Analysis of Flow-Water Quality Relationships at Scott River Gage

Prepared by:
Eli Asarian, Riverbend Sciences

For:
Klamath Tribal Water Quality Consortium

10/7/2019

Summary:

High water temperatures, low dissolved oxygen, and high pH 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. In this memo, I use linear regression and non-parametric quantile regression to analyze the relationships between flow, air temperature, and daily summaries of QVIR's water temperature, dissolved oxygen, and pH data collected during the months of May–October in the years 2007–2018. The purpose of this analysis is to assess the importance of instream flows to water quality in the Scott River.

The results indicate that water quality in the Scott River is generally better when flows are high. During months when flows are high (May and June), there is a stronger correlation between flow and daily maximum water temperature than between air temperature and daily maximum water temperature, indicating that flow is the dominant driver of water temperature during those months. Flows typically progressively decline over the summer to reach a low in September. Under the current climate and land use, flows are so low in August and September that they provide very little cooling influence on water temperature during those months, in contrast to strong cooling effects in May and June. The correlation between flow and daily maximum pH is relatively strong in all months during the May–October period, with higher flows associated with lower (i.e., better) pH. Daily minimum dissolved oxygen (for both concentration and percent saturation) is also correlated with flow during all months May–October, although the correlation is weaker in September and October. The correlation between flow and daily mean dissolved oxygen is generally weak except during the months of May and June when high flows increase dissolved oxygen by cooling water temperatures (due to physics, colder water is capable of holding more oxygen).

The non-parametric quantile regressions fit flexible curves to quantiles (i.e., percentiles) in the relationships between flow and each water quality variable (e.g., daily maximum pH). These curves can then be used to provide estimates of the probability (i.e., percent of days) that a water quality threshold is expected to be exceeded for a given flow (Figure 1, Table 1). Flow thresholds can then be derived by selecting the desired probability and water quality threshold. In this memo, I emphasize the relatively protective 5% probability of exceeding a water quality threshold; however, users of this memo can select a different probability if desired. The flows associated with a 5% probability of exceeding water quality thresholds are 195 cfs for dissolved oxygen daily average <8 mg/L, 33 cfs for dissolved oxygen daily minimum <6 mg/L, 574 cfs for dissolved oxygen saturation daily minimum <90%, 238 cfs for dissolved oxygen saturation daily minimum <85%, 73 cfs for pH maximum >8.5, and 280 cfs for water temperature daily maximum >22 °C (Figure 1, Table 1).

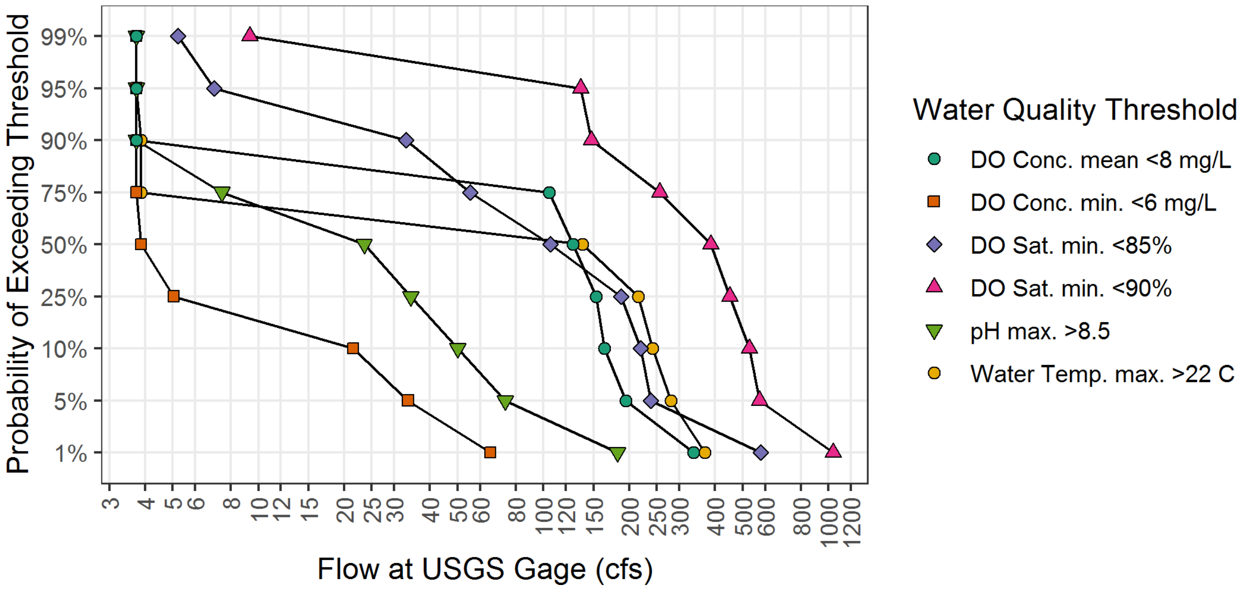


Figure 1. Percent of days (i.e., probability) on which water quality thresholds are expected to be exceeded in the Scott River at various flows. Results are based on non-parametric quantile regressions of daily summaries of water quality data collected by the Quartz Valley Indian Reservation and streamflow data from the U.S. Geological Survey at the Scott River gage during the months May–October in the years 2007–2018. Note: the x-axis is plotted on a log scale.

Table 1. Flow associated with a given probability (1% to 99%) of exceeding water quality thresholds. See Figure 1 for additional explanation (this table is the same data as Figure 1).

	Flow (cfs) associated with a given probability of exceeding water quality threshold								
Water quality threshold	**99%**	**95%**	**90%**	**75%**	**50%**	**25%**	**10%**	**5%**	**1%**
Water temperature maximum >22 C	4	4	4	4	137	215	241	280	368
pH maximum >8.5	4	4	4	7	24	34	50	73	182
DO percent saturation minimum <90%	9	135	147	256	386	451	528	573	1040
DO percent saturation minimum <85%	5	7	33	55	106	187	219	238	579
DO concentration daily minimum <6 mg/L	4	4	4	4	4	5	22	34	65
DO concentration daily mean <8 mg/L	4	4	4	105	127	153	164	195	336

Introduction and Methods:

The Scott River is located in Siskiyou Count in northwest California, USA and is tributary to the Klamath River. 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.

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). Parameters include water temperature, dissolved oxygen (DO), pH, specific conductance, and turbidity. QVIR Environmental Director Crystal Robinson compiled these data and provided them to me. I conducted informal QA/QC of the data by plotting time series of each parameter with daily average streamflow from the Scott River USGS gage 11519500[1] and air temperature from the Quartz Hill[2] Remote Automated Weather Station (RAWS), reviewing field calibration datasheets for some years, discussing with QVIR staff, and then removing suspicious values. In the future, the dataset could likely be further improved by conducting a more formal QA/QC process and correcting for fouling and calibration drift using USGS methods (Wagner 2006). Future correction could allow some data excluded that was excluded from this analysis due to calibration drift and biofouling to be made usable. In most years, the datasondes were programmed to report dissolved oxygen saturation relative to sea level, so I re-calculated percent saturation appropriate for the site elevation (804.4 m) using the rMR package (Moulton 2018) in R (R Core Team 2019).

Following QA/QC, I calculated daily summaries (minimum, mean, and maximum) for air temperature and water quality parameters. Summaries were only calculated for days when >=80% of the measurements for a parameter were present.

I used linear regression and graphical analysis to explore relationships between the parameters, with an emphasis on streamflow, and compared observed values to regulatory and biological thresholds (Table 2). Unless otherwise noted, analyses were confined to the period May–October because that is the period when water quality is impaired.

In addition, I used non-parametric quantile regression to estimate the daily average streamflow[3] associated with various quantiles (0.01 to 0.99, equivalent to 1-99% probabilities) of exceeding of regulatory and biological thresholds. Non-parametric quantile regression was performed in R using the quantregGrowth package (Muggeo et al. 2013). Whereas linear regression estimates the mean of the response variable given a value of a predictor variable, quantile regression estimates the 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 regression is particularly useful when other variables besides the primary predictor variable affect the response variable (Cade and Noon 2003). For example, water temperature is affected by air temperature in addition to streamflow. 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

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

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. I experimented with several combinations of these options and ended up running non-parametric quantile regression for all variables using the same set of options[4] that appeared to fit well. The curves were then used to estimate the probability (i.e., percent of days) that a water quality threshold is expected to be exceeded (i.e., violated) for a given flow. Flow thresholds can then be derived by selecting the desired probability and water quality threshold. In this memo, I emphasize the relatively protective 5% probability of exceeding a water quality threshold, which is derived from the 0.95 quantile for pH and water temperature (since exceedances for those parameters are values greater than the threshold) and the 0.05 quantile for dissolved oxygen (since exceedances for this parameter are values less than the threshold); however, users of this memo select a different probability if desired.

Table 2. Regulatory and biological thresholds used for this analysis.

