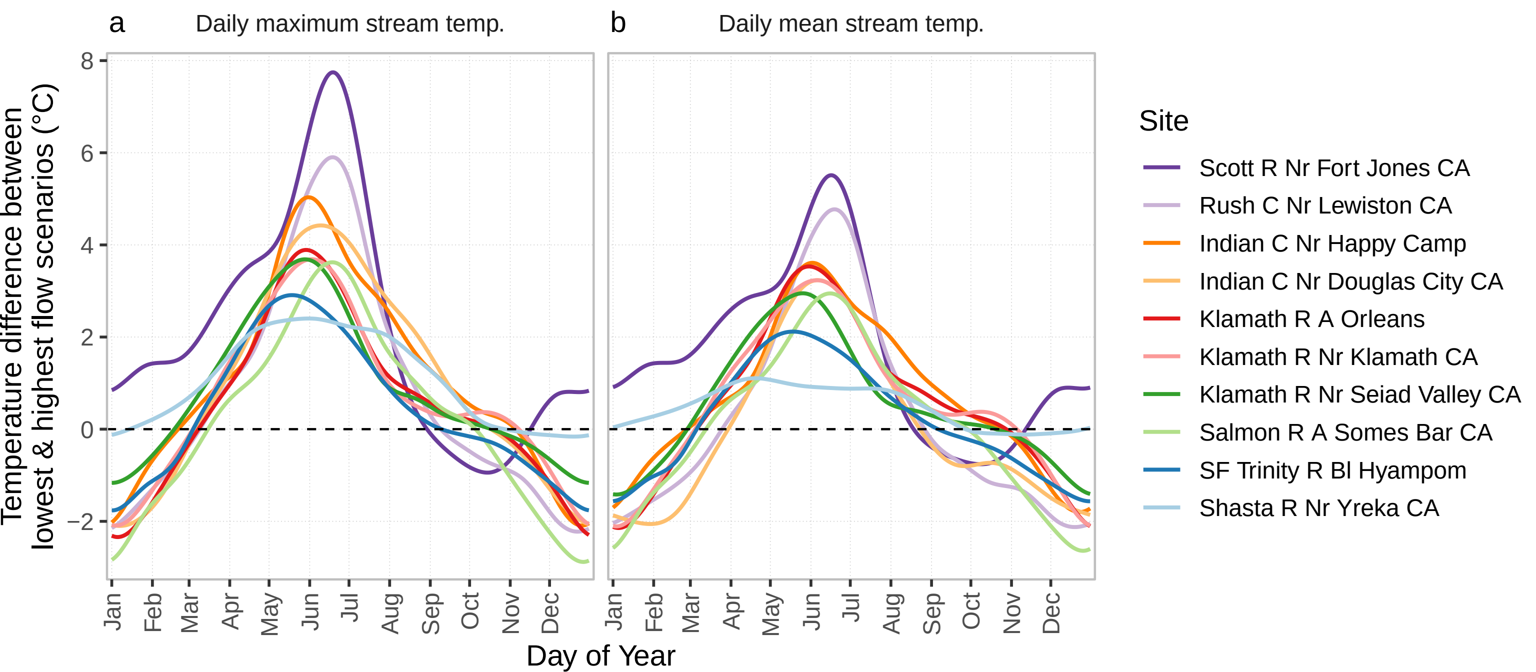
a Daily maximum stream temp.
b Daily mean stream temp.
Flow (cfs)
Flow (cms)
Log10 flow (Z-score)
4206
1761
738
309
129
54
23
10
4
119.1
49.9
20.9
8.7
3.7
1.5
0.6
0.3
0.1
2.0
1.5
1.0
0.5
0
-0.5
-1.0
-1.5
-2.0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Day of Year

Figure 7.



