Relationships Between Water Temperature, Air Temperature, and River Flows in the Scott River near Fort Jones, California

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Executive Summary

High water temperatures are stressful to juvenile salmon and steelhead in the Scott River. The Quartz Valley Indian Reservation (QVIR) Environmental Department monitors water quality at the U.S. Geological Survey (USGS) Scott River gage using multi-parameter sondes. The Klamath National Forest also monitors water temperature at the same site. During the months of May–July, water temperatures are generally much cooler in years with high river flow than in years with low river flow. In this memo, we develop a statistical model to analyze the relationships between daily flow, air temperature, and water temperature data collected during the months of May–October,1995–2018. We then use that model to predict daily water temperatures under a variety of scenarios with different combinations (i.e., high, typical, and low) of flows and air temperatures. Additional flow scenarios include the USFS first-priority Schedule D water right and the California Department of Fish and Wildlife's 2017 Interim Instream Flow Criteria. The CDFW and USFS flows do not consistently track any particular water year type throughout the entire season but instead represent extreme drought conditions in May, then represent high flow year conditions in September and October. The purpose of this analysis is to quantitatively assess the importance of instream flows to water temperature in the Scott River.

The model results suggest that flow and air temperature both have strong effects on water temperature. The cooling effect of high flow varies across the season, with greater effects in May–July than August, and almost no effect in September and October. For example, relative to the lowest-flow scenarios, the water temperatures predicted under the highest-flow scenarios are 6.3 °C cooler on June 1, 3.5 °C cooler on August 1, and similar on October 1. With short days and naturally lower air temperatures than earlier months, water temperatures are almost always less than 22 °C in September and October regardless of flow. Consistent with patterns seen in the measured data, the model predicts that annual maximum water temperatures occur later in the season in high-flow years (i.e., late July or early August) than in low-flow years (i.e., early/mid-July), extending the duration of the period when cool water habitat is available for fish.

Annual maximum daily maximum water temperatures (i.e., the single hottest temperature of the entire year) are up to 4.4 °C cooler in the highest-flow scenarios than the scenarios with the lowest flow. Higher flows delay and diminish the magnitude and frequency of exceedances of the biologically important 22 °C temperature threshold, but exceedances are still predicted during days with the hottest air temperatures each year which typically occur in July and/or August.

If the flow on days which dropped below the CDFW instream flow criteria could instead be maintained at CDFW instream flow criteria, the model predicts that the date of onset of water temperatures greater than 22 °C would be delayed during drought years, average annual degree-days exceedance of 22 °C (a metric of cumulative thermal stress) would be reduced from 95 to 36, and average annual maximum temperature would be reduced to from 25.6 °C to 24.2 °C. Maintaining flows at levels equivalent the USFS water right would also cool water temperatures, but less cooling would occur than with the higher CDFW instream flow criteria.

While flow appears to be an important driver of water temperatures in the Scott River in the months of May–August, it is difficult to recommend a single flow threshold based solely on temperature.

We are currently preparing a manuscript for peer-review, which if published would supersede this technical memorandum.

Introduction and methods

Scott River study area

The Scott River is located in Siskiyou County in northwest California, USA and is tributary to the Klamath River (Figure 1). The climate is Mediterranean with precipitation occurring primarily in winter and spring. Elevations in the Scott River's mountainous headwaters exceed 2500m (Foglia et al. 2013). The human population is focused primarily in the alluvial Scott Valley at the center of the Scott River watershed. Most valley land is privately owned while the higher elevations are primarily National Forest. Irrigated agriculture is the dominant land use in the valley. In the summer and fall, river flows are depleted by withdrawal of groundwater and surface water for agricultural irrigation (Van Kirk and Naman 2008). There are ongoing efforts to model interactions between groundwater and surface water (Foglia et al. 2013, Tolley et al. 2018). In response to Sustainable Groundwater Management Act regulations, Siskiyou County is leading development of a groundwater sustainability plan for the valley.

The low-gradient streams of the Scott Valley have extremely high intrinsic potential for coho salmon, although the habitat is currently impaired (NMFS 2014). High water temperatures in the Scott River are stressful to culturally and economically important salmon and steelhead (NCRWQCB 2006). Various waterbodies within the Scott River sub-basin are listed as impaired under the Clean Water Act. California's North Coast Regional Water Quality Control Board developed Total Maximum Daily Loads (TMDLs) for water temperature and sediment in 2006 (NCRWQCB 2006). Portions of the river are also listed for biostimulatory conditions, pH, dissolved oxygen, and aluminum, but TMDLs have not yet been developed for those parameters.