Threshold	**Justification**
Streamflow <40cfs	U.S. Forest Service first priority water right for July 16–31 and October 1–31 (Superior Court for Siskiyou County 1980)***
Streamflow <30cfs	U.S. Forest Service first priority water right for August 1–September 30 (Superior Court for Siskiyou County 1980)***
DO <8 mg/L 7-day average**	NCRWQCB (2018) Basin Plan aquatic life-based objective
DO <6 mg/L daily minimum	NCRWQCB (2018) Basin Plan aquatic life-based objective
DO saturation <90% daily minimum (at natural water temperature)*	NCRWQCB (2018) Basin Plan wet season objective if aquatic life-based objective not achievable due to natural conditions
DO saturation <85% daily minimum (at natural water temperature)*	NCRWQCB (2018) Basin Plan dry season objective if aquatic life-based objective not achievable due to natural conditions
pH >8.5 daily maximum	NCRWQCB (2018) Basin Plan objective
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 NCRWQCB (2018) Basin Plan for details. The default DO objectives are the aquatic life-based objectives. If aquatic life-based objective are not achievable due to natural conditions, then NCRWQCB can apply site specific background DO requirements as water quality objectives by calculating the daily minimum DO necessary to maintain 85% DO saturation during the dry season and 90% DO saturation during the wet season under site salinity, site atmospheric pressure, and natural receiving water temperatures. The method(s) used to estimate natural temperatures for a given waterbody or stream length may include comparison with reference streams, simple calculation, or computer models.

** For ease of calculation, in this analysis I use daily average rather than a 7-day average. Exceedances of a 7-day average would likely occur less frequent than exceedances of the daily average.

*** See Appendix A for details. The U.S. Forest Service first priority 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.

[4] 1) not allowing the curves for different quantiles to cross, 2) forcing monotonicity, 3) lambda = 2, 4) a varying penalty of (1:k)^3

Results and Discussion:

Summary of all parameters

Figure 2 and Figure 3 present a time series and monthly summary, respectively, of the 2007–2018 data.

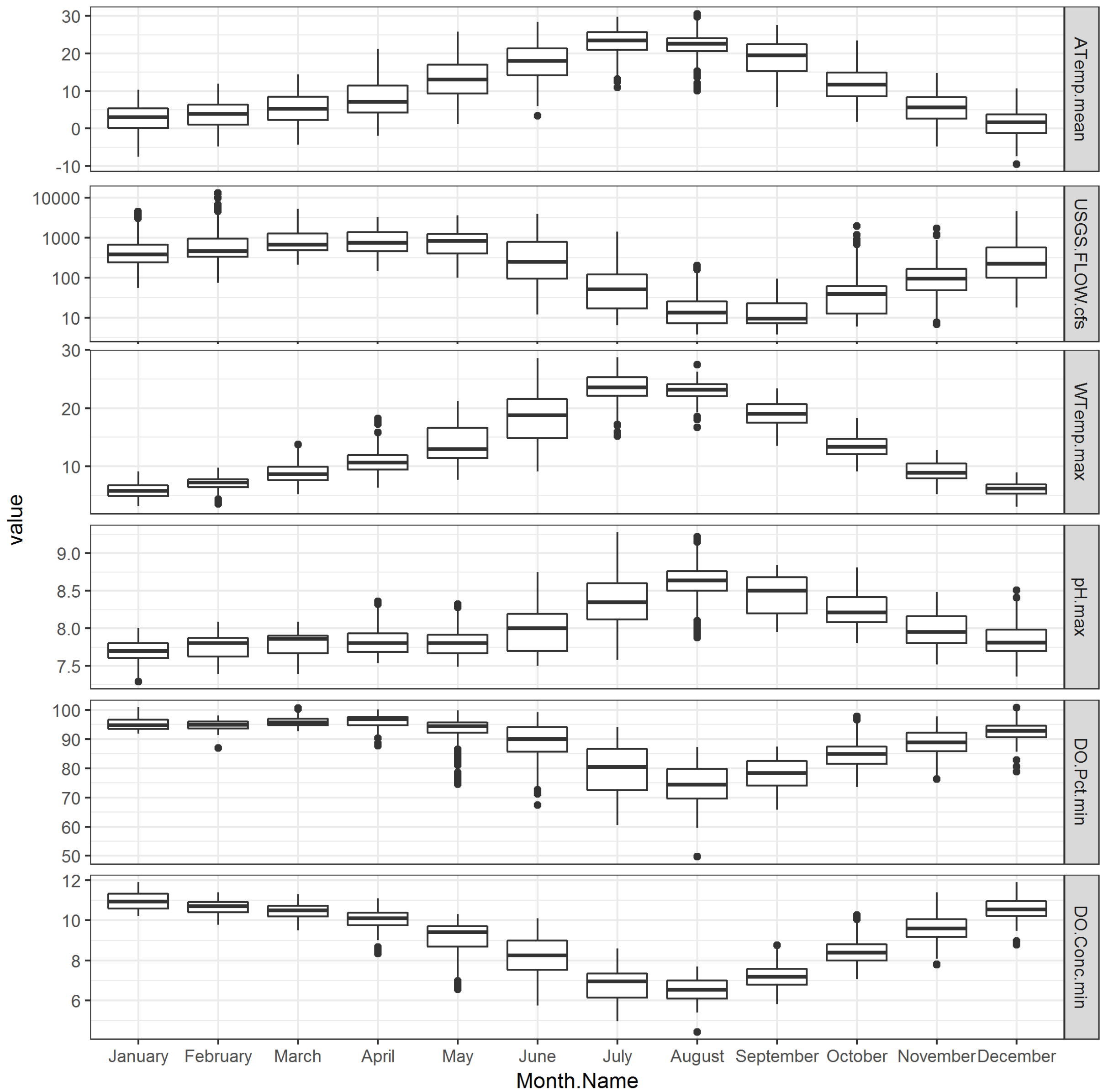


Figure 2. Boxplot of daily average air temperature at Quartz Hill (top panel) and daily average streamflow, daily maximum water temperature, daily maximum pH, and daily minimum dissolved oxygen concentration and percent saturation in the Scott River at the USGS gage (bottom five panels) for the months January–December in the years 2007–2018. The horizontal line inside the box is median, the upper and lower edges of the box are 25th and 75th percentiles, the upper whisker extends to the highest value that is within 1.5 times the interquartile range (75thminus 25th percentile) from the box's edge, and points plotted beyond the whiskers are outliers.

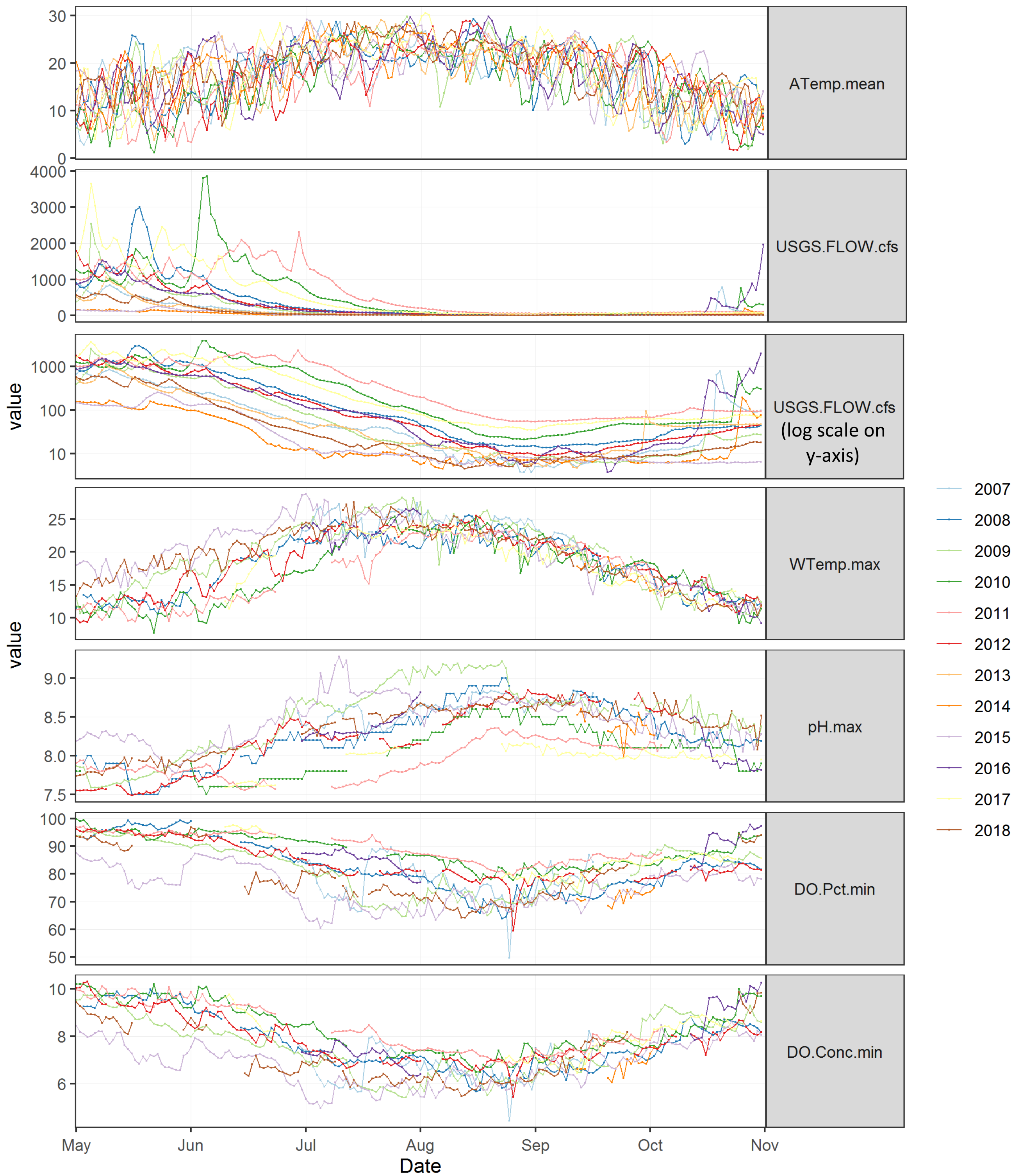


Figure 3. Time series of daily average air temperature at Quartz Hill (top panel) and daily average streamflow (second and third panels), daily maximum water temperature, daily maximum pH, and daily minimum dissolved oxygen concentration and percent saturation in the Scott River at the USGS gage (bottom five panels) for the months May–October in the years 2007–2018.