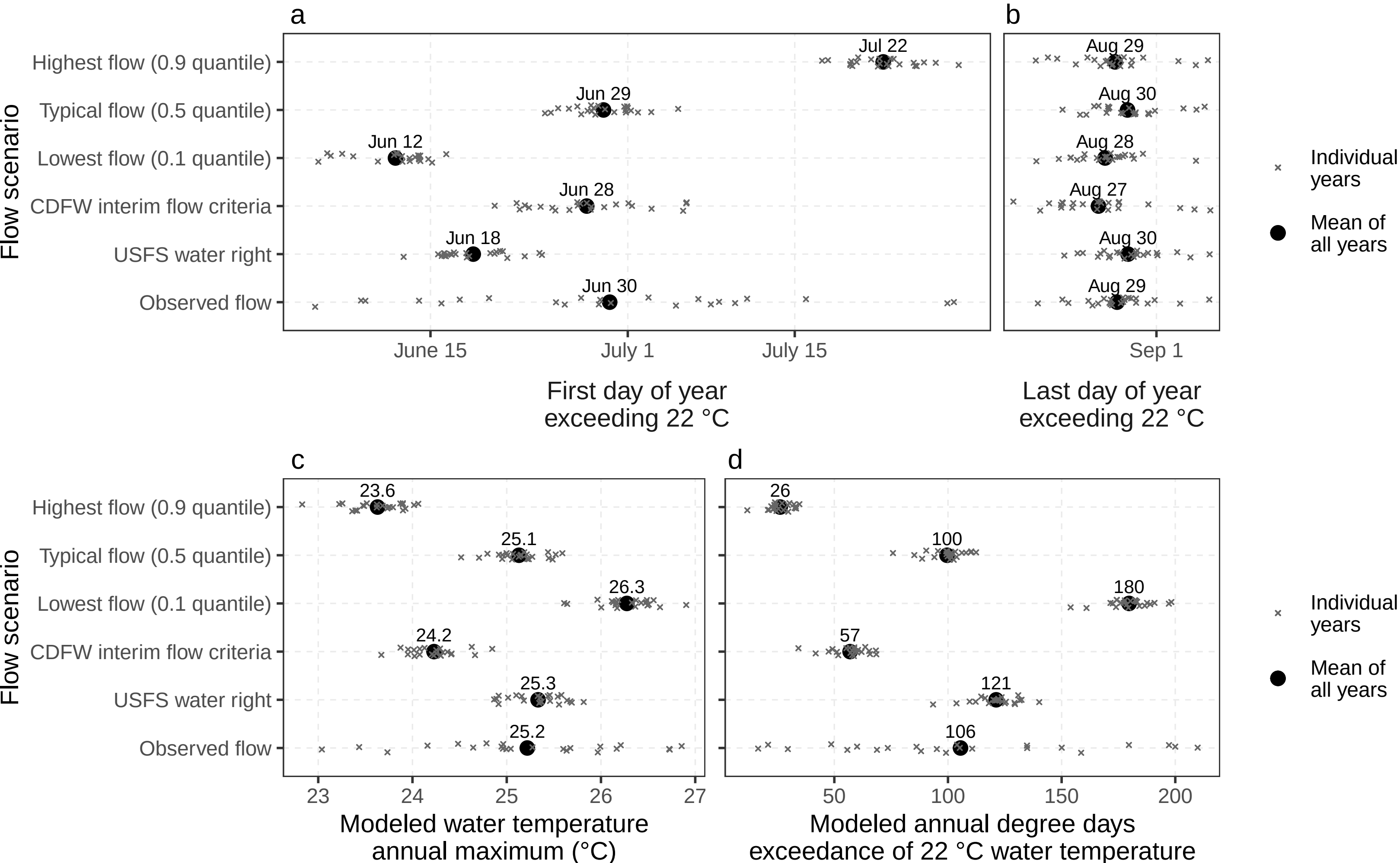
Coolest air temperatures
(0.1 quantile)
Typical air temperatures
(0.5 quantile)
Hottest air temperatures
(0.9 quantile)
Daily maximum stream temp. (°C)
Daily mean stream temp. (°C)
Day of year
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Flow scenario
Highest flow
(0.9 quantile)
CDFW interim
flow criteria
USFS water right
Typical flow
(0.5 quantile)
Lowest flow
(0.1 quantile)
Lowest flow
minus
highest flow

Figure 8.



a
Daily maximum stream temp.
b
Daily mean stream temp.
Temperature difference between
lowest & highest flow scenarios (°C)
8
6
4
2
0
−2
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Day of Year
Site
Scott R Nr Fort Jones CA
Rush C Nr Lewiston CA
Indian C Nr Happy Camp
Indian C Nr Douglas City CA
Klamath R A Orleans
Klamath R Nr Klamath CA
Klamath R Nr Seiad Valley CA
Salmon R A Somes Bar CA
SF Trinity R Bl Hyampom
Shasta R Nr Yreka CA

Figure 9.


a
b
c
d
Flow scenario
Highest flow (0.9 quantile)
Typical flow (0.5 quantile)
Lowest flow (0.1 quantile)
CDFW interim flow criteria
USFS water right
Observed flow
Jul 22
Jun 29
Jun 12
Jun 28
Jun 18
Jun 30
June 15
July 1
July 15
First day of year exceeding 22 °C
Aug 29
Aug 30
Aug 28
Aug 27
Aug 30
Aug 29
Sep 1
Last day of year exceeding 22 °C
Individual years
Mean of all years
23.6
25.1
26.3
24.2
25.3
25.2
23
24
25
26
27
Modeled water temperature annual maximum (°C)
26
100
180
57
121
106
50
100
150
200
Modeled annual degree days exceedance of 22 °C water temperature