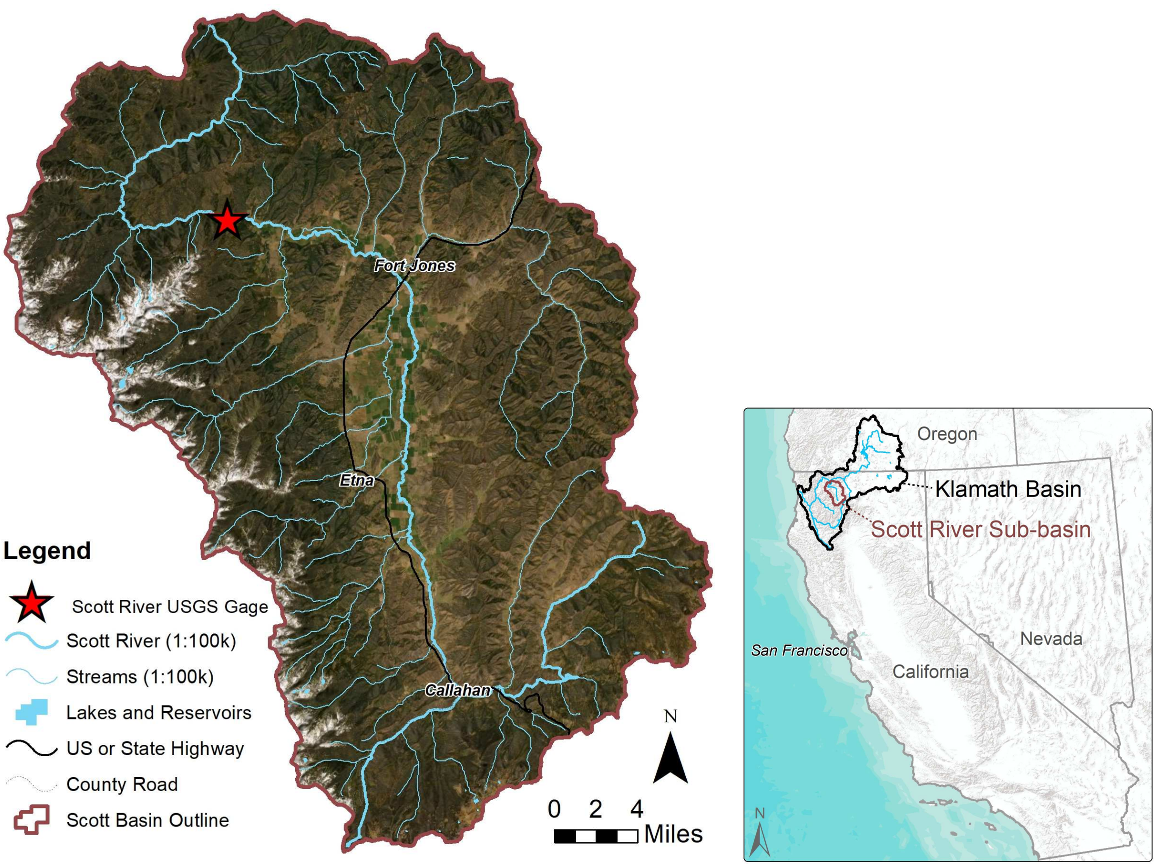

Figure 1. Maps showing the location of the USGS gage within the Scott River watershed, and the Scott River watershed in relation to California and the Klamath Basin.

Data sources and data preparation

Water temperature and river flow

Since 2007, the Quartz Valley Indian Reservation (QVIR) Environmental Department has been using YSI multi-parameter datasondes to monitor water quality in the Scott River at the U.S. Geological Survey (USGS) gage 11519500 near the outlet of Scott Valley (QVIR 2008, 2009, 2011, 2013, 2016; Asarian and Kann 2013) (Figure 1). Parameters include water temperature, dissolved oxygen (DO), pH, specific conductance, and turbidity. Measurements are recorded every 30 minutes. In a previous analysis of the QVIR sonde data for the years 2007–2012 and 2014–2018, these data were compiled, reviewed, and any suspicious values (e.g., when there were calibration issues or probes appear to have been exposed to air) were removed (Asarian 2019).

The U.S. Forest Service (USFS) also monitors water temperature at this same site. For the years 1995–1998, 2006, and 2010–2016, these data were compiled, reviewed, and any suspicious values were removed as part of a Klamath basin-wide stream temperature analysis (Asarian et al. 2020).

We calculated and compiled daily summary statistics (minimum, mean, and maximum) of the USFS and QVIR water temperature data. For days on which these daily summaries were available from both entities, we averaged the values together.

Daily average streamflow for USGS gage 11519500 were downloaded from the USGS National Water Information System (NWIS)[1].

Air temperature

The USFS monitors air temperature at a Remote Automated Weather Station (RAWS) located at the top of Quartz Hill[2], approximately 5 miles east-southeast of the USGS flow gage. Following review and removal of suspicious values, we calculated daily summaries (minimum, mean, and maximum) from the air temperature data. For a small number of days lacking measured air temperature data, we estimated missing air temperature values using linear regression (r^2=0.90) between the measured Quartz Hill air temperature and modeled air temperature data for the closest 4km-resolution grid cell from PRISM[3] (Daly et al. 2008).

Data analysis

Model calibration

We used the *nlme* package version 3.1-137 (Pinheiro et al. 2018) in R (R Core Team 2019) to develop a linear mixed effects model to estimate daily maximum water temperatures under varying flow and air temperature conditions. We calibrated the model using all available data from the years 1995–2018. We compared several alternative model configurations using Akaike information criterion (AIC); however, in the interest of brevity this memo focuses almost exclusively on the final model. The only results presented in this memo for alternative models is a time series graph in Appendix B that compares the predictions of the final model with an alternative model that excludes flow (i.e., uses only air temperature and day of the year). We also developed a similar model for daily mean water temperatures but do not report those results in this memo.

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[1] https://waterdata.usgs.gov/ca/nwis/uv?site_no=11519500
[2] https://raws.dri.edu/cgi-bin/rawMAIN.pl?caCQUA
[3] http://www.prism.oregonstate.edu/explorer/

The relationship between water temperature and flow varies over the course of the year as a result of numerous other variables which follow their own seasonal cycles. For example, the source and flow paths of river water varies seasonally according to precipitation form (i.e., snow and rain), groundwater dynamics of hillslope and alluvial aquifers, and irrigation management (i.e., water withdrawals and subsequent return flows back the river via surface or groundwater). In addition, the effects of flow on water temperature could be seasonally mediated by variables that affect the intensity and duration of solar radiation striking the water, such as day length, solar angle, cloud cover, wildfire smoke, and leaf out and leaf fall of deciduous riparian vegetation. Some of these variables follow exactly the same seasonal trajectory each year while the timing of others fluctuate within ranges, but all have an annual cycle. It is not possible to include all these individual factors in a statistical model, so instead we use a harmonic regression approach by including annual sine-waves as proxies representing the implicit aggregation of these factors. Harmonic regression (also known as trigonometric regression and periodic regression) uses paired sine and cosine terms to represent periodicity (Cox 2006). For daily periodicity, the day of the year (1 to 365) is multiplied by 2π/365 (Helsel et al. 2020). Inclusion of both the sine and cosine (i.e., rather than just one) is needed to allow to the phase (i.e., timing) of the cycle to fit the data (Helsel et al. 2020). In our regression, we use paired sine and cosine terms to allow three elements to vary as a smooth cycle over the course of the year: 1) water temperature, and 2) the slope of the relationship between flow and water temperature. Harmonic regression to model the annual cycle of water temperature (i.e., #1 in the previous sentence) has been commonly used for many decades (Kothandaraman 1971, Johnson et al 2020); however, in the context of water temperature modeling we are not aware of previous application of this technique to covariates (i.e., predictor variables) other than day, although it as used in other disciplines (Bodeker et al. 1998, Roundy et al. 2017). Our final regression equation is:

$$T_w = \beta_0 + \beta_1 T_a + \beta_2 \sin(dn) T_a + \beta_3 \cos(dn) T_a + \beta_4 Q + \beta_5 \sin(dn) Q + \beta_6 \cos(dn) Q + \beta_7 \sin(dn) + \beta_8 \cos(dn) + \varepsilon$$

Where T_w = daily maximum water temperature in units of degrees Celsius, T_a = daily mean air temperature, Q = daily mean flow in units of log base 10 cubic feet per second, d = day of the year (ranges from 1 [January 1] to 365 [December 31]), $n = 2\pi/365$, ε is an autocorrelation term, and β_0, β_1, β_2, β_3, β_4, β_5, β_6, β_7 and β_8 are coefficients. The autocorrelation term (corCAR1, first order with a continuous time covariate) is included because water temperatures on adjacent days are highly correlated with each other. We also included a random intercept for year.