Water Temperature

Air temperature and flow are both correlated with water temperature (Figure 4, Figure 5). 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 0.70 vs. 0.23 as shown in the left panels in Figure 4 and Figure 5); however, the relationship varies by month. In May and June, the air/water temperature correlation is weaker than flow/water temperature correlation, while the reverse occurs in August through October. In July, the strength of the correlations are approximately equal. When flows are high, water temperatures are cooler than would be expected based solely on air temperatures (e.g., the blue dots in Figure 4 generally fall below the regression trend line). When air temperature are low, water temperatures are cooler than would be expected solely based on flows (e.g., the blue dots in Figure 5 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. The 0.95 quantile regression line crosses the 22 °C threshold at 280 cfs (Figure 6, Figure 1, Table 1), meaning that when flow is ≥280 cfs, there is only a 5% probability that that water temperatures will exceed 22 °C.

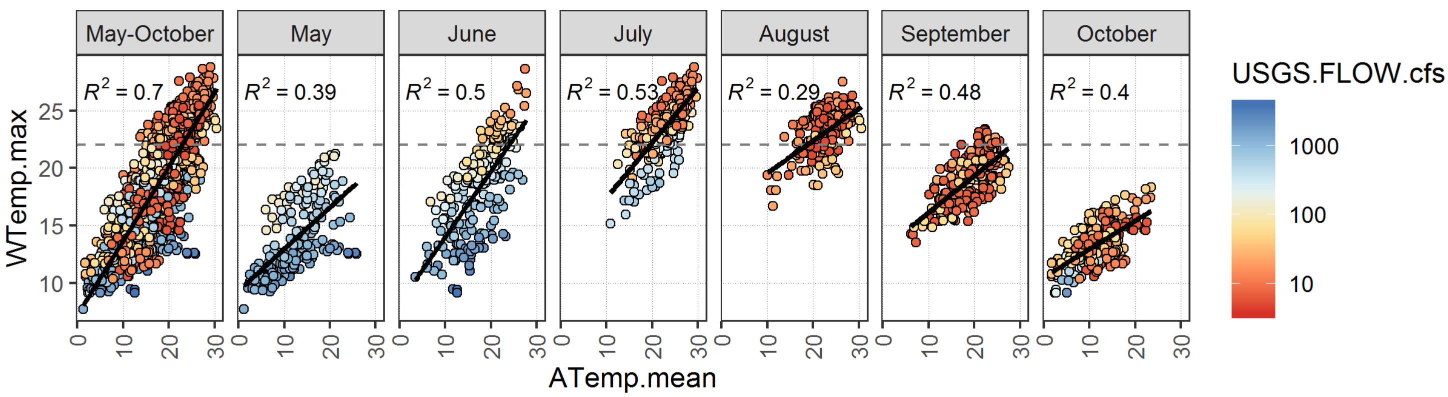


Figure 4. Regression of daily maximum water temperature vs. daily average air temperature, for the months May–October in the years 2007–2018. Each point (day) is shaded according to daily average flow. R^2 is the coefficient of determination which indicates the strength of the correlation (0 = no correlation,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

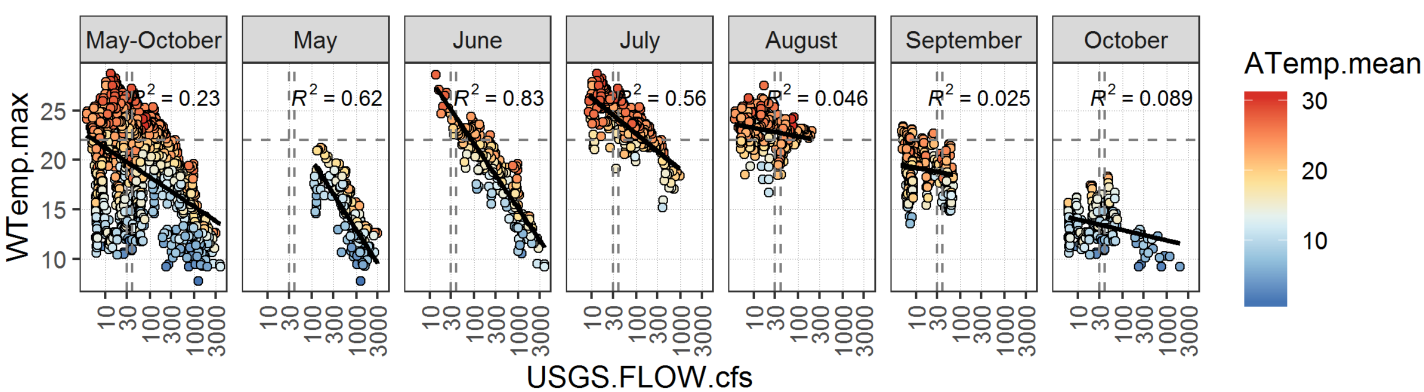


Figure 5. Linear regression of daily maximum water temperature vs. daily average flow, for the months May–October in the years 2007–2018. Each point (day) is shaded according to air temperature. R^2 is the coefficient of determination which indicates the strength of the correlation (0 = no correlation, 1 = perfect correlation).

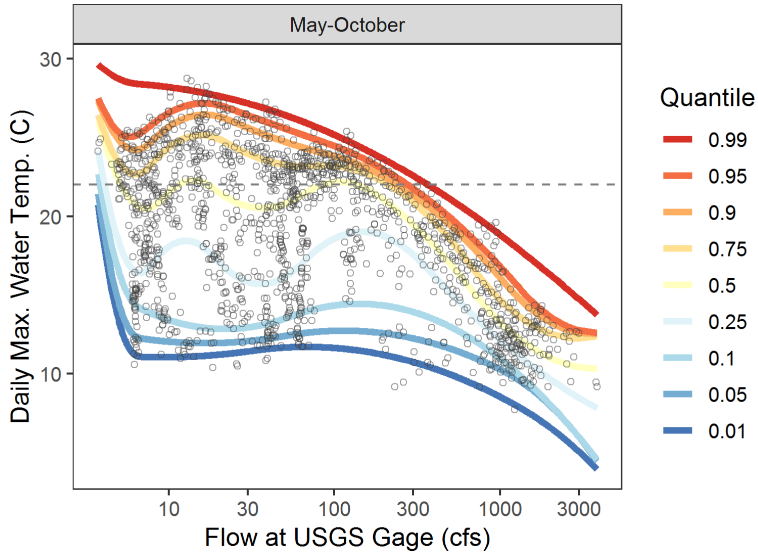


Figure 6. Non-parametric quantile regression of daily maximum water temperature vs. daily average flow, for the months May–October in the years 2007–2018.

pH

The correlation between flow and daily maximum pH is relatively strong in all months during the May through October period (Figure 7). Most exceedances of pH greater than 8.5 occurred when flow dropped below 40 cfs. pH fluctuates daily in response to cycles of photosynthesis and respiration by periphytic algae and aquatic plants attached to the riverbed, reaching a low around sunrise and a high in the late afternoon or early evening. Daily pH range (calculated as daily maximum minus daily minimum) can be used as a coarse proxy to indicate the productivity of the periphyton and aquatic plants. Daily maximum pH values are higher when daily pH range is higher (Figure 8A), indicating that pH range. pH range has a similar correlation to flow as daily maximum pH (Figure 7, Figure 8B).

Periphyton and aquatic plants take time (days to weeks) to reach maximum biomass once growing conditions become favorable (clear water and long sunny days) in summer. Therefore, flow in preceding weeks may be just as important, if not more important, of a driver of pH than a current day's flow is. Given the gradual seasonal recession of flow (Figure 2, Figure 3) a current day's flow is highly correlated with flow in preceding weeks.

The 0.95 quantile regression line crosses the pH 8.5 threshold at 73 cfs (Figure 9, Figure 1, Table 1), meaning that when flow is ≥73 cfs, there is only a 5% probability that that pH will exceed 8.5.