Model scenarios

We used non-parametric quantile regression to calculate the flow[4] and air temperature associated with various quantiles (0.05, 0.50, and 0.95, equivalent to 5%, 50%, 95% exceedance probabilities) for each day of the year. For flow, the 0.50 quantile represents a typical year, the 0.05 quantile represents the years with very low flow conditions, and the 0.95 quantile represents years with very high flow conditions. We calculated similar quantiles (0.05, 0.50, and 0.95) for air temperatures. All non-parametric quantile regressions were performed in R using the quantregGrowth package (Muggeo et al. 2013). Whereas linear regression is used to predict the conditional mean of the response variable given a value of a predictor variable, quantile regression is used to predict the conditional median or other quantiles of the response variable (Cade and Noon 2003). Quantile regression is less affected by outliers than linear regression and is useful when the assumptions of linear regression are not met. Quantile

[4] Flow was base 10 log-transformed prior to non-parametric quantile regression, and then back-transformed into original units (cfs) for presenting in this memo's tables and figures.

regression is particularly useful when other variables besides the primary predictor variable affect the response variable (Cade and Noon 2003). Non-parametric quantile regression is a type of quantile regression that allows flexible curves rather than straight lines. The quantregGrowth packages provides several options including: 1) whether curves for different percentiles are allowed to cross, 2) whether curves are forced to be monotonic (e.g., one variable tends to increase [or alternatively, decrease] as the other variable increases), 3) a lambda value which determines the amount of "wiggle" in the curves, and 4) a penalty term used to prevent under-smoothing. We experimented with several combinations of these options and ended up running non-parametric quantile regression for all variables using the same set of options that appeared to fit well: 1) allowing the curves for different quantiles to cross, 2) not forcing monotonicity, 3) lambda = 2, 4) a varying penalty of (1:k)^3.

We then used the linear mixed effects model to predict water temperatures under 15 different scenarios representing combinations of air temperatures (cool = 0.05 quantile, typical = 0.50 quantile, hot = 0.95 quantile) and flows (low = 0.05 quantile, typical = 0.50 quantile, high = 0.95 quantile, and USFS = the USFS Schedule D first-priority water right, and CDFW = CDFW Interim Instream Flow Criteria). The USFS first-priority Scheduled D water right varies by month and day, from a high of 200 cfs in November through March to a low of 30 cfs in August and September (Superior Court for Siskiyou County 1980)(Appendix A). The California Department of Fish and Wildlife Interim Instream Flow Criteria vary by month and day, from a minimum of 62 cfs in September to a high of 362 in February (CDFW 2017). Interestingly, the CDFW and USFS flows do not consistently track any particular quantile through the entire season. They are extreme drought conditions in May (0.05 quantile) but high flows in September (and lesser extent August and October).

Finally, we used the linear mixed effects model to predict water temperatures under eight additional scenarios which pair the observed air temperature time series for 1995-2018 with eight flow conditions: observed USGS flows in addition to the five flows used in the other scenarios (low, typical, high, USFS, and CDFW) as well as two additional scenarios in which the CDFW and USFS flows are used as minimums that are supplanted by observed USGS flows on days when the observed flows are higher.

In this memo, daily maximum water temperatures are compared to a threshold of 22 °C (Table 1).

Table 1. Regulatory and biological thresholds used for this analysis.

Threshold	Justification
Streamflow <40cfs	U.S. Forest Service first priority Schedule D water right for July 16–31 and October 1–31 (Superior Court for Siskiyou County 1980)*
Streamflow <30cfs	U.S. Forest Service first priority Schedule D water right for August 1–September 30 (Superior Court for Siskiyou County 1980)*
Water temperature daily maximum >22 °C	Not an adopted objective. When the mainstem Klamath River exceeds 22-23 °C, juvenile salmonids congregate in thermal refugia at tributary confluences (Sutton et al. 2007, Sutton and Soto 2012, Brewitt and Danner 2014). Similar results have been found in the Scott River (Maurer 2007).

Table notes:
* See Appendix A for details. The U.S. Forest Service first priority Schedule D water right varies by month and day, from a low of 30 cfs in August–September to a high of 200 cfs in November–March.

Results and Discussion

Measured water temperature, air temperature, and flow

The daily time series of measured water temperatures for all available years (1995–1998 and 2006–2018) shows that during the months of May-July, water temperatures were highly variable between years (Figure 1). During those months, water temperatures during highest-flow years are up to almost 10°C cooler than during lowest-flow years. In contrast, during the months of August through October inter-annual differences in water temperature are much less pronounced. Annual maximum water temperatures occur 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.

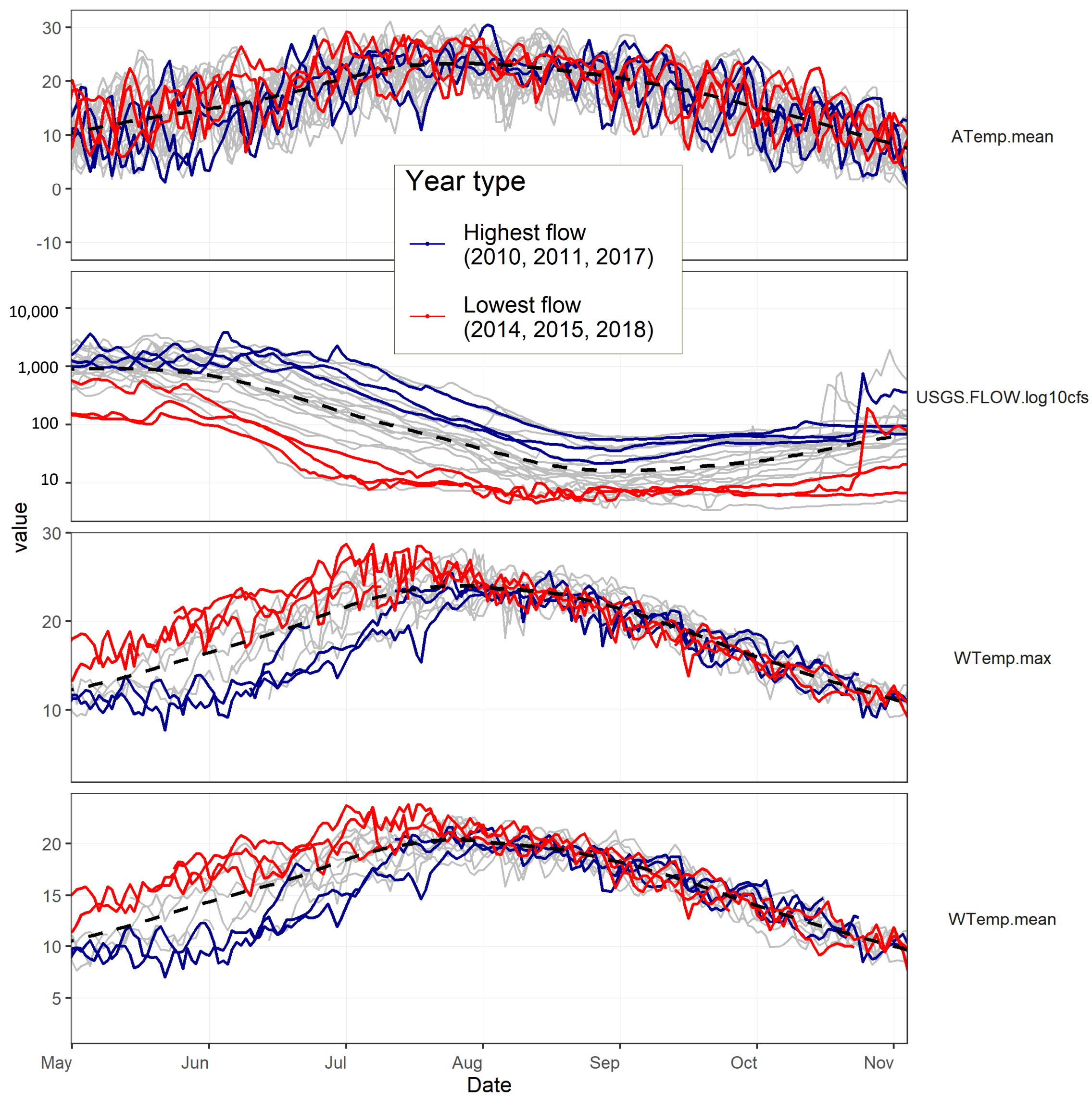

Figure 2. Time series of daily mean air temperature, daily mean flow, daily maximum water temperature, and daily mean water temperature for May 1 through Nov 1 for the years 1995–1998 and 2006–2018. Dark blue lines are high-flow years, red lines are low-flow years, gray lines are other years. Black dashed lines are a LOESS (LOcally Estimated Scatterplot Smoothing) smoothers representing the conditions typical for the time of year.

Air temperature and flow are both correlated with water temperature (Figure 2, Figure 3). When combining all days together across the entire May-October period, the correlation between air temperature and water temperature is much stronger than the correlation between flow and water temperature (i.e., r^2 0.67 vs. 0.17 as shown in the left panels in Figure 2 and Figure 3); however, the relationship varies by month. In May through July, the air/water temperature correlation is weaker than flow/water temperature correlation, while the reverse occurs in August through October. When flows are high, water temperatures are cooler than would be expected based solely on air temperatures (e.g., the blue dots in Figure 2 generally fall below the regression trend line). When air temperatures are low, water temperatures are cooler than would be expected solely based on flows (e.g., the blue dots in Figure 3 generally fall below the regression trend line). Potential mechanisms for the cooling effect of high flows include faster downstream transport of water from cool headwater areas, greater thermal mass which is more resistant to heating, and greater accretion of cool groundwater.

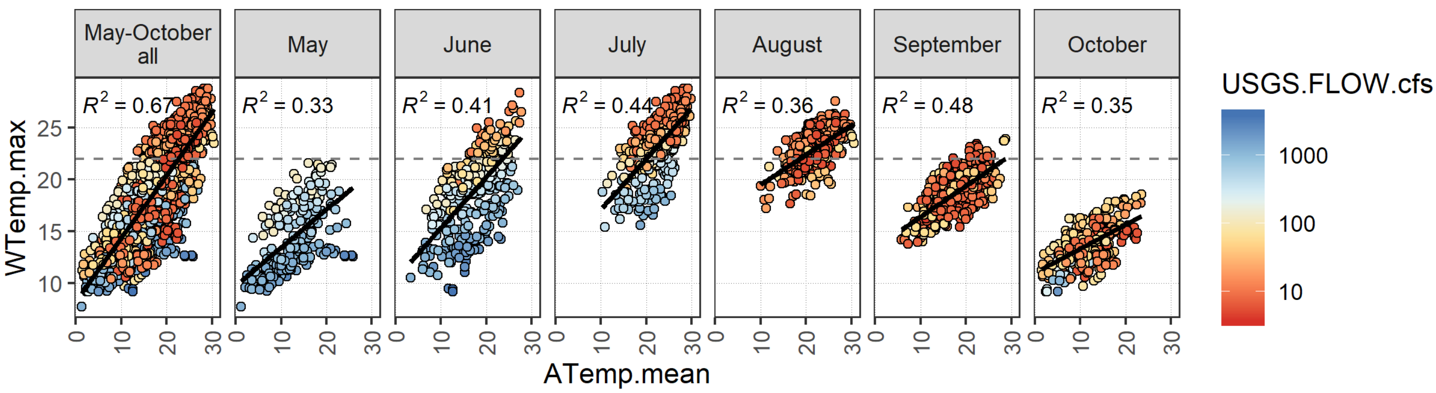

Figure 3. Regression of daily maximum water temperature vs. daily average air temperature, for the months May–October in the years 2007–2018. Each point (day) is shaded according to daily average flow. r^2 is the coefficient of determination which indicates the strength of the correlation (0 = no correlation, 1 = perfect correlation).