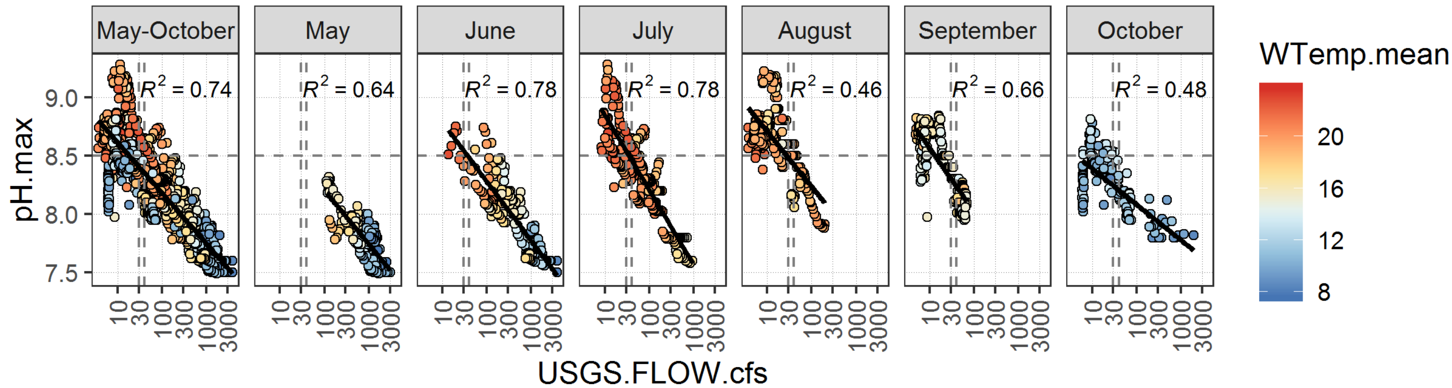


Figure 7. Linear regression of daily maximum pH vs. daily average flow, for the months May–October in the years 2007–2018. Each point (day) is shaded according to water temperature. R^2 is the coefficient of determination which indicates the strength of the correlation (0 = no correlation, 1 = perfect correlation).

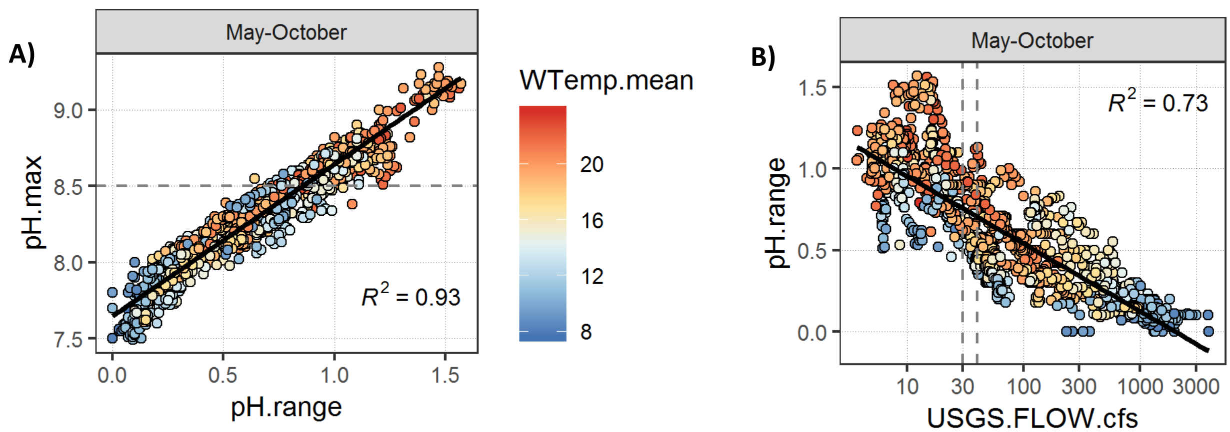


Figure 8. Linear regression of A) daily maximum pH vs. daily pH range, B) daily pH range vs. daily average flow, for the months May–October in the years 2007–2018. Each point (day) is shaded according to water temperature. R^2 is the coefficient of determination which indicates the strength of the correlation (0 = no correlation, 1 = perfect correlation).

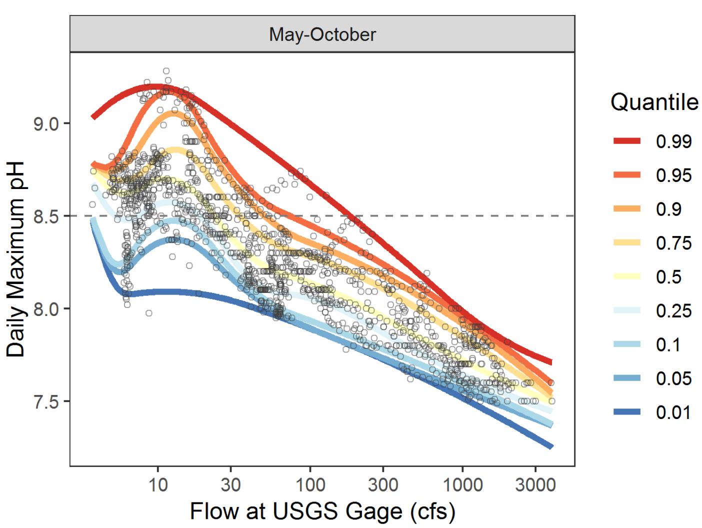


Figure 9. Non-parametric quantile regression of daily maximum pH vs. daily average flow, for the months May–October in the years 2007–2018.

Dissolved oxygen (DO)

The correlation between flow and daily minimum DO is stronger in May through August than September and October, for both percent saturation (Figure 10) and concentration (Figure 11). The flow/DO concentration correlation (Figure 10) is weaker than the flow/DO percent saturation correlation (Figure 11), likely because minimum DO concentration is directly affected by water temperature (cooler water holds more oxygen) whereas minimum DO saturation is determined by the productivity of periphytic algae and aquatic plants. Minimum DO concentrations below 6 mg/L occurred almost solely when flows were less than 40 cfs (Figure 11 left panel). DO below 85% and 90% saturation were common even at relatively high flows (i.e., greater than 100 cfs and 300 cfs, respectively). Daily mean DO concentrations below 8 mg/L are only correlated with flow in May and June (Figure 12). Discussion of periphyton and aquatic plants in the pH section above is also largely applicable to DO as well.

For both concentration (Figure 13) and percent saturation (Figure 14), daily minimum DO is correlated with water temperature. For most months, flow is a better predictor of daily minimum DO percent saturation than water temperature is (Figure 10, Figure 13); however, the reverse occurs for daily minimum DO concentration (Figure 11, Figure 14).

The 0.05 quantile regression line crosses dissolved oxygen thresholds at 195 cfs for dissolved oxygen daily average <8 mg/L, 33 cfs for dissolved oxygen daily minimum <6 mg/L, 574 cfs for dissolved oxygen saturation daily minimum <90%, and 238 cfs for dissolved oxygen saturation daily minimum <90%, (Figure 15, Figure 1, Table 1), meaning that when flow is greater than or equal to those values, there is only a 5% probability that those water quality thresholds will be exceeded.

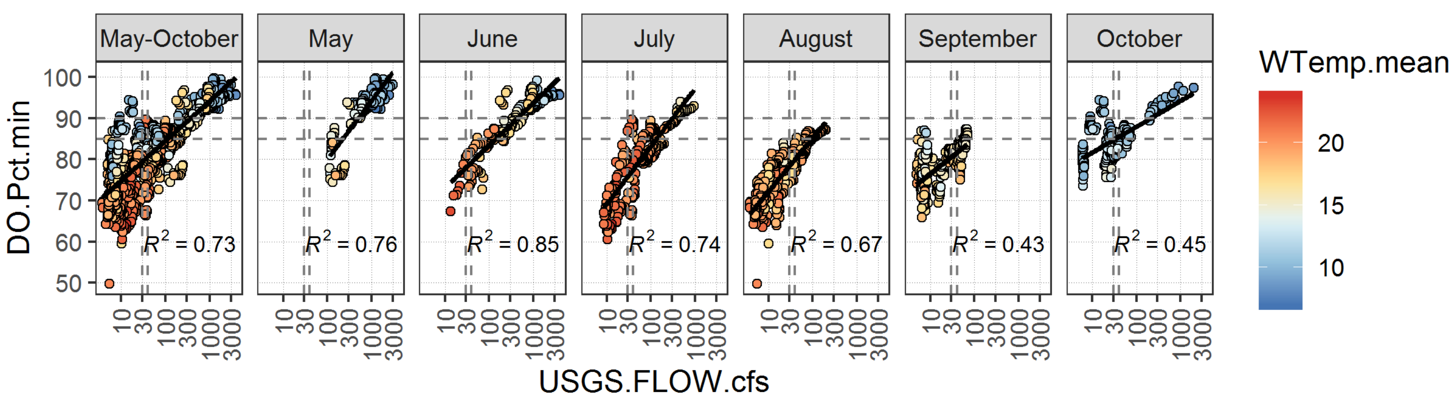


Figure 10. Regression of daily minimum dissolved oxygen percent saturation vs. daily average flow, for the months May–October in the years 2007–2018. Each point (day) is shaded according to water temperature. R^2 is the coefficient of determination which indicates the strength of the correlation (0 = no correlation, 1 = perfect correlation).

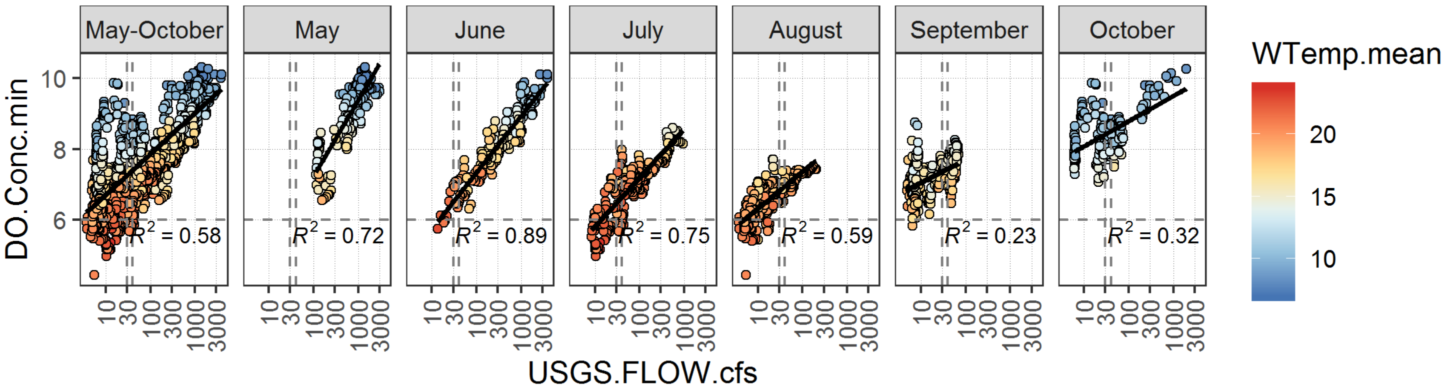


Figure 11. Regression of daily minimum dissolved oxygen concentration vs. daily average flow, for the months May–October in the years 2007–2018. Each point (day) is shaded according to water temperature. R^2 is the coefficient of determination which indicates the strength of the correlation (0 = no correlation, 1 = perfect correlation).

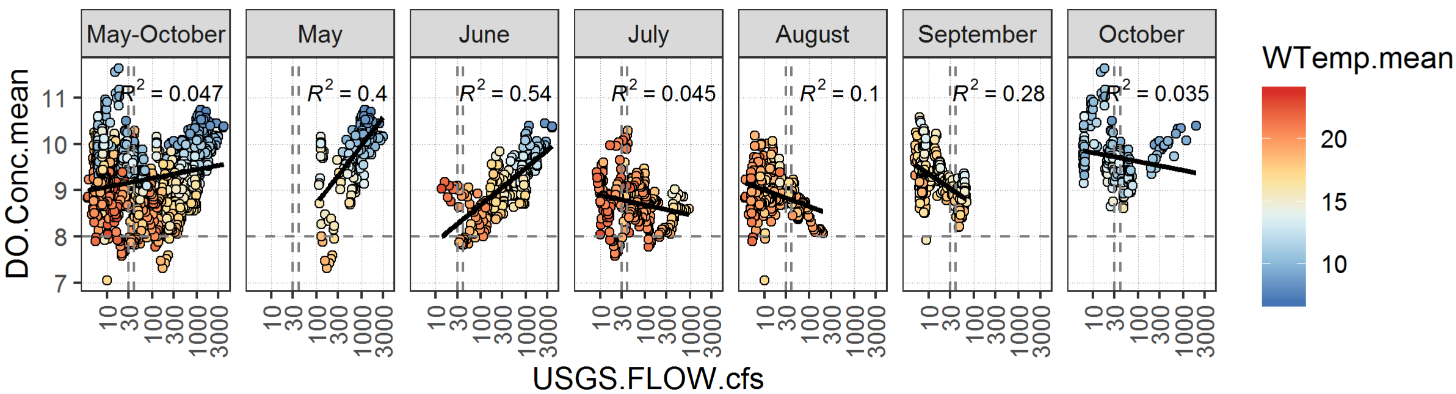


Figure 12. Regression of daily mean dissolved oxygen concentration vs. daily average flow, for the months May–October in the years 2007–2018. Each point (day) is shaded according to daily average flow. R^2 is the coefficient of determination which indicates the strength of the correlation (0 = no correlation, 1 = perfect correlation).

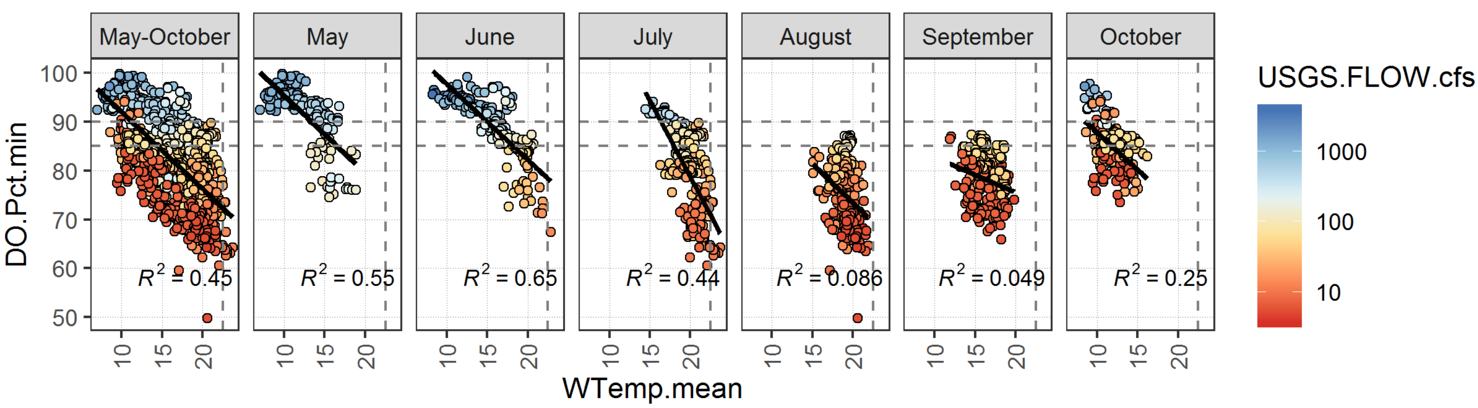


Figure 13. Regression of daily minimum dissolved oxygen percent saturation vs. daily average water temperature, for the months May–October in the years 2007–2018. Each point (day) is shaded according to daily average flow. R^2 is the coefficient of determination which indicates the strength of the correlation (0 = no correlation, 1 = perfect correlation).

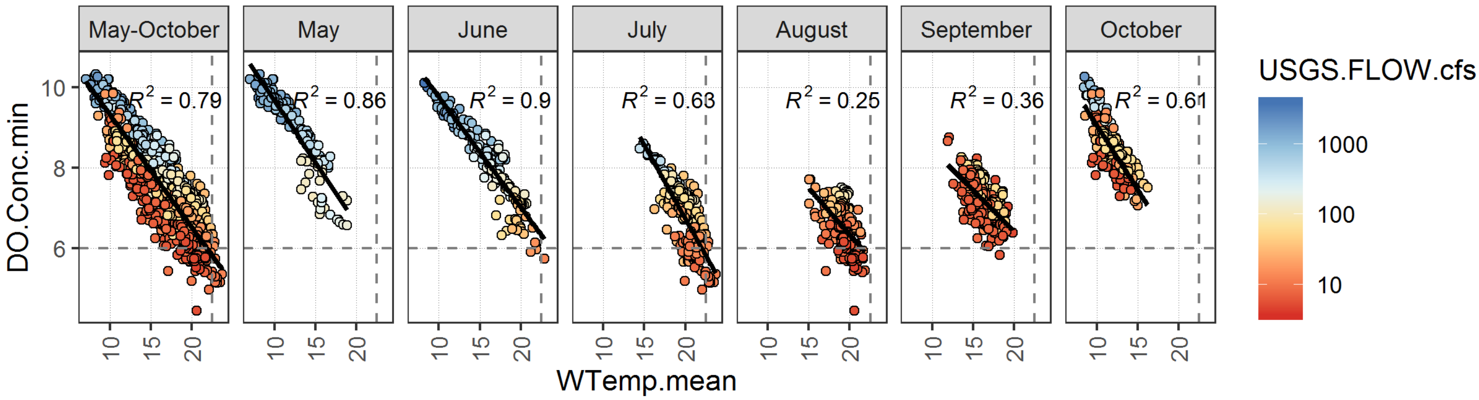
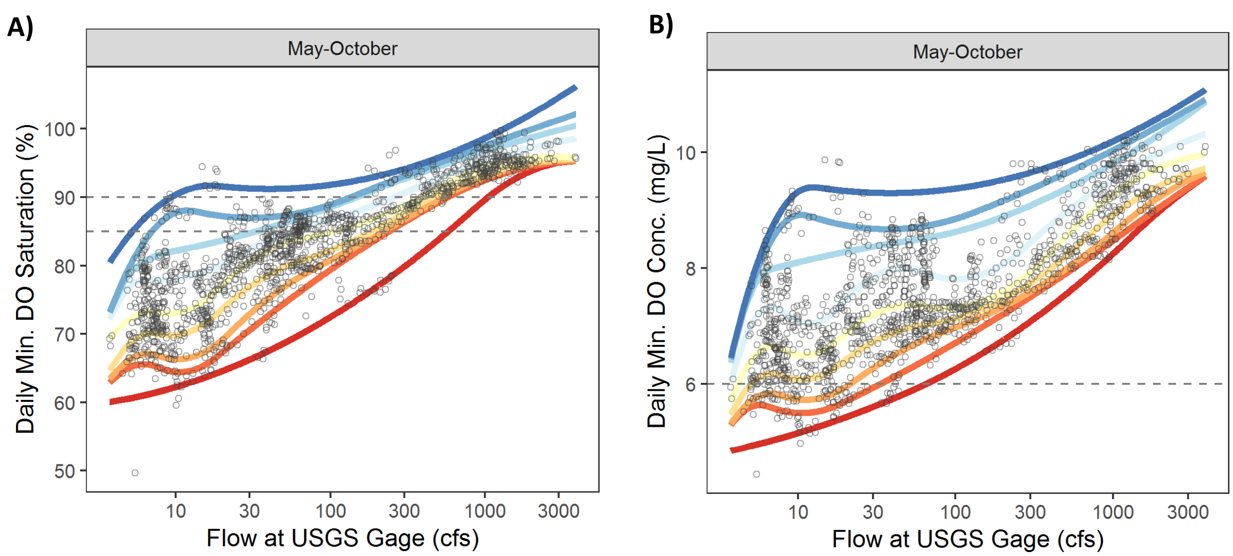


Figure 14. Regression of daily minimum dissolved oxygen concentration vs. daily average water temperature, for the months May–October in the years 2007–2018. Each point (day) is shaded according to daily average flow. R^2 is the coefficient of determination which indicates the strength of the correlation (0 = no correlation, 1 = perfect correlation).



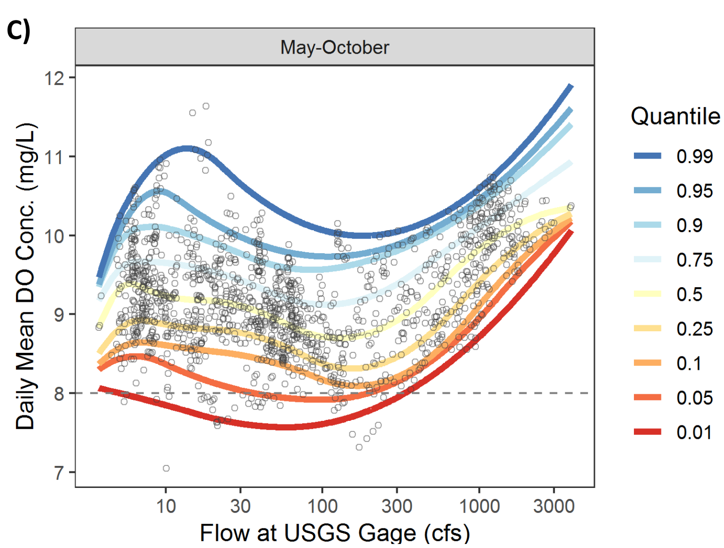


Figure 15. Non-parametric quantile regression of A) daily minimum dissolved oxygen saturation vs. daily average flow, B) daily minimum dissolved oxygen concentration vs. daily average flow, and C) daily mean dissolved oxygen concentration vs. daily average flow, for the months May–October in the years 2007–2018.

References Cited:

Asarian, E. and J. Kann. 2013. Synthesis of Continuous Water Quality Data for the Lower and Middle Klamath River, 2001-2011. Prepared by Kier Associates and Aquatic Ecosystem Sciences for the Klamath Basin Tribal Water Quality Work Group. 50p. + appendices. https://klamathwaterquality.com/documents/Klamath_2001_2011_sonde_rpt_20130502_final.pdf

Brewitt, K.S. and E.M. Danner. 2014. Spatio-Temporal Temperature Variation Influences Juvenile Steelhead (*Oncorhynchus mykiss*) Use of Thermal Refuges. Ecosphere 5:art92. doi: 10.1890/ES14-00036.1.

Cade BS, and Noon BR. 2003. A gentle introduction to quantile regression for ecologists. Frontiers in Ecology and the Environment 1: 412–420.

Maurer, S. 2007. 2007 Scott River Cold Water Patch (Thermal Refugia) Investigation Summary Report.

Moulton, T.L. 2018. rMR: Importing Data from Loligo Systems Software, Calculating Metabolic Rates and Critical Tensions. R package version 1.1.0. https://CRAN.R-project.org/package=rMR

Muggeo, V.M.R., M. Sciandra, A. Tomasello, and S. Calvo. 2013. Estimating growth charts via nonparametric quantile regression: a practical framework with application in ecology. Environmental and Ecological Statistics, 20, 519-531.

North Coast Regional Water Quality Control Board (NCRWQCB). 2018. Water Quality Control Plan for the North Coast Region. June 18, 2018. North Coast Regional Water Quality Control Board, Santa Rosa, CA.

Quartz Valley Indian Reservation (QVIR). 2008. Water Quality Monitoring and Assessment Report 2007. By Crystal Bowman, Environmental Director, QVIR, Fort Jones, CA. 59 p. https://www.klamathwaterquality.com/documents/Final%20QVIRWaterQuality_2008.pdf

Quartz Valley Indian Reservation (QVIR). 2009 (QVIR). Water Quality Monitoring and Assessment Report 2008. By Crystal Bowman, Environmental Director, QVIR, Fort Jones, CA. 65 p. https://www.klamathwaterquality.com/documents/qvir_2009_wq_monitor_report_2008.pdf

Quartz Valley Indian Reservation (QVIR). 2011. Water Quality Monitoring and Assessment Report 2011. Prepared by the QVIR Environmental Department Staff. Fort Jones, CA. 34 p. https://www.klamathwaterquality.com/documents/2011_water_quality_assessment_report_final.pdf

Quartz Valley Indian Reservation (QVIR). 2013. Water Quality Monitoring and Assessment Report 2013. Prepared by the QVIR Environmental Department Staff. Fort Jones, CA. 41 p. https://www.klamathwaterquality.com/documents/2013%20Water%20Quality%20Assessment%20Report_FINAL.pdf

Quartz Valley Indian Reservation (QVIR). 2016. Quality Assurance Project Plan 2016 Revision Water Quality Sampling and Analysis. CWA 106 grant identification # I-96927206-0. Prepared by the QVIR Tribal Environmental Protection Department, Fort Jones, CA. 126 p.

R Core Team. 2019. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Superior Court for Siskiyou County. 1980. Scott River Adjudication: Decree No. 30662. Scott River Stream System, Siskiyou County, 24 p.

Sutton, R.J., M.L. Deas, S.K. Tanaka, T. Soto, and R.A. Corum. 2007. Salmonid Observations at a Klamath River Thermal Refuge under Various Hydrological and Meteorological Conditions. River Research and Applications 23:775–785.

Sutton, R. and T. Soto. 2012. Juvenile Coho Salmon Behavioural Characteristics in Klamath River Summer Thermal Refugia. River Research and Applications. doi: 10.1002/rra.1459. doi:10.1002/rra.1459.

Wagner, R.J., Boulger, R.W., Jr., Oblinger, C.J., and Smith, B.A. 2006. Guidelines and standard procedures for continuous water-quality monitors—Station operation, record computation, and data reporting: U.S. Geological Survey Techniques and Methods 1–D3, 51 p. + 8 attachments; accessed April 10, 2006, at http://pubs.water.usgs.gov/tm1d3

Appendix A

As shown in the following excerpt from the Scott River adjudication (Superior Court for Siskiyou County 1980), the U.S. Forest Service 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.

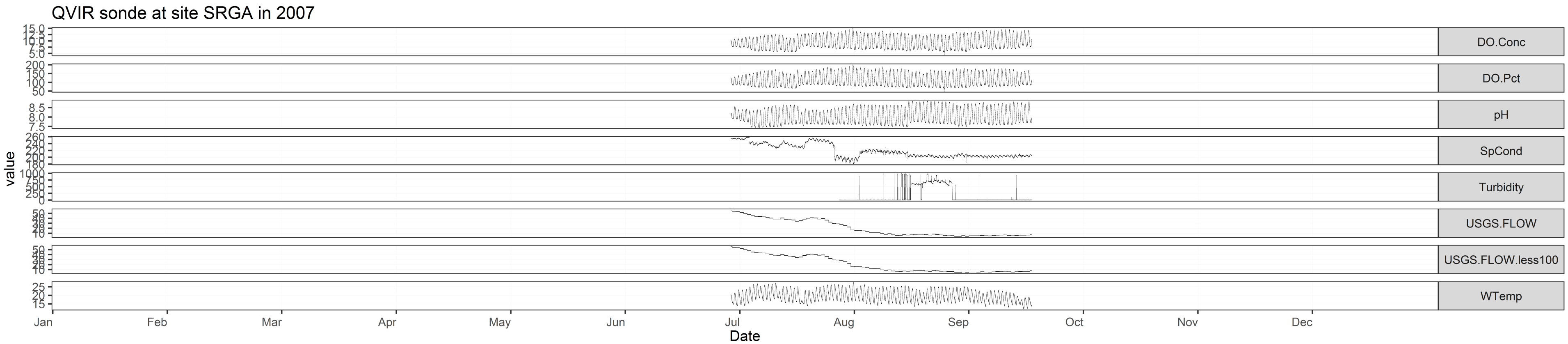
Period	Allotment, in cfs
January	200
February	200
March	200
April	150
May	150
June 1 - 15	150
June 16 - 30	100
July 1 - 15	60
July 16 - 31	40
August	30
September	30
October	40
November	200
December	200

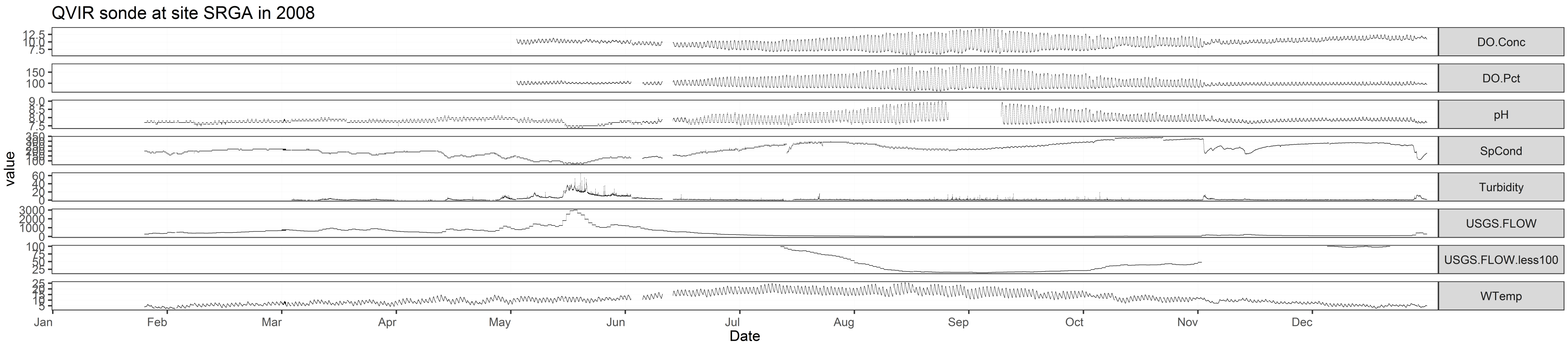
These amounts are necessary to provide minimum subsistence-level fishery conditions including spawning, egg incubation, rearing, downstream migration, and summer survival of anadromous fish, and can be experienced only in critically dry years without resulting in depletion of the fishery resource.

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.

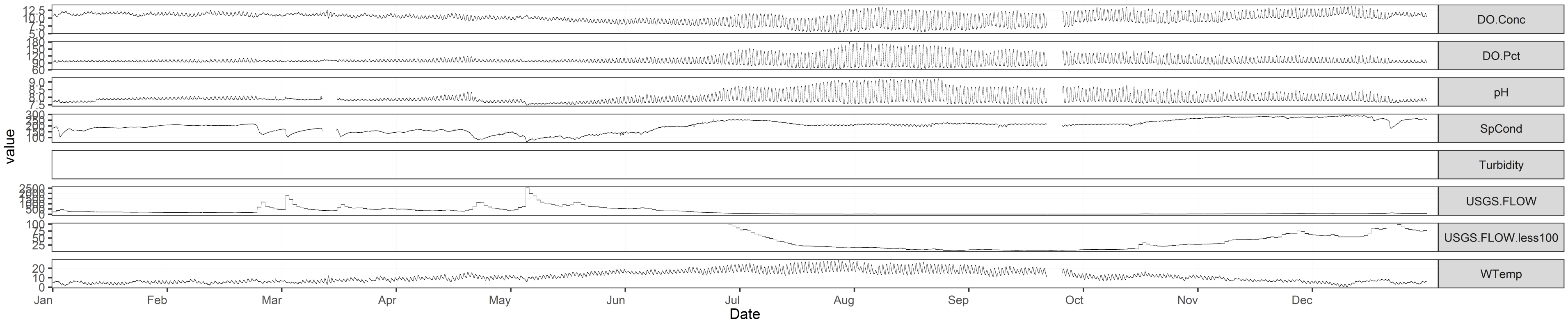
Appendix B

Time series of 30-minute QVIR sonde data and daily average USGS flow data. USGS.FLOW is flow in cfs units. USGS.FLOW.less100 is only flows less than 100 cfs, included here to allow the flows to be legible during low-flow periods.

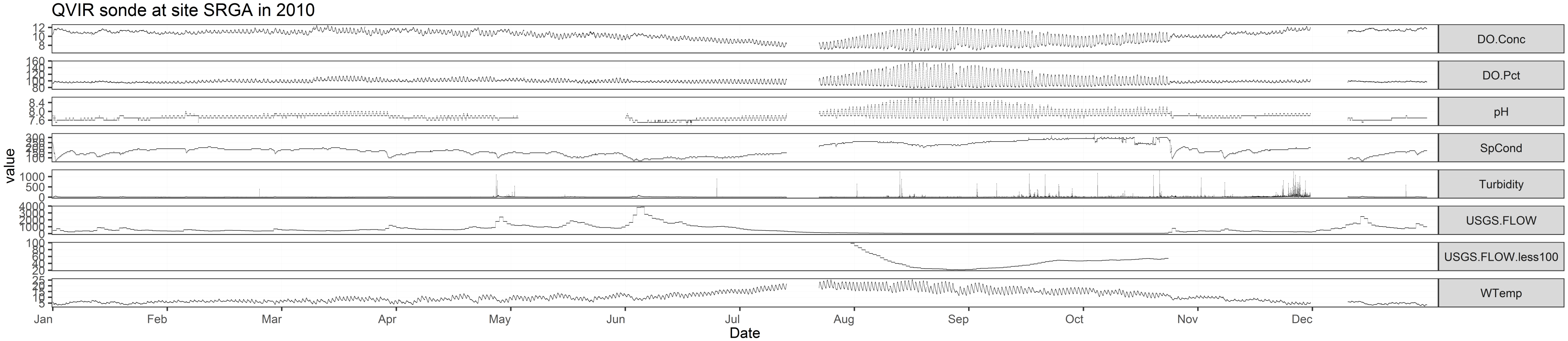




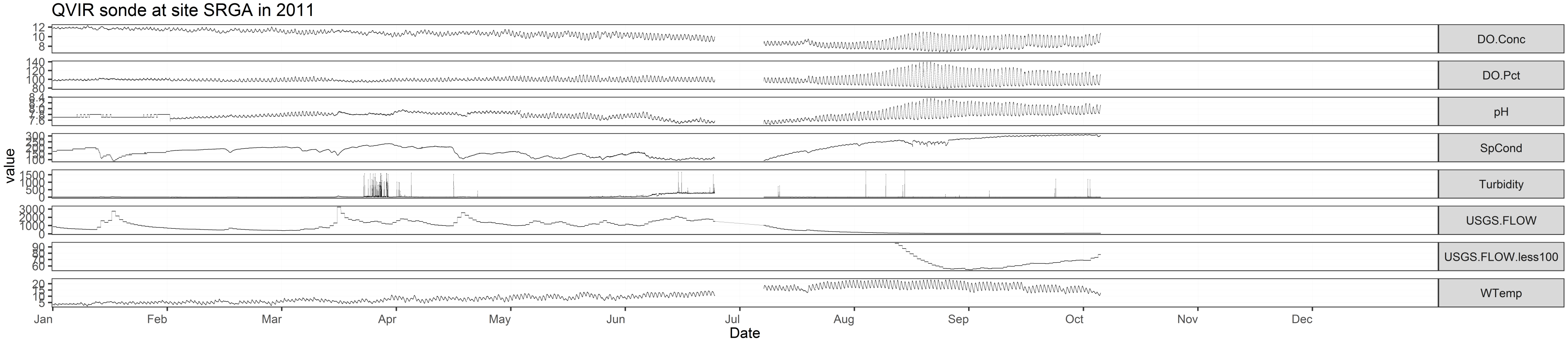
QVIR sonde at site SRGA in 2009

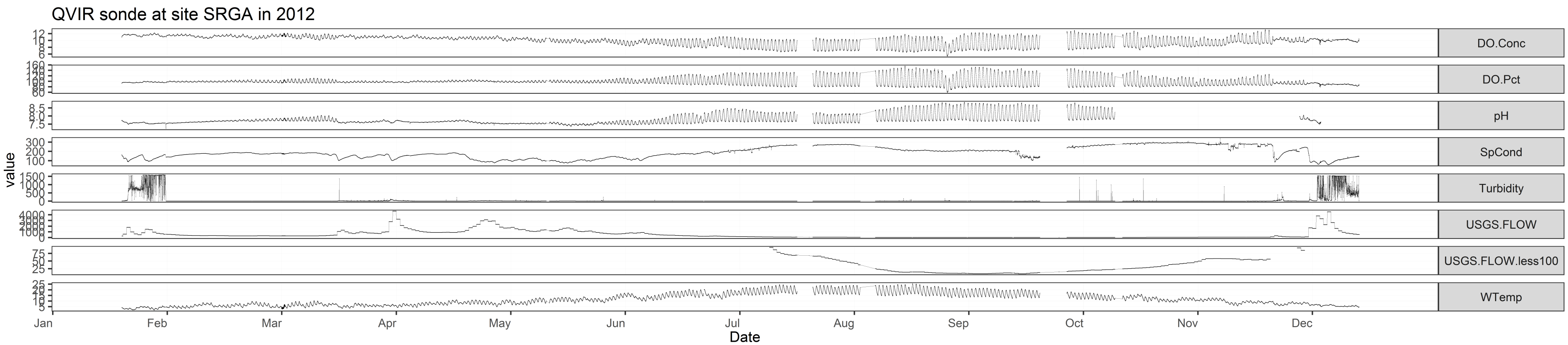


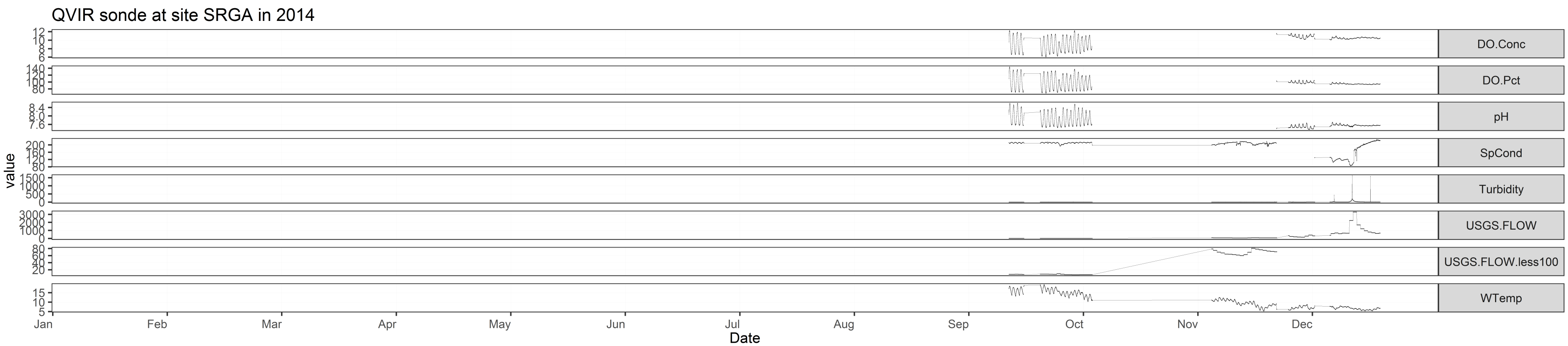
QVIR sonde at site SRGA in 2010

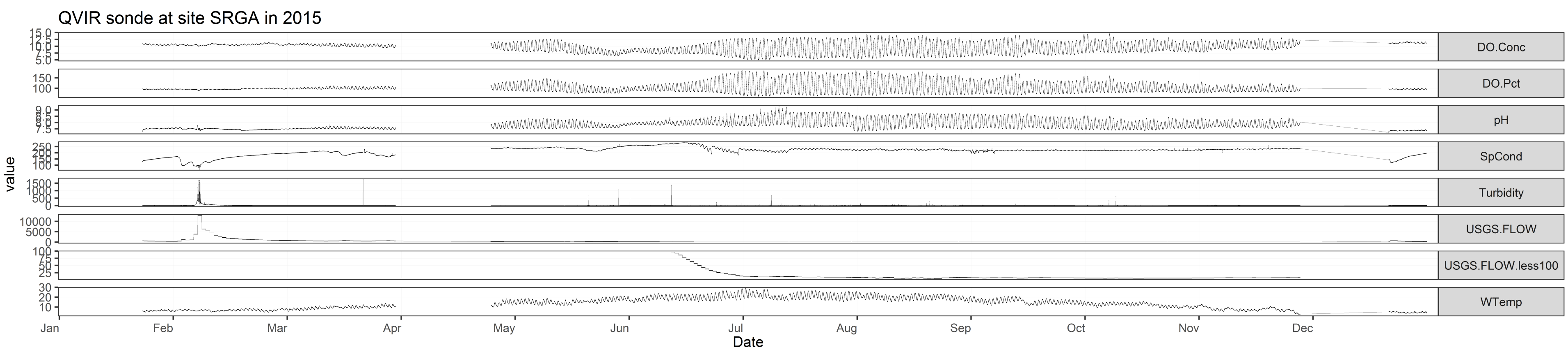


QVIR sonde at site SRGA in 2011

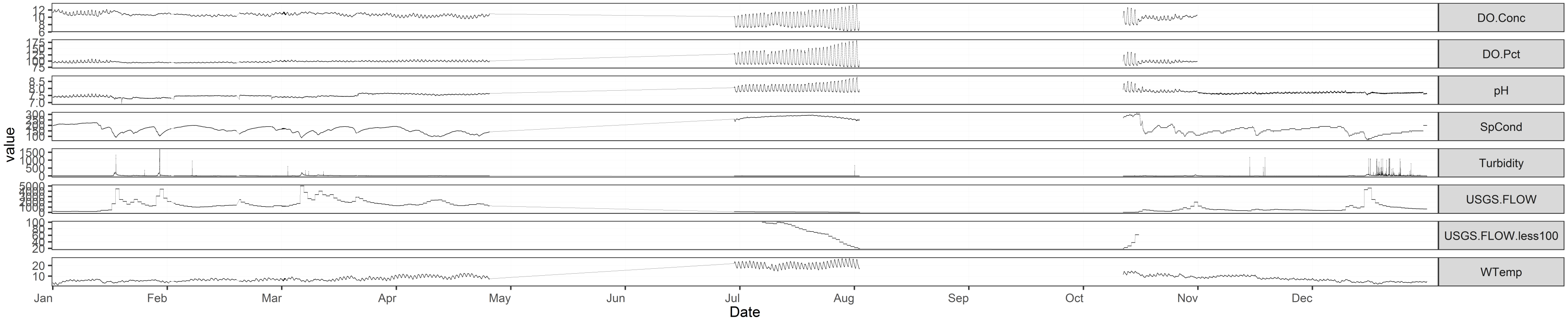



QVIR sonde at site SRGA in 2012
value
DO.Conc
DO.Pct
pH
SpCond
Turbidity
USGS.FLOW
USGS.FLOW.less100
WTemp
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Date

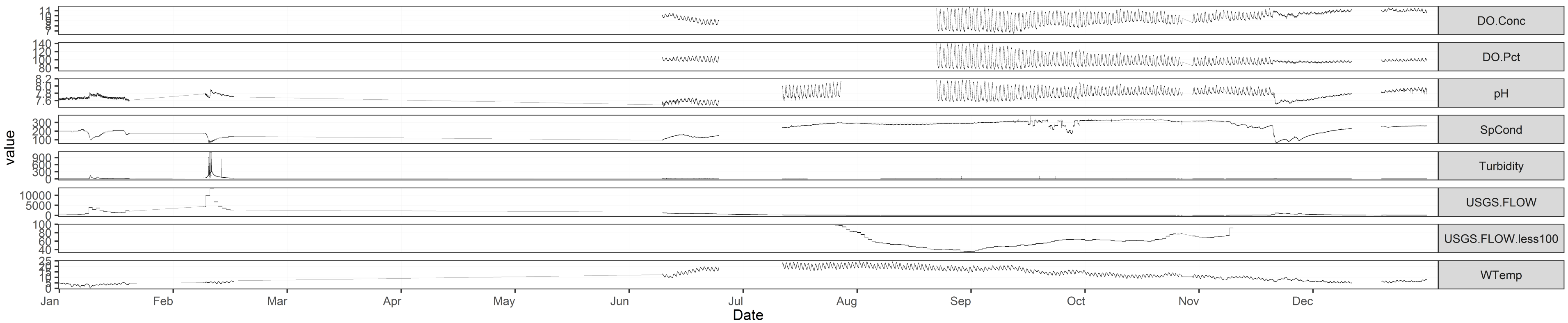

QVIR sonde at site SRGA in 2014
value
DO.Conc
DO.Pct
pH
SpCond
Turbidity
USGS.FLOW
USGS.FLOW.less100
WTemp
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Date


QVIR sonde at site SRGA in 2015
value
DO.Conc
DO.Pct
pH
SpCond
Turbidity
USGS.FLOW
USGS.FLOW.less100
WTemp
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Date

QVIR sonde at site SRGA in 2016



QVIR sonde at site SRGA in 2017



QVIR sonde at site SRGA in 2018