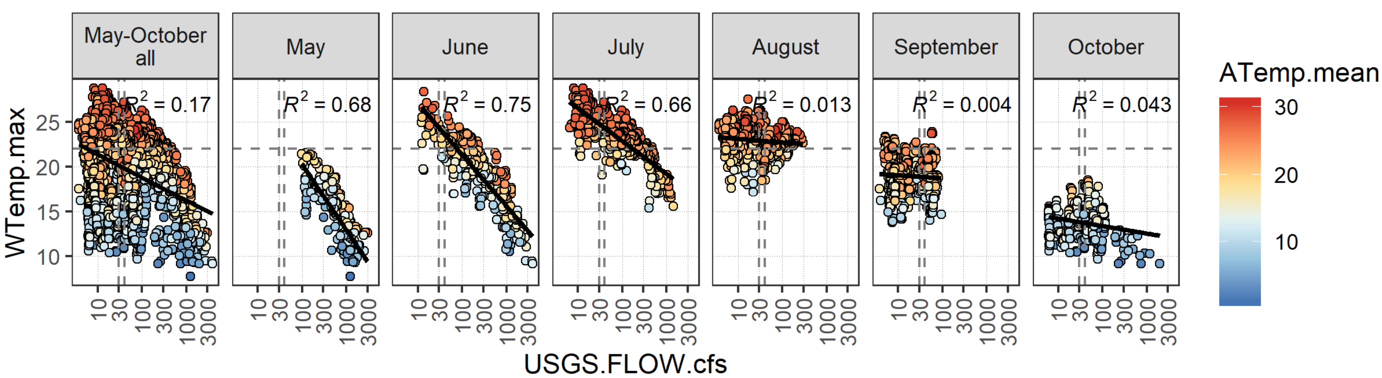

Figure 4. Linear regression of daily maximum water temperature vs. daily average flow, for the months May–October in the years 2007–2018. Each point (day) is shaded according to air temperature. r^2 is the coefficient of determination which indicates the strength of the correlation (0 = no correlation, 1 = perfect correlation).

Model calibration

The model predicts daily maximum temperatures quite well, with a root mean squared error (RMSE) of 1.17 °C (Figure 4). Similar to the pattern in the measured data (i.e., Figure 1) in the May-July period, the model predicts cool water temperatures during high-flow years and warm water temperatures during low-flow years (Figure 5). The complete time series of measured and modeled water temperature data for all years is available in Appendix B.

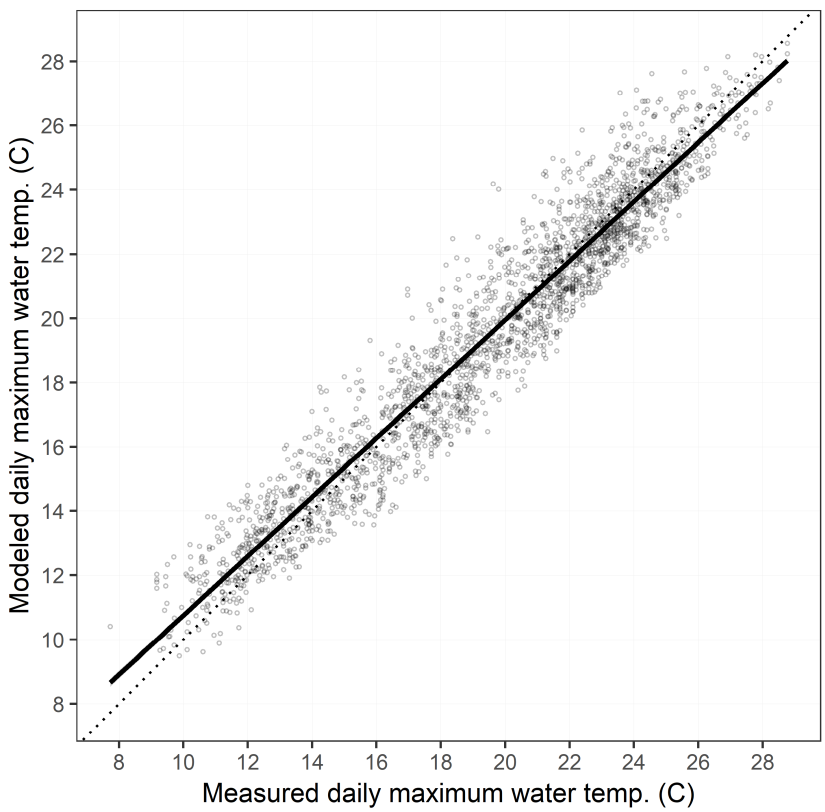

Figure 5. Modeled vs. measured daily maximum water temperature for May 1 through Nov 1 for the years 1995–1998 and 2006–2018. Thick solid line is a linear regression and the thin dotted line is the 1:1 (Y=X) line.

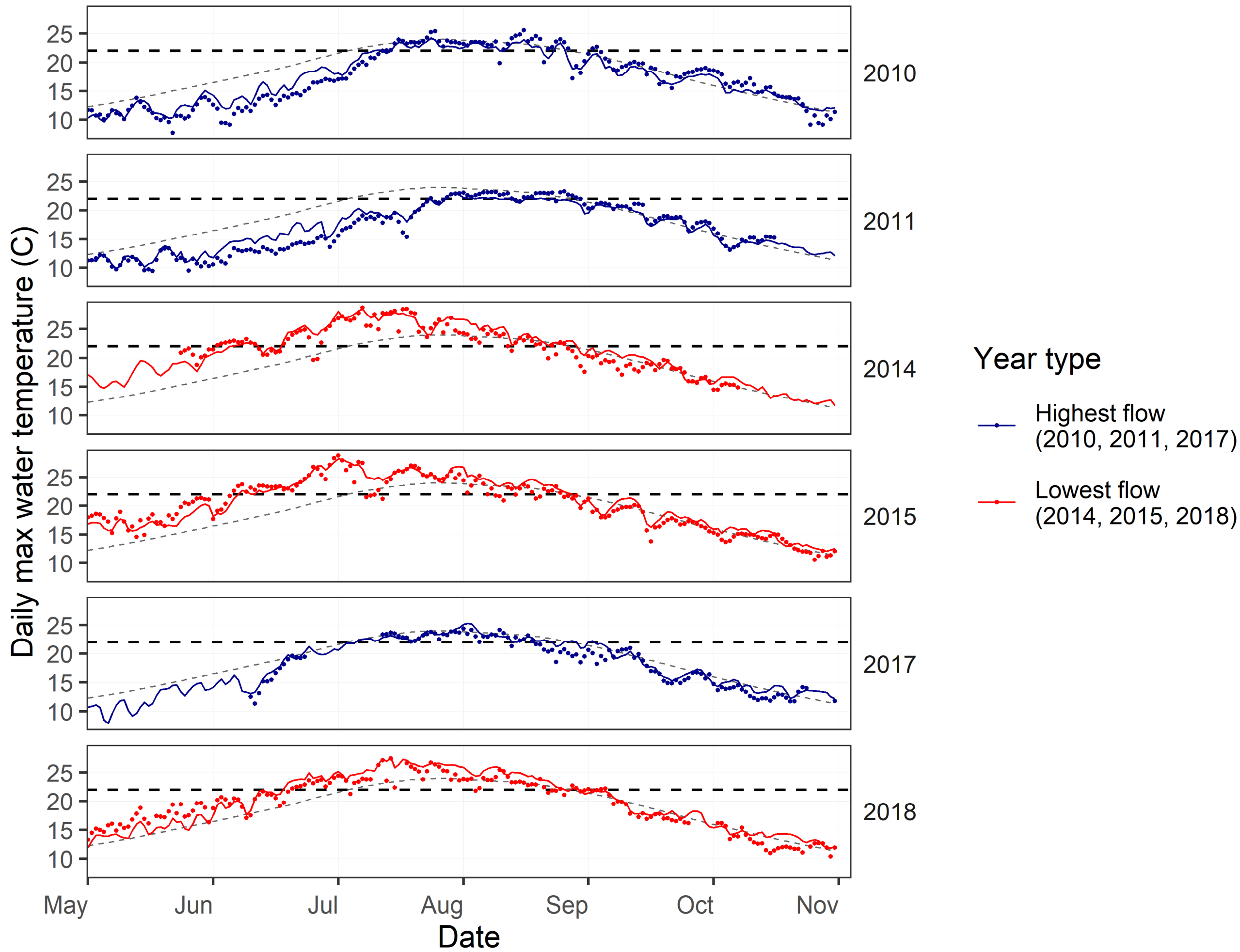

Figure 6. Daily time series of measured (dots) and modeled (solid lines) daily maximum water temperature in the Scott River at the USGS gage for three example high-flow years (2011, 2011, and 2017) and three example low-flow years (2014, 2015, 2018). Horizontal dashed line at 22 °C indicates a temperature threshold for juvenile salmonids. Curved grey dashed line is LOESS smoother of daily measured maximum water temperature for all years 1995-2018 which indicates typical conditions for the time of year (see explanation in Figure 1 above). A similar plot of all years is available in Appendix B.

Model scenarios

The results from the twelve model scenarios show that flow and air temperature both have strong effects on water temperature (Figure 6). The effect of flow varies across the season, with greater effects in May–July than August, and almost no effect in September and October. For example, relative to the lowest-flow scenarios, the water temperatures predicted under the highest-flow scenarios are 6.3 °C cooler on June 1, 3.5 °C cooler on August 1, and identical on October 1 (Figure 6). With short days and lower naturally lower air temperatures than earlier months, water temperatures are almost always less than 22 °C in September and October regardless of flow (e.g., gray lines in bottom panel of Figure 6).

Consistent with patterns in the measured data (Figure 1), modeled annual maximum water temperatures occurred later in the season in high-flow years (i.e., late July or early August) than in low-flow years (i.e., early/mid-July) (Figure 6), extending the duration of the period where cool water habitat is available for fish.

A second set of scenarios where we predicted daily maximum water temperatures pairing the observed air temperature time series for 1995-2018 with eight flow scenarios (Figure 7). These scenarios provide an indication of the range (e.g., due to air temperatures) in water temperature associated with each flow scenario. Summaries of annual maximum temperatures and the timing of exceedances of 22 °C are provided in Figure 8 and Figure 9, respectively. Compared to the lowest flow scenario (0.05 quantile), the highest flow scenario (0.95 quantile) has annual maximum temperatures that are 4.4 °C cooler (Figure 9) and temperatures first reach 22 °C 40 days later (Figure 8); there is also a 10-day difference in the last day of the year that has temperatures >22 °C. The scenario with observed flows has the most interannual variation in the annual maximum temperature (Figure 9) and timing of exceedances 22 °C (Figure 8), because it includes very low flows as well as very high flows. Water temperatures reach 22 °C 12 days earlier with the USFS flows than with observed flows (Figure 8) because the USFS flows are much lower than average observed flows in May and June. In contrast, in the scenario in which USFS flows are treated as minimums (supplanted by observed flows on days when observed flows are higher), temperatures reach 22 °C on a similar date as in the observed flow scenario. Due to high July and August flows in the CDFW scenarios, annual maximum water temperatures are 1.2–1.4 °C cooler in the CDFW scenarios than the observed flow scenario (Figure 9). Patterns of inter-scenario differences in annual degree-days exceedance of 22 °C (Figure 10) are similar to those of annual maximum temperature (Figure 9). While the CDFW flows and USFS flows are both predicted to improve (i.e., cool) temperatures relative to current conditions, these improvements would be greater with the higher CDFW flows.

Future work

We are currently preparing a manuscript for peer-review, which if published would supersede this technical memorandum. The manuscript will include cross-validation, additional analyses, and literature context.

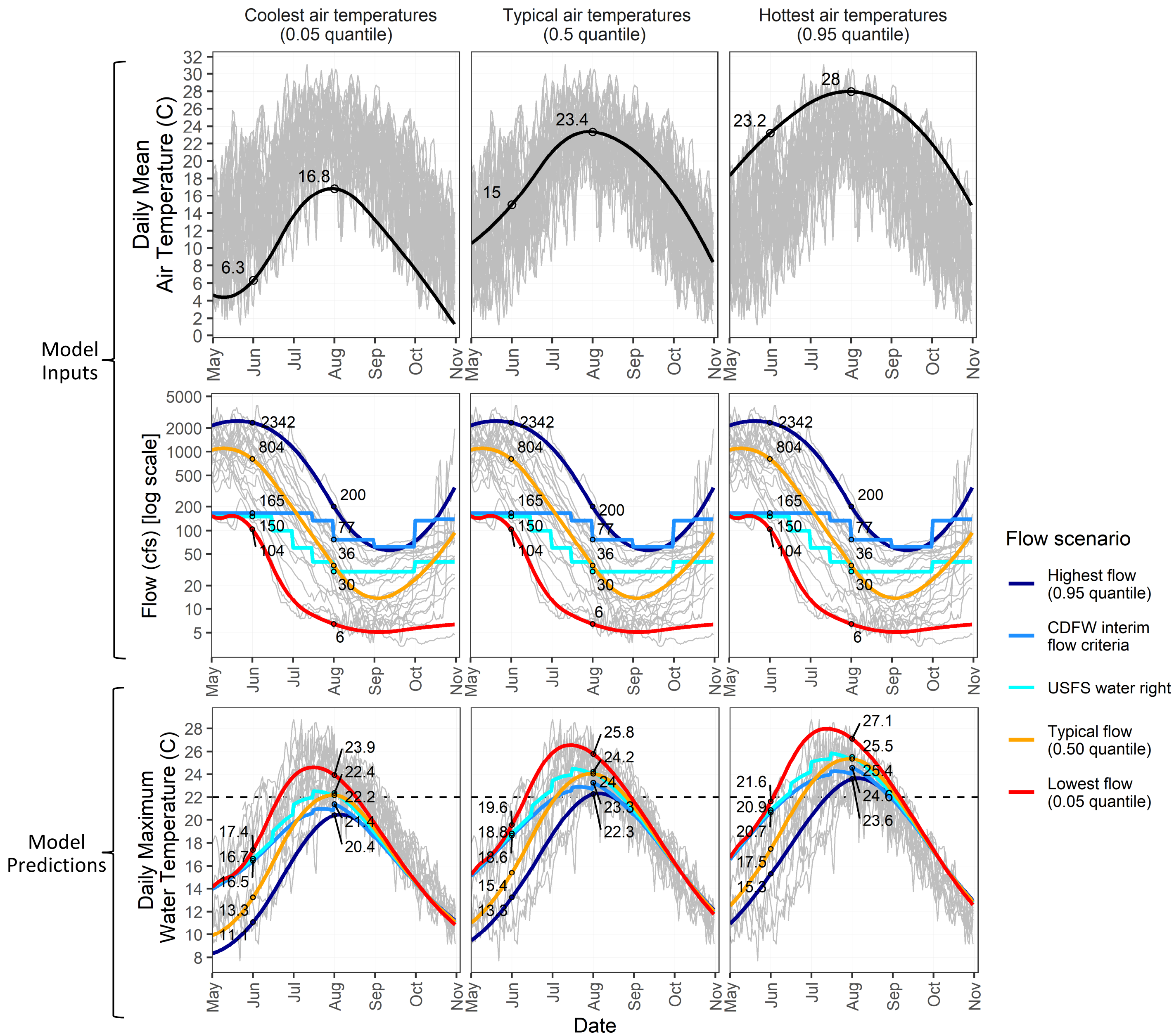

Figure 7. Air temperature (top panels) and flow (middle panels) inputs to statistical model, and predicted water temperatures (bottom panels) at Scott River USGS gage under 15 different scenarios. These scenarios represent combinations of cool/typical/hot air temperatures (arranged in columns) and high/CDFW/USFS/typical/low flows (shown by color). For context, observed values for 1995–2018 are shown as thin gray lines. Data values are labeled for June 1 and August 1. There is only a single black line (rather than five colored lines) in each of the top panels because the figure is arranged with air temperature scenarios as columns, so temperatures are identical within each column.

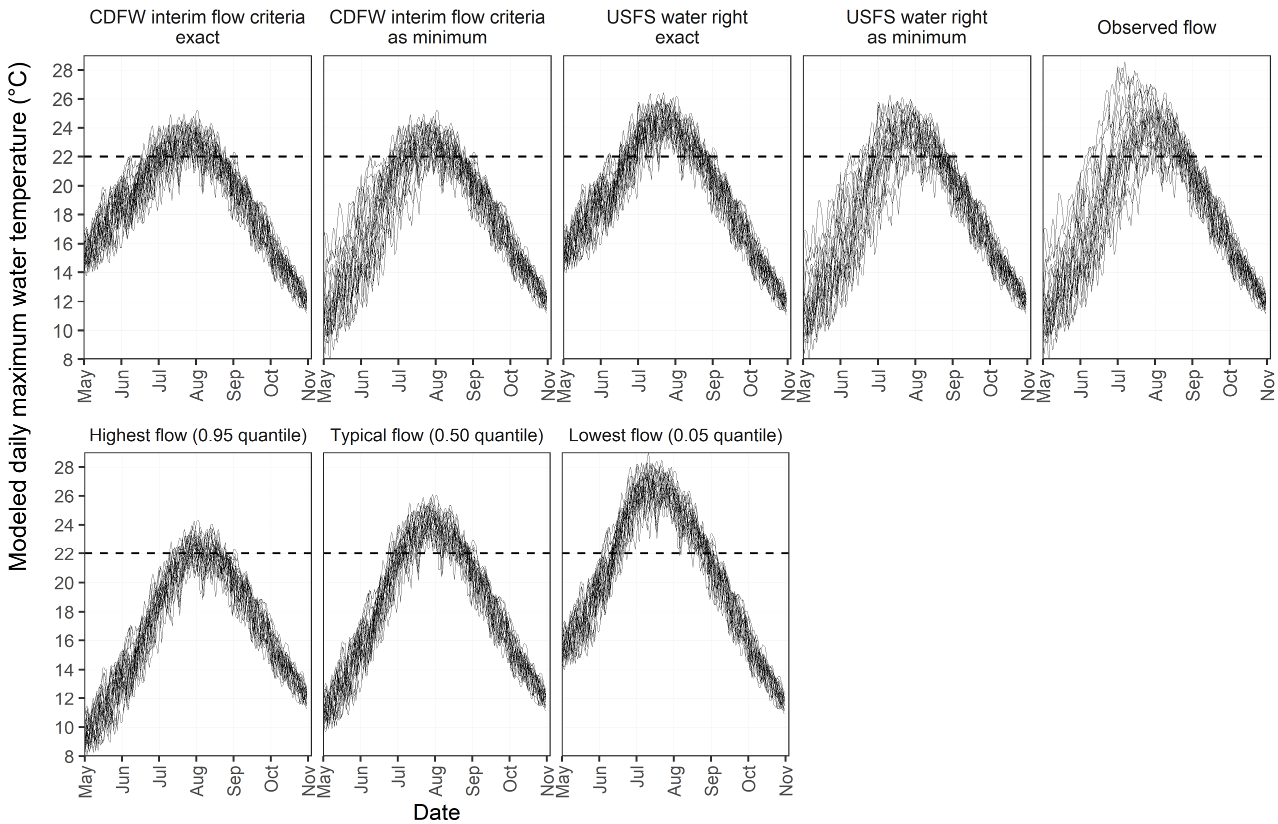

Figure 8. Daily maximum water temperatures at Scott River USGS gage predicted with a statistical model pairing observed air temperatures for 1995–2018 with eight different flow conditions: observed time series of USGS flows, three quantile flow scenarios (as show in middle panel of Figure 6), and four flow scenarios based on the CDFW interim instream flow criteria and USFS water right. Two scenarios use the exact flows (based on month and day) specified in the CDFW flow criteria and USFS water right (as show in middle panel of Figure 6), while the two other treat the CDFW flow criteria and USFS water right as minimums that are supplanted by the observed flows when the observed flows are higher.

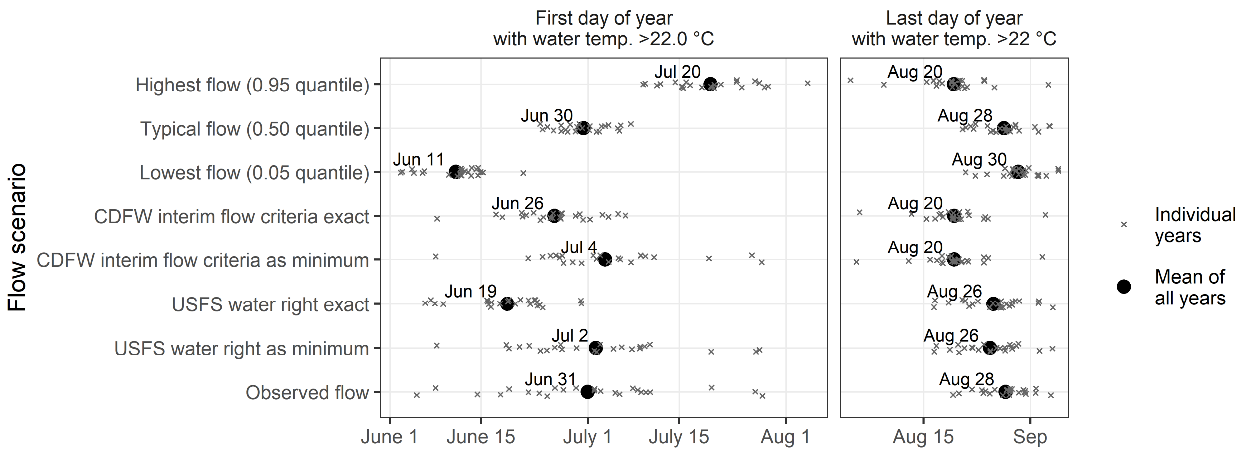

Figure 9. First and last day each year when daily maximum temperatures at Scott River USGS gage exceed 22 °C in predictions from a statistical model pairing observed air temperatures for 1995–2018 with the same eight flow conditions shown in Figure 7. Points for individual years are offset slightly to avoid obscuring each other.

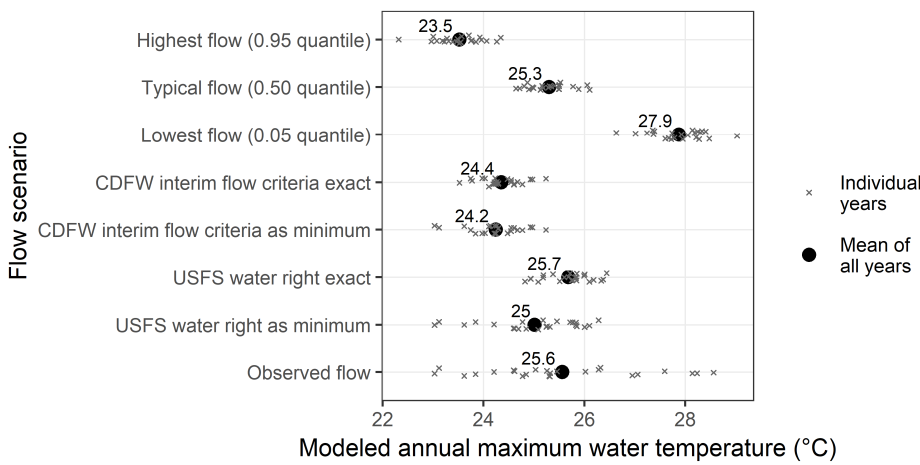

Figure 10. Annual maximum water temperatures at Scott River USGS gage predicted using a statistical model pairing observed air temperatures for 1995–2018 with the same eight flow conditions shown in Figure 7. Points for individual years are offset slightly to avoid obscuring each other. Data labels are shown for the mean of all years.

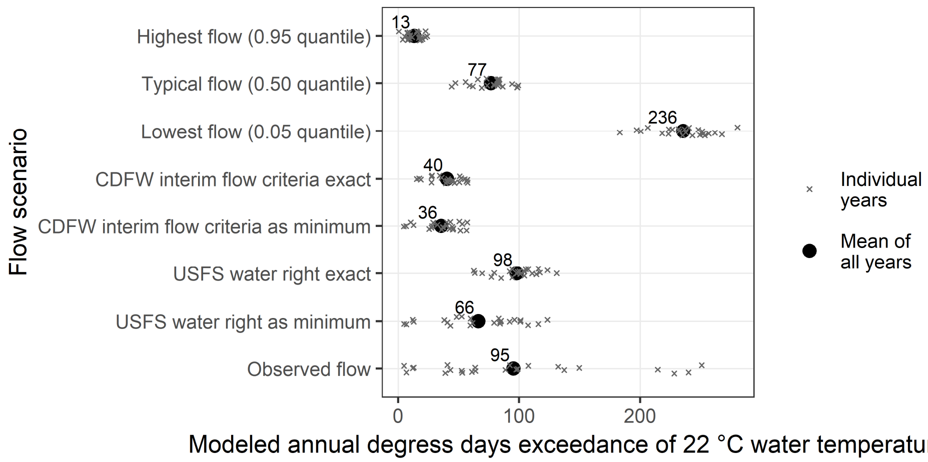

Figure 11. Annual degree-days of water temperatures exceeding 22 °C at Scott River USGS gage predicted using a statistical model pairing observed air temperatures for 1995–2018 with the same eight flow conditions shown in Figure 7. We calculated degree-days by subtracting 22 from all daily maximum water temperatures and summing all positive values by year. Points for individual years are offset slightly to avoid obscuring each other. Data labels are shown for the mean of all years.

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Appendix A

As shown in the following excerpt from the Scott River adjudication (Superior Court for Siskiyou County 1980), the U.S. Forest Service Schedule D first priority water right varies by month and day:

43. Instream Use on Scott River

The U. S. Forest Service has a right to stream flow in the Scott River measured at the USGS gage below Fort Jones in the following amounts for instream use for fish and wildlife within the Klamath National Forest.

Period	Allotment, in cfs
January	200
February	200
March	200
April	150
May	150
June 1 - 15	150
June 16 - 30	100
July 1 - 15	60
July 16 - 31	40
August	30
September	30
October	40
November	200
December	200

These amounts are necessary to provide minimum subsistence-level fishery conditions including spawning, egg incubation, rearing, downstream migration, and summer survival of anadromous fish, and can be experienced only in critically dry years without resulting in depletion of the fishery resource.

The priority of such right is equal and correlative with first priority rights in Schedule D4. The allotment will be considered satisfied when the flow on the particular day equals or exceeds the allotment or the average flow past the gage during the preceding 10 days equals or exceeds the allotment.

Appendix B

Daily time series of measured (i.e., observed)[blue dots] and modeled (i.e., predicted)[green lines] daily maximum water temperatures in the Scott River at the USGS gage: