Trends and Sensitivities of Low Streamflow Extremes to Discharge Timing and Magnitude in Pacific Northwest Mountain Streams

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Key Points

1. Hydrologic drought is more sensitive to precipitation amount than air temperature in the Pacific Northwest.
2. Hydrologic drought indices have generally declined from 1948 to 2013 in the Pacific Northwest.
3. *Mean annual streamflow* has declined and the streamflow *center of timing* has occurred earlier.

1. Abstract

Path analyses of historical streamflow data from the Pacific Northwest indicate that the precipitation amount has been the dominant control on the magnitude of low streamflow extremes compared to the air temperature-affected timing of snowmelt runoff. The relative sensitivities of low streamflow to precipitation and temperature changes have important implications for adaptation planning because global circulation models produce relatively robust estimates of air temperature changes but have large uncertainties in projected precipitation amounts in the Pacific Northwest. Quantile regression analyses indicate that low streamflow extremes from the majority of catchments in this study have declined from 1948 to 2013, which may significantly affect terrestrial and aquatic ecosystems, and water resource management. Trends in the 25th percentile of *mean annual streamflow* have declined and the *center of timing* has occurred earlier. We quantify the relative influences of total precipitation and air temperature on the annual low streamflow extremes from 42 stream gauges using *mean annual streamflow* as a proxy for precipitation amount effects and streamflow *center of*

timing as a proxy for temperature effects on low flow metrics, including *7q10 summer* (the minimum 7-day flow during summer with a 10-year return probability), *mean August*, *mean September*, *mean summer*, *7q10 winter*, and *mean winter* flow metrics. These methods have the benefit of using only readily available streamflow data, which makes our results robust against systematic errors in high elevation distributed precipitation data. Winter low flow metrics are weakly tied to both *mean annual streamflow* and *center of timing*.

Index Terms: Drought (1812), Extreme Events (1817), Climate Impacts (1807), Land Atmosphere Interactions (1843)

Keywords: drought, streamflow sensitivity, hydrologic drought, temperature sensitivity, precipitation sensitivity, trend analysis

2. Introduction

Hydrologic drought is a condition or event that leads to abnormally low streamflow, or lake, reservoir, and/or groundwater levels (e.g. Van Loon, 2015), most often caused by precipitation deficit (Van Loon and Van Lanen, 2012). These low streamflow extremes have consequences for water supply planning and design (Gan, 2000; Iglesias et al., 2007; Schoen, et al., 2007, Woodhouse, et al., 2010), waste-load allocation (Golladay and Battle, 2002; Hernandez and Uddameri, 2013; Momblanch et al., 2015), aquatic ecosystems habitat (Davis, J., et al., 2015; Dijk et al., 2013; Gibson et al., 2005; Goode et al., 2013; Isaak et al., 2010; Meyer et al., 1999; Tetzlaff and Soulsby, 2013), quantity and quality of water for irrigation (Connor et al., 2012; Hansen, Lowe, and Xu, 2014; Mosley, 2015; Xu, Lowe, and Adams, 2014), and recreation (Smakhtin, 2001; Thomas, 2013). Low streamflow hydrology has gained increased attention as we understand more about climate warming and increasing climate variability (Hamlet and Lettenmaier, 2007; Jain, Hoerling, and Eischeid, 2005; Milly et al., 2008; Stewart, Cayan, and Dettinger, 2005), which in the western U.S. is manifested primarily as a trend of increasing dryness in dry years (e.g., Luce and Holden, 2009).

The Pacific Northwest U.S. is characterized by a warm summer (June, July, and August) season and a cool winter (December, January, February) season, henceforth referred to as the summer and winter seasons, respectively (Figure 1c). The majority of precipitation falls in winter as mountain snow. The melting of the seasonal snowpack in snow-dominated basins, and the onset of spring and early summer rains in rain-dominated basins often produces the annual hydrograph peak (Figure 1a). Winter low flows that occur before this peak may be a result of extended periods of cold air temperature ceasing snow melt and slowing evapotranspiration. The tail of the hydrograph recession from the spring peak generally produces the annual low flow. The summer dry season commonly coincides with the agricultural growing season, and drought years can pose severe economic consequences for farmers because of decreased crop yields (Al-Kaisi, et al., 2013; Banerjee, et al., 2013).

A growing concern in the western U.S. is an increasing frequency and severity of hydrologic drought in response to a lengthening dry season as snowmelt creeps earlier in response to warming temperatures (Barnett et al., 2005; Barnett et al., 2008; Cayan et al., 2001; Déry et al., 2009; Ficke et al., 2007; Godsey et al., 2013; Hamlet et al., 2005; Jung and Chang, 2011; Leppi et al., 2012; Luce et al., 2014a; Lutz et al., 2012; Nayak et al., 2010; Regonda, et al., 2005; Stewart et al., 2005; Tague and Grant 2009; Westerling et al., 2006). Mountain snowpacks are expected to accumulate less snow in response to warming air temperatures as the fraction of precipitation that falls as snow decreases (e.g. Abatzoglou, 2011; Abatzaglou et al., 2014; Groisman et al., 2004; Hamlet et al., 2005; Hantel and Hirtl-Wielke, 2007; Knowles et al., 2006; Lettenmaier and Gan, 1990; Luce et al., 2014a; Mote, 2006; Mote et al., 2005; Mote, 2003; Pierce et al., 2008; Woods, 2009). Historical snowpack declines have also been associated with mountain precipitation decreases in the Pacific Northwest (Luce et al., 2013). As a consequence of decreased snow storage under climate change conditions, hydrologic models project increasing drought severity for the region (Dai, 2011; Rind et al., 1990; Sheffield and Wood, 2008; Strzepek et al., 2010).

Declines in summer low flows associated with shifts in snowpack melt timing and precipitation amounts have been documented (e.g. Leppi et al., 2012, Lins and Slack, 2005, Luce and Holden, 2009). Important questions remain as to whether these shifts have yielded a response in hydrologic drought extremes, and if so, what the sensitivity of hydrologic drought is to these alternative pathways (warming effects on snow versus precipitation effects). In this latter question, we also expect some spatial variability in relative sensitivity as some snowpacks are more sensitive to temperature variations (Nolin and Daly, 2006), and as spatially variable subsurface drainage processes influence the translation of water inputs into streamflow (Tague and Grant, 2009).

Increased evapotranspiration driven by increased incoming longwave radiation is also expected to be a factor affecting low flow magnitudes in the longer term (Roderick et al., 2014). In recent history, however, increases in net radiation have been small compared to interannual low flow variability and low flow trends (e.g. Luce et al., 2013;

Milly and Shmakin, 2002). Low flow variability has historically been more closely related to total precipitation in a wide range in climates in Australia (Jones et al., 2006), and in Hawaii (Safeeq and Fares, 2012).

The distinction in mechanism between temperature- and precipitation– induced changes in hydrologic drought is important because global circulation models produce relatively consistent temperature change estimates across models, which have relatively high skill levels when compared to historic data. These same models produce inconsistent results in projected precipitation amounts due to our incomplete mechanistic understanding of the complex precipitation drivers (Abatzaglou et al., 2014; Blöschl and Montanari, 2010; Deidda et al., 2013; IPCC, 2007; IPCC, 2012; Johnson and Sharma, 2009; Sun et al., 2011). This uncertainty in future precipitation is particularly important because *mean annual streamflow* has been shown to be more sensitive to precipitation than to temperature (Nash and Gleick, 1991; Ng and Marsalek, 1992; Risbey and Entekhabi, 1996), and streamflow projections become more uncertain when moving from mean values to extreme values (Blöschl and Montanari, 2010; Blöschl et al., 2007; IPCC, 2007; Seneviratne et al., 2012). As an example of the kinds of uncertainty we face, increased precipitation amount and/or intensity could mitigate extreme low streamflow in cooler areas (Kumar et al., 2012). Alternatively, decreased high-elevation precipitation could yield snow and streamflow declines substantially greater than predicted for what are usually considered areas with resilient snowpacks (Nolin and Daly, 2006). Predictive models of climate-driven processes, such as wild fire occurrence and extent, are also often complicated by a joint dependence on precipitation and air temperature (Holden et al., 2012).

The goal of this study is to provide insights into the temperature and precipitation controls on extreme low streamflow in the Pacific Northwest. Specific objectives include 1) to explore trends in low flow indices, 2) to explore trends in *mean annual streamflow* and streamflow *center of timing*, and 3) to understand the relative role of precipitation and air temperature effects on low flows. To accomplish these objectives, we perform quantile trend analysis on low flow indices and path analysis between low flow indices, *center of timing* of annual hydrographs, and *mean annual streamflow* from 42 stream gauges from 1948 to 2013. The *mean annual streamflow* primarily reflects precipitation effects (Milly and Dunne, 2002; Sun et al., 2014; Wolock and McCabe, 1999), while the *center of timing* reflects both temperature and precipitation effects (Barnett et al., 2008; Stewart et al., 2005). The use of *mean annual streamflow* and *center of timing* allow us to perform this analysis using only streamflow, which has the advantages of 1) being an integrated value of all hydrologic processes of the catchment, 2) being relatively easy to measure accurately and obtain, and 3) the data is readily available. Path analysis allows us to separate temperature and precipitation effects on low flow metrics by accounting for the correlation between descriptor variables (Alwin and Hauser, 1975; Holden et al., 2012).

3. Methods

3.1 Data

We selected 42 stream gauges in the Pacific Northwest U.S. based on length of data record and basin disturbance. Of the 42 gauges used in this study, 36 are part of the GAGES II dataset (Falcone et al., 2010; Falcone, 2011), which provides geospatial attributes including anthropogenic influences used to assess agricultural withdraws.

Additional gauges that met data record length requirements from the HCDN network (Slack et al., 1993) were selected, including Boundary Creek and Big Wood River in Idaho, Kettle River, Similkameen River, and Okanogan River in Washington, and the North Fork of the Flathead River in Montana. This set of stream gauges is similar to those used in Luce and Holden (2009) (Table 1), but we have excluded the Chehalis River near Grand Mound, WA because of a reservoir on an upstream tributary (Skookumchuck Reservoir) operated primarily for base flow support.

Basin areas range from 142 km^2 to 35,094 km^2 with an average of 3153 km^2. Average annual flows range from 48 mm to 3896 mm with an average of 1070 mm. Mean catchment elevations are obtained from an analysis of an ESRI world terrain data set resampled to 100m in ArcMAP™, and range from 229m to 2640m. Dimensionless catchment form factors are calculated at the ratio of the catchment area to the square of the catchment length, and range from 0.19 to 0.52 (Horton, 1932). The flow regime of each catchment was classified as snow-dominated, rain-dominated, or transitional based on the *center of timing*, following Wenger, et al., 2010. This method classifies catchments with a mean *center of timing* greater than 200 (18 April) as snow dominated (27 catchments), less than 150 (27 February) as rain-dominated (6 catchments), and between 200 and 150 as transitional (9 catchments). Average base flow index from catchments range from 0.43 to 0.81 (Wolock, 2003).

Daily values of stream discharge from the 1948 water year (1 October 1947 to 30 September 1948) to the 2013 water year were downloaded from USGS Water Services (2012). Three out of the 42 gauges had missing data. Boulder Creek at Maxville, MT and MF Rock Creek near Philipsburg, MT were both missing data from the 2007 water year.

The Quinault River at Quinault Lake, WA was missing low flow data in the 2013 water year. We did not attempt to estimate flow for these data gaps. Additional small gaps in hydrograph data were filled by linear temporal interpolation for the Chehalis River, American River, and Sandy River. These gaps were up to 3 days and all were on the falling limb of hydrographs. The gapfilling is not expected to affect low flow statistics because lower flows occur elsewhere in the annual hydrographs, regardless of year boundary (water year, dry year, calendar year). Nearby precipitation gauges did record precipitation up to 0.2 inches at the American River coincident with missing data. Considering interception by vegetation, we expect the influence of these precipitation events play a very minor role in flow statistics (Savenije, 2004; Waring and Schlesinger, 1985).

3.2 Analysis

Annual streamflow statistics are commonly calculated using the 1 October through 30 September water year convention. Based on the climate variability of Pacific Northwest streamflow, it is appropriate to calculate the *mean annual streamflow* and streamflow *center of timing* using the water year convention. However, a relative frequency distribution of the timing of low flow events reveals a binomial distribution with the largest peak centered on September and October (Figure 1b). This coincides with the boundary between water years. We therefore define a “dry year” extending from 1 June to 31 May similar, but more regionally appropriate, to the “drought year” (April to March) used in Douglas et al. (2000). Low streamflow metrics are calculated using the dry year because it is not divided during the time of year that annual low flows generally occur. Low flow metrics calculated for dry years are assumed to be sensitive to the *mean annual streamflow* and the streamflow *center of timing* calculated for preceding water years. That is, the low flow metrics typically occur after the hydrograph peak. These methods avoid situations where a low flow measure occurs before the hydrograph peak that initiates the streamflow recession. *Mean annual streamflow* and *center of timing* from a water year affect low flow statistics from the dry year defined by the same year number (Figure 1a). For example, *center of timing* and *mean annual* streamflow from the 1949 water year influence the low flow measures from the 1949 dry year. The use of a water year for calculating the predictor variables and a dry year for calculating the response variables delineates a clear cause and effect between event hydrograph characteristics and low flow magnitudes.

Four summer (*min7q summer*, *mean summer*, *mean August*, and *mean September*) and two winter (*mean winter*, *min7q winter*) low flow statistics (Hisdal et al., 2010), were calculated for each dry-year. Minimum seven-day average discharge (*min7q*) was obtained for each gauge for each dry year by first smoothing hydrographs with a seven day moving average filter. Annual minimum values were obtained for both summer (*min7q summer*) (Dittmer, 2013) and winter (*min7q winter*) (Novotny and Stefan, 2007) seasons. Summer and winter seasons were defined by 1 June to 15 November and 16 November to 31 May, respectively because of a minimum in the frequency of low flow events (Figure 1b). Mean flows were simply the mean of daily stream discharge values over the given time period (Chang et al., 2012; Jefferson et al., 2008; Tague et al., 2008). *Mean summer* and *mean winter* flows were calculated using time periods from 15 July to 15 September and 15 November to 15 March, respectively. *Center of timing* was calculated as the number of days to reach one-half of the total streamflow for a water year (Barnett et al., 2008; Cayan et al., 2001; Stewart et al., 2005). *7q10* is the annual minimum streamflow for seven consecutive days that has a probability of occurrence of one in ten years. It is commonly used to allocate the amount of pollutants permitted to be discharged into a stream so that concentrations remain below a legal limit (U.S. Environmental Protection Agency, 1986).

Temporal trends of flow variables at each gauge are calculated using linear quantile regression (Table 2). Trends in *the 7q10 summer* and *7q10 winter* are detected by quantile regression using annual values of *min7q summer* and *min7q winter*, respectively. This novel approach uses the 10th percentile to detect trends in the *7q10* statistics, which corresponds to the 10-year return interval. The slope of the linear quantile regression model (in mm/year) indicates whether the *7q10* statistics were increasing (positive slope) or decreasing (negative slope). Following Luce and Holden (2009), trends in *mean annual streamflow* were detected by quantile regression to the 25th percentile because the primary pattern observed is decreases in the driest years. Trends in all other flow statistics are detected using quantile regression of the median. In contrast to Chang et al. (2012), we did not attempt to build predictive models, but calculate trends to attribute observed declines to precipitation and temperature effects.

The precision of trends from quantile regression is a function of the density of data near the quantile of interest (Cade and Noon, 2003). Student's t-statistics are obtained by using a direct estimation of the asymptotic standard error of the quantile regression slope estimator assuming a non-iid error model (Koenker and Hallock, 2001). This method utilizes the Huber sandwich method, which presumes local linearity of the conditional quantile function (Huber, 1967; Koenker, 2005). P-values are obtained from the t-distribution.

Changes in low flow variables for each station are calculated as:

$$\left(\frac{F_{2013}}{F_{1948}}\right)-1 \tag{1}$$

where F_{1948} and F_{2013} are the estimated values of the different flow variables (F) at 1948 and 2013 respectively, as modeled by linear quantile regression. Changes are thus computed in reference to a modeled value of the flow variable in 1948 and 2013.

It is important to account for spatial correlation (cross correlation) and temporal correlation (autocorrelation or serial correlation) of discharge data when determining trend significance in time of nearby gauges. Serial correlation may increase the incidence of significant trends, and spatial correlation accounts for the number of trends that would happen by chance alone. We account for spatial correlation of the gauges by calculating the field significance using bootstrap methods described by Douglas et al. (2000) and applied by Burn and Elnur (2002). This method provides a robust estimate of the number of gauges that would show significant trends by chance at a given significance value (Table 2). We use 600 repetitions and a local and global significance value of $\alpha=0.10$ for this study following Burn and Elnur (2002).

We account for serial correlation by adjusting the significance level of trends for an effective sample size. We do this by taking advantage of an equality for the variance of the mean statistic

$$VAR_{\overline{X}} = \frac{\mathrm{var}(X)}{n} = \frac{lrv(X)}{N} \tag{2}$$

where $VAR_{\bar{x}}$ is the variance of the mean, *var(X)* is the variance of the sample, *n* is the effective sample size, *lrv(X)* is the long range variance of the sample (explained below), and N is the number of observations, or the unadjusted sample size. Since we are not actually concerned with $VAR_{x,-}$, we solve for n as follows:

$$n = N\frac{\mathrm{var}(X)}{lrv(X)} \tag{3}$$

We estimate $lrv(X)$ using an estimate of the spectral density function at frequency zero by fitting an autoregressive model (Thiebaux and Zwiers, 1984). The original student's t-statistic from quantile regression is then adjusted using

$$t_{adj} = t_{orig}\frac{\sqrt{n-2}}{\sqrt{N-2}} \tag{4}$$

The p-value corresponding to the adjusted t-statistic gives the significance of trends adjusted for serial correlation in the data set.

The sensitivity of low flow statistics to *mean annual streamflow* and *center of timing* is evaluated using path analysis, which is a special case of structural equation modeling where all variables are measured. Path analysis quantifies the direct and indirect influences of correlated predictor variables on response variables (Alwin and Hauser, 1975). In our model, *mean annual streamflow* (*XAF*) is an exogenous variable, meaning it has no explicit causes and no causal links from other variables (Figure 2). *Center of timing* (*XCT*) and the low flow metrics (*XSTAT*) are endogenous variables, meaning that there are causal links leading to them from other variables as is shown by the arrows, or paths. Thus, we assume that the *center of timing* in the Pacific Northwest is influenced by both air temperature and the *mean annual streamflow*, which is a proxy for precipitation amount (Moore et al., 2007). The effects of air temperature on streamflow timing were lumped with all other external effects on streamflow timing that are not related to *mean annual streamflow* (*Xu*). The low flow metric is influenced by both the *center of timing* and the *mean annual streamflow*. All other effects on low flow metrics for a given year are treated as random effects (*Xv*). By definition, *Xu* and *Xv* represent the range of variables that affect streamflow timing and the low flow metric other than temperature and precipitation, and are uncorrelated to each other or the measured variables to which they were not directly connected. This allowed for substantial simplification of the structural equations and interpretation of the path analysis:

$$X_{stat} = \beta_{statAF} X_{AF} + \beta_{statCT} X_{CT} \tag{5}$$

$$X_{CT} = \beta_{CTAF} X_{AF} \tag{6}$$

The total association between variables is given by their correlation coefficients, ρ (Figure 2). Total association is the sum of direct effects, indirect effects, and spurious effects. The net effect, *NE*, is the sum of direct and indirect effects. A spurious effect is a correlation caused by variables, not accounted for in the model, that may affect both *mean annual streamflow* and *center of timing*. Direct effects of *mean annual streamflow* and *center of timing* are represented by the β coefficients in equations 5 and 6, which are standardized regression coefficients described by two subscripts. The first subscript depicts the response variable and the second subscript depicts the predictor variable. In our path analysis, the net effect of the *mean annual streamflow* on the low flow metric is the sum of direct and indirect effects.

$$NE_{\mathrm{stat}} = \beta_{\mathrm{stat\ AF}} + \beta_{\mathrm{stat\ CT}} \beta_{\mathrm{CT\ AF}} \tag{7}$$

The net effect of the *center of timing* on the flow metric is just the direct effect because there is no indirect effect.

4. Results

All gauges showed declines in *mean annual streamflow* during the 65 years of this study, with an average decline of 23% (Table 2, Figure 3). However, only 28.6% of these declines were significant at the α=0.10 level after accounting for serial correlation. Nearly all gauges showed a shift in the *center of timing* toward earlier runoff. The *center of timing* is an average of 7.8 days earlier than it was in 1948, and 19% of gauges had significant trends at the α=0.10 significance level.

7q10 summer statistics show an average decrease of 27%. Geographically, *7q10 summer* trends are significantly negative in the Washington and northern Oregon Cascades as well as the western Idaho Rockies and Snake River Plain (Figure 4). Gauges in western Washington and the central Rocky Mountains in Montana and Idaho also show declines in *7q10 summer*, but trends are less significant. *Mean August*, *mean September*, and *mean summer* flows show the same general spatial pattern as the *7q10 summer* statistic with varying significance of trends. *Mean September* flows are declining more and more significantly in central and western Washington, while *mean August* flows are declining more in Idaho, eastern Washington, and Oregon. *7q10 summer* trends are generally more significant than *mean August* and *mean September* flow trends and largely negative across the Pacific Northwest, with the exception of Donner und Blitzen River near Frenchglen in southeast Oregon (Figure 4). The majority of *min7q* at Donner und Blitzen occur in December, January, and February. Donner und Blitzen winter low flows are lower than summer low flows in 47 of the 65 dry years in our record, and trends in *7q10 winter* are not significant.

Path analysis results show that the net effect of the *mean annual streamflow* is generally higher on summer low flow metrics than is the effect of *center of timing* (e.g. Figure 2 *NE values*). Points falling on the 1:1 line in Figure 5 would be equally affected by both *mean annual* discharge and *center of timing*. Those gauges falling below the line are more strongly affected by the *mean annual* discharge. This can be interpreted as the relative influence of flow timing vs. flow amount, or temperature effects vs. precipitation effects, on low flow metrics. Winter low flow measures generally show both lower net effects and a mixed influence of flow timing and amount. Correlation plots show a much larger influence of the *center of timing* on low flow statistics when the correlation between *mean annual streamflow* and *center of timing* is not taken into account (Figure 6). The largest differences between correlations and net effects occur at high correlations to the *mean annual streamflow*.

Although the net effect of *mean annual streamflow* on summer low flow metrics is higher than the net effect of *center of timing*, subtle geographic patterns exist (Figure 7). For example northwestern Washington exhibits low net effects of both *mean annual streamflow* and *center of timing*, while western Idaho is dominated by sensitivity to *mean annual streamflow*. Geographic patterns in net effect on winter flow metrics are largely absent.

5. Discussion

Trend analyses indicate that low flow metrics have declined in the Pacific Northwest U.S. from water year 1948 to 2013 (Table 2, Figures 3 and 4). The majority of gauges show declining *mean August* and *mean September* flows, similar to findings by Chang et al. (2012). *Mean august* flows have declined 22% on average, which agrees with trends in the central Rocky Mountains U.S. from 1950-2008 (Leppi et al., 2012). Although the number of gauges showing statistically significant trends is relatively low, all statistics except *mean summer*, *mean winter*, and *7q10 winter* have more significant trends than we would expect by chance (field significance). *Mean summer* flows have declined 22% on average, similar to previous studies in the Pacific Northwest (Luce and Holden, 2009) and the Rocky Mountains U.S. (Rood et al., 2008). Only 16.7% of gauges have significant trends in *mean summer* flows (less than 21.4%, which would be expected by chance), while *mean August* and *mean September* have 28.6% and 26.2% of gauges showing significant trends. The disparity between *mean summer* and the monthly significance is a result of mean July discharge being extremely variable. July flows either contain the falling limb of the snowmelt hydrograph, or the hydrograph recession is nearly complete, and dry stable flow conditions dominate. Mean July flow (not shown) is poorly correlated to both *center of timing* and *mean annual streamflow*.

Our path analysis results indicate that the amount of precipitation that falls in a catchment has historically been the dominant control on the magnitude of low flow metrics compared to the air temperature-affected timing of snowmelt runoff (Figure 5). There is debate as to whether historical and future projection trends in precipitation in the Pacific Northwest are increasing, decreasing, or staying the same (Abatzoglou et al., 2014; Barnett, 2008; Luce et al., 2013; Regonda et al., 2005). The uncertainty in future precipitation estimates combined with the high sensitivity of low streamflow magnitudes to precipitation totals, as is supported by this study, allows for the possibility for seldom-studied precipitation effects to overshadow well-studied temperature effects in climate change projections.

There is wide acceptance in the scientific community that the amount of precipitation has a dominant effect on low streamflow magnitudes (Nash and Gleick, 1991; Ng and Marsalek, 1992; Risbey and Entekhabi, 1996). However, those relationships are tenuous when using historical data. One cause of uncertainty in historical precipitation trends is that they are often taken from large weather station networks, which are biased toward lower elevations. They thus provide an incomplete view of mountain basin precipitation totals, which are the dominant source of runoff in most of the Pacific Northwest. Uncertainty in future precipitation trends result from studies averaging many global circulation model projections of precipitation since there is a wide range of estimates among them. Many of these studies include sound disclaimers of this range and the methods incorporated to deal with them (Elsner et al., 2010). Conclusions, however, tend to focus on the hydrologic model results. Although it is tempting to assume no change in precipitation, such an approach can overstate our certainty in specific outcomes, and where nonlinear effects, say on aquatic biota, are at play, propagating uncertainty in climate models can be important in clarifying where risks are high (e.g. Wenger et al., 2013). The approach used to quantify the relative sensitivities of low flow extremes to temperature and precipitation in this paper has the benefit of using only readily available streamflow data, and thus avoids errors associated with uncertainty in distributed precipitation data sets (Henn et al., 2015; Lundquist et al., 2015).

Results from this analysis are dependent on the assumed model structure presented in Figure 2. We chose a simple model that relies only on readily available stream discharge data. We assume *mean annual streamflow* represents precipitation amount effects and is not affected by other variables in the model. *Center of timing* is a function of both precipitation amount and air temperature effects. Very similar path analysis models have been used to evaluate the sensitivity of annual and seasonal runoff to measured precipitation and temperature from weather stations (Li et al., 2011), and burned area to streamflow *center of timing* and *mean annual streamflow* (Holden, et al., 2011). Although Zhang et al. (2014) uses five factors to attribute spring snowmelt peak streamflow from mountain basins, two factors are less important for low flows (antecedent soil storage and frozen soils), and precipitation was split into spring and winter. More complicated path analyses are commonly used in studies when trying to unravel more complex relationships between nonlinear variables (see Riseng et al., 2004; Sun et al., 2013). To our knowledge, path analyses have not been performed on low flow extremes. More complicated model structures (e.g. one that incorporates a measure of available energy for evapotranspiration) are not expected to improve attribution of low flows and would not be possible to construct solely with streamflow data.

The model is dependent on the climatic seasonality of the Pacific Northwest where winter precipitation amount is proportional to the *center of timing* (i.e. all else being equal, a deeper snow pack will lead to a later *center of timing*). A possible shortcoming with the model is a relationship between the fraction of precipitation that falls as snow, a function of air temperature, and streamflow, which is assumed to be independent of air temperature (Berghuijs et al., 2014). We assume this relationship has minimal consequences on our results because historical data and modeling studies show that the influence of precipitation amounts on annual flow outweigh the influence of snow fraction as mediated by air temperature (Milly and Dunne, 2002; Nash and Gleick, 1991; Ng and Marsalek, 1992; Risbey and Entekhabi, 1996; Sun et al., 2014).Because the maximum percent of land in any of the 36 basins that is classified as irrigated agriculture is 8% and the mean value is 0.7% (Falcone et al., 2010), declines in streamflow related to land use change and irrigation are expected to have a minimal influence on the analysis presented in this paper. The five gauges in this study that have land classified as irrigated in excess of 1% are the Wenatchee 12459000 (3.9%), Salmon at Salmon, ID 13302500 (3.5%), Big Wood 13139510 (2.4%), Salmon at White Bird, ID (1.9%), and Okanogan 12445000 (1.4%) (Table S1). The attribution of low flow declines is more difficult in these basins as they may be influenced by changes in irrigation practices (Samani and Skaggs, 2008; Ward and Pulido-Velazquez, 2008). These basins do not, however, have unique responses compared to the other gauges in this study (Figure S1). In addition, temporary increases in runoff from areas that have burned during this study period are also assumed to have minimal influence on this study (e.g. Adams et al., 2012; Brown et al., 2005; Helvey, 1980; Luce et al., 2005).

Increases in evapotranspiration associated with increased longwave radiation are expected to contribute to decreases in summer low flows in the region (Roderick et al., 2014). Unfortunately, lack of detailed, long term information on either evaporation, or precipitation in high mountain environments (e.g. Dettinger, 2014) makes closure of the energy and mass balance difficult over some of the more critical areas for water supply (Viviroli et al., 2007). However, if we note 1) that interannual variations in water yield are generally more strongly affected by variations in precipitation than evaporation or catchment storage (Milly and Dunne, 2002), and 2) that the historical increase in incoming energy available for evaporation is small relative to observed flow changes

(Luce et al., 2013), we can expect that the influence of natural evapotranspiration variations on low flows over the historical period has been minor compared to precipitation amounts. Note that we consider changes in net radiation here, not "potential evapotranspiration" (PET) because PET has less influence in natural systems. PET may well have decreased over the period as well (Donohue et al., 2010; McVicar et al., 2012). Changes in low flows related to changes in irrigation, however, are more challenging to assess given that advances in technology may apply less water, but more water may be transpired and thus "lost" from the system (Samani and Skaggs, 2008; Ward and Pulido-Velazquez, 2008). We can mitigate the impacts of these changes by 1) selecting basins with relatively low proportions under irrigation, 2) contrasting across multiple basins with varying degrees of irrigation, and 3) encouraging readers to consider the robustness of particular findings in particular locations to the influence of changed (increased or decreased) irrigation.

The sensitivity of low flow metrics to annual flow can easily be framed as the sensitivity of hydrologic drought to precipitation amount, which is commonly expressed as an elasticity (Sankarasubramanian et al., 2001). Although we do not use a direct measure of precipitation, the application is analogous to a previous empirical sensitivity study performed in the Pacific Northwest (Safeeq et al., 2014).

Low flow declines in the Pacific Northwest U.S. have strong implications for the health of aquatic ecosystems (Table 2, Figures 3 and 4). *7q10 summer*, which is often used in the environmental regulation of the release of effluent into streams, has declined by 27% from water year 1984 to water year 2013. This pattern agrees with historic data from the middle Columbia Basin, U.S. (Dittmer, 2013). As low streamflows decline, the risks to ecosystems from high pollutant concentrations will increase unless discharge permits are continually updated to incorporate this knowledge (U.S. Environmental Protection Agency, 1986). While winter low flows are important to fall spawning fish, which rely on stable flows characteristic of snow-melt dominated systems for incubation of eggs (Chisholm et al., 1987; Dare and Hubert, 2002; Prowse and Culp, 2003), summer low flows may serve as a critical constraint to nearly all fish taxa. Summer discharge is both positively correlated to the amount of habitat available for foraging and negatively correlated to the stream temperature (Isaak et al., 2010; Luce et al., 2014b), which controls fish metabolism and therefore their need for food (Caissie, 2006; Dunham et al., 2007). The combination of high temperature and low habitat availability associated with low summer flows can be a major stressor, particularly for coldwater fishes such as salmonids. In extreme cases high water temperatures and hypoxia associated with low flows can exceed the tolerances of migrating salmonids and other fishes, leading to fish kills (McBryan et al., 2013; Mantua et al., 2010).

6. Conclusions

We performed quantile trend analysis on low flow indices and path analysis between low flow indices, *center of timing*, and *mean annual streamflow* from 42 stream gauges in the Pacific Northwest U.S. to quantify the trends and sensitivities of extreme low streamflows to precipitation and air temperature effects. The analysis utilized in this paper benefits from using only readily available streamflow data, which makes our results robust against systematic errors in high elevation distributed precipitation data. Our study suggests that the amount of precipitation has historically had the dominant influence on extreme summer low flows compared to warming temperatures. The *mean* *annual streamflow* represents the basin integrated total precipitation and the *center of timing* represents the combined effect of temperature effects on mountain snow packs and precipitation effects. Path analysis allows us to separate the influences of these effects on low flow metrics. Given unchanging precipitation, warming temperatures would be expected to yield declines in low flows in the majority of basins, based on empirical sensitivities between air temperatures and streamflows. Increasing precipitation could moderate timing related effects in many places, or decreasing precipitation could produce an even more potent effect on low flows.

The majority of gauges in this study show declining trends in low streamflow indices. The decline in *7q10* indices is of environmental and economic interest because of its use in the regulation of effluent discharge into streams. Summer low flow indices generally show more significant and larger magnitude of decline than winter indices. The *7q10 summer* flows have decreased by an average of 27% from 1948 to 2013. *Mean August*, *mean September*, and *mean summer* flows have declined an average of 22%, 21%, and 22% respectively. *Mean winter* and *7q10 winter* metrics show varying trends with low significance. Trends in low flow metrics, especially *7q10 summer*, suggest that environmental regulations that are a function of low flow extremes should be reevaluated on a regular basis.

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9. Tables

Table 1. List of stream gauges used in this study.

Site	Name	LON	LAT	Basin Area (km^2)	Average Annual Flow 1948-2013 (mm / year)	Average Elevation (m)	Flow Regime	Catchment Form Factor	Base-Flow Index
10396000	DONNER UND BLITZEN RIVER NR FRENCHGLEN, OR	-118.87	42.79	518	219	1,889	S	0.36	0.68
12010000	NASELLE RIVER NR NASELLE, WA	-123.74	46.37	142	2,708	296	R	0.38	0.44
12020000	CHEHALIS RIVER NR DOTY, WA	-123.28	46.62	293	1,790	403	R	0.41	0.43
12035000	SATSOP RIVER NR SATSOP, WA	-123.49	47.00	774	2,428	229	R	0.32	0.51
12039500	QUINAULT RIVER AT QUINAULT LAKE, WA (excluded 2013)	-123.89	47.46	684	3,896	791	R	0.24	0.52
12048000	DUNGENESS RIVER NR SEQUIM, WA	-123.13	48.01	404	883	1,278	S	0.46	0.60
12054000	DUCKABUSH RIVER NR BRINNON, WA	-123.01	47.68	172	2,219	1,084	T	0.20	0.54
12134500	SKYKOMISH RIVER NR GOLD BAR, WA	-121.67	47.84	1,386	2,637	1,059	T	0.52	0.56
12186000	SAUK RIVER AB WHITECHUCK RIVER NR DARRINGTON, WA	-121.47	48.17	394	2,614	1,186	S	0.33	0.57
12189500	SAUK RIVER NR SAUK, WA	-121.57	48.42	1,849	2,159	1,153	S	0.51	0.60
12321500	BOUNDARY CREEK NR PORTHILL, ID	-116.57	49.00	251	748	1,490	S	0.34	0.68
12330000	Boulder Creek at Maxville, MT (missing 2007)	-113.23	46.47	185	219	2,111	S	0.45	0.78
12332000	Middle Fork Rock Cr nr Philipsburg, MT (missing 2007)	-113.50	46.18	319	332	2,172	S	0.40	0.75
12355500	N F Flathead River nr Columbia Falls, MT	-114.13	48.50	4,009	682	1,647	S	0.29	0.71
12358500	Middle Fork Flathead River nr West Glacier, MT	-114.01	48.50	2,922	898	1,721	S	0.19	0.68
12370000	Swan River NR Bigfork, MT	-113.98	48.02	1,738	611	1,528	S	0.24	0.74
12401500	KETTLE RIVER NR FERRY, WA	-118.77	48.98	5,698	251	1,345	S	0.22	0.67
12413000	NF COEUR D ALENE RIVER AT ENAVILLE, ID	-116.25	47.57	2,318	743	1,169	T	0.44	0.66
12431000	LITTLE SPOKANE RIVER AT DARTFORD, WA	-117.40	47.78	1,722	159	728	T	0.47	0.76
12442500	SIMILKAMEEN RIVER NR NIGHTHAWK, WA	-119.62	48.98	9,194	232	1,454	S	0.34	0.66
12445000	OKANOGAN RIVER NR TONASKET, WA	-119.46	48.63	18,803	145	1,253	S	0.35	0.67
12451000	STEHEKIN RIVER AT STEHEKIN, WA	-120.69	48.33	831	1,565	1,538	S	0.45	0.64
12459000	WENATCHEE RIVER AT PESHASTIN, WA	-120.62	47.58	2,590	1,085	1,292	S	0.41	0.68
12488500	AMERICAN RIVER NR NILE, WA	-121.17	46.98	204	1,042	1,476	S	0.23	0.66
13120000	NF BIG LOST RIVER AT WILD HORSE NR CHILLY, ID	-114.02	44.00	298	305	2,640	S	0.40	0.74
13139510	BIG WOOD RIVER AT HAILEY, ID	-114.32	43.52	1,658	262	2,351	S	0.51	0.74
13168500	BRUNEAU RIVER NR HOT SPRING, ID	-115.72	42.77	6,812	48	1,720	S	0.28	0.62
13185000	BOISE RIVER NR TWIN SPRINGS, ID	-115.73	43.66	2,150	511	1,955	S	0.45	0.74
13186000	SF BOISE RIVER NR FEATHERVILLE, ID	-115.31	43.50	1,645	404	2,141	S	0.39	0.73
13235000	SF PAYETTE RIVER AT LOWMAN, ID	-115.62	44.09	1,181	642	2,078	S	0.39	0.75
13302500	SALMON RIVER AT SALMON, ID	-113.90	45.18	9,738	181	2,269	S	0.32	0.76
13313000	JOHNSON CREEK AT YELLOW PINE, ID	-115.50	44.96	552	574	2,174	S	0.24	0.71
13317000	SALMON RIVER AT WHITE BIRD, ID	-116.32	45.75	35,094	292	1,977	S	0.38	0.73
13336500	SELWAY RIVER NR LOWELL, ID	-115.51	46.09	4,947	690	1,680	S	0.48	0.70
13337000	LOCHSA RIVER NR LOWELL, ID	-115.59	46.15	3,056	848	1,585	S	0.21	0.68
14020000	UMATILLA RIVER ABOVE MEACHAM CREEK, NR GIBBON, OR	-118.32	45.72	339	613	1,208	T	0.52	0.64
14113000	KLICKITAT RIVER NR PITT, WA	-121.21	45.76	3,359	432	937	T	0.34	0.73
14137000	SANDY RIVER NR MARMOT, OR	-122.14	45.40	681	1,809	1,020	T	0.43	0.68
14178000	N Santiam R blw Boulder Cr nr Detroit, OR	-122.10	44.71	559	1,662	1,275	T	0.45	0.72
14185000	SOUTH SANTIAM RIVER BELOW CASCADIA, OR	-122.50	44.39	451	1,663	911	R	0.47	0.54
14222500	EAST FORK LEWIS RIVER NR HEISSON, WA	-122.47	45.84	324	2,058	581	R	0.35	0.55
14091500	Metolius R nr Grandview, OR	-121.48	44.63	818	1,686	1,278	T	0.29	0.81

Table 2. Trends in summer and winter low flow metrics, which were calculated for the dry year, and the independent variables, which were calculated for the water year (see Figure 1). The percent of gages showing significant trends was calculated using equations 2, 3, and 4. The field significance, which is the number of gauges that would show significant trends by chance, was calculated using bootstrap methods described by Douglas et al. (2000) and applied by Burn and Elnur (2002). Average percent declines were calculated using equation 1.

	Low Flow Statistic	Percent of Gauges Showing Negative Trends	Percent of Gauges Showing Significant Trends (α = 0.10)	Percent of Gauges Showing Significant Trends Accounting for Serial Correlation (α = 0.10)	Percent of Gauges with Significant Trends necessary to be *Field Significant* (α = 0.10)	Average Percent Decline from 1948 to 2011	Quantile
summer	7q10 Summer	95.2%	52.4%	35.7%	21.4%	26.6%	0.10
summer	Mean August Flow	95.2%	31.0%	28.6%	21.4%	22.2%	0.50
summer	Mean September Flow	95.2%	28.6%	26.2%	16.7%	20.5%	0.50
summer	Mean Summer Flow (July 15 -> Sept. 15)	100.0%	19.0%	16.7%	21.4%	21.8%	0.50
winter	7q10 Winter	66.7%	9.5%	7.1%	16.7%	7.9%	0.10
winter	MeanWinter Flow (Nov. 15 -> March 15)	73.8%	4.8%	2.4%	19.0%	5.7%	0.50
independent	Mean Annual Streamflow	100%	33.3%	28.6%	21.7%	22.6%	0.25
independent	Center of Timing (days earlier)	90.5%	21.4%	19.0%	19.0%	7.8*	0.50

* median number of days earlier

10. Figures

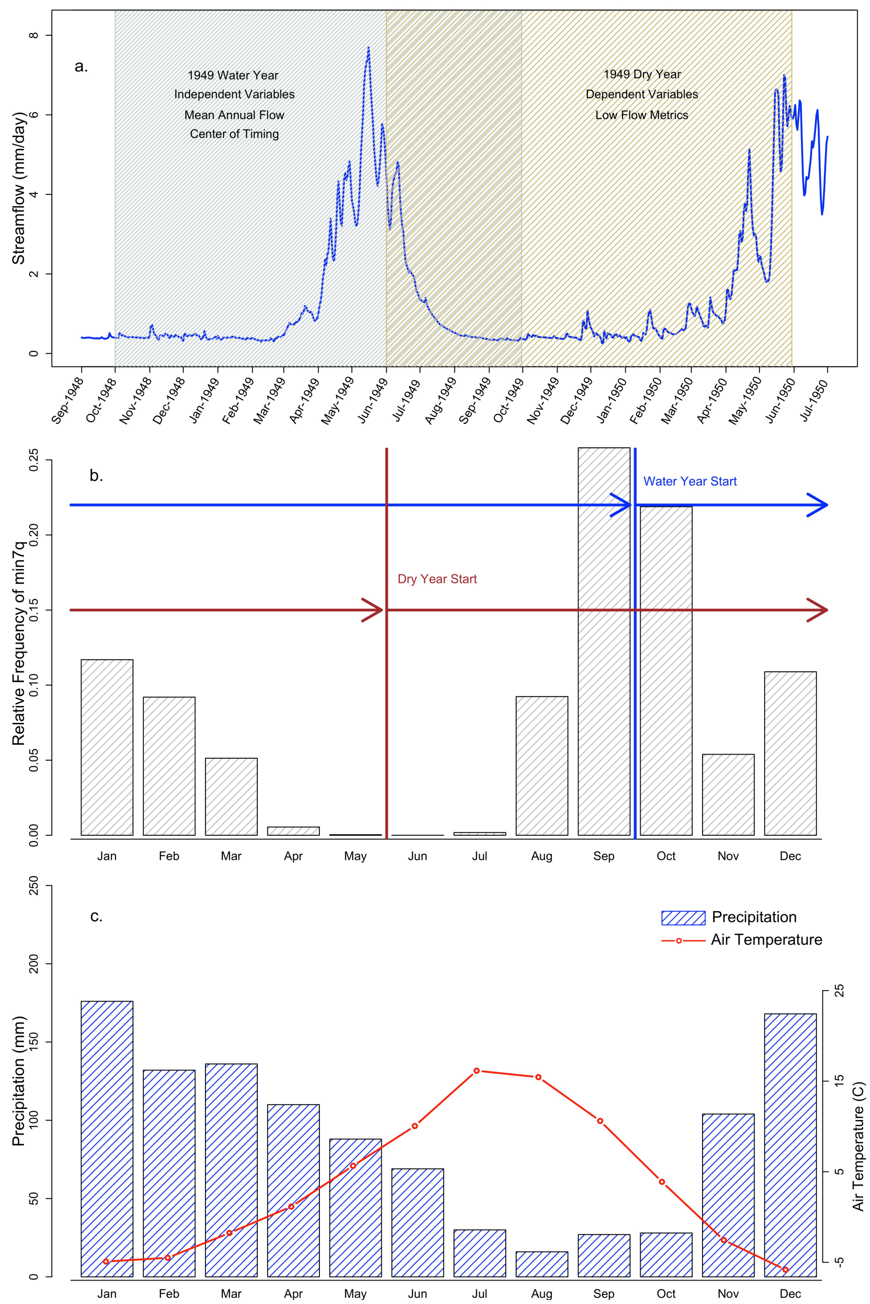

Figure 1a) A typical Pacific Northwest hydrograph characterized by snowmelt events showing the water year and dry year, and b) a relative frequency distribution of the timing of low flow events showing a binomial distribution with the largest peak centered on September and October. Blue lines show the division between water years, which occurs at the peak of low flow. Figure 1c) shows typical monthly precipitation and air temperatures showing that times of increased precipitation and air temperature are out of phase.

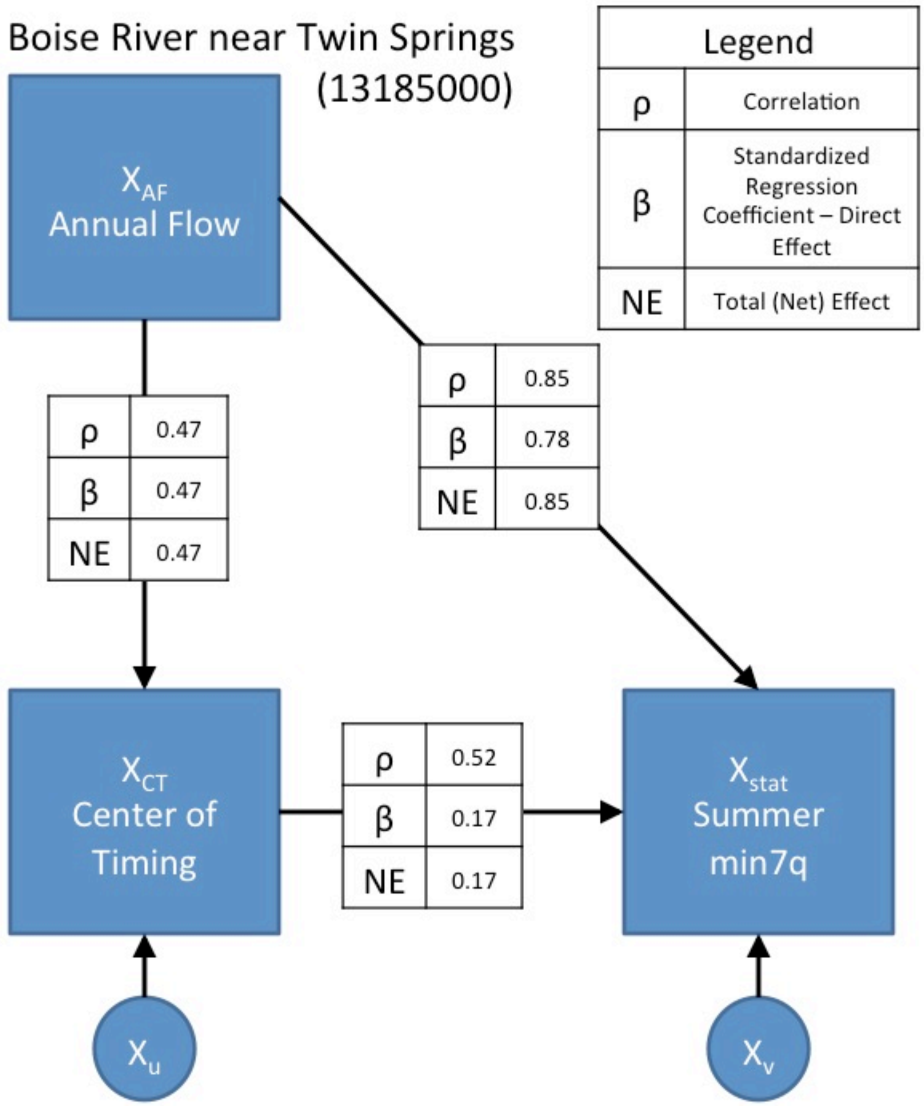

Figure 2. Example path diagram for *min7q summer* for the Boise River near Twin Springs, Idaho. The path diagram used for path analyses shows the assumed model of *mean annual streamflow* and *center of timing* influence on the flow metric or interest. *XAF* is considered an exogenous variable, which is to say that it is not influenced by other variables in this model. *XCT* and *Xstat* are both endogenous variables. Xu represents air temperature and other factors that may affect streamflow timing that are not related to *mean annual streamflow*. Xv represents any additional factor that may affect low flow metrics. Path directions as indicated by the arrows are determined by causal links between variables as explained in the Methods: Analysis section. Causality can be evaluated by comparing the net effects between the variables. In this example, the *mean annual streamflow* has the dominant effect (0.85) on *min7q summer* compared to *center of timing* (0.17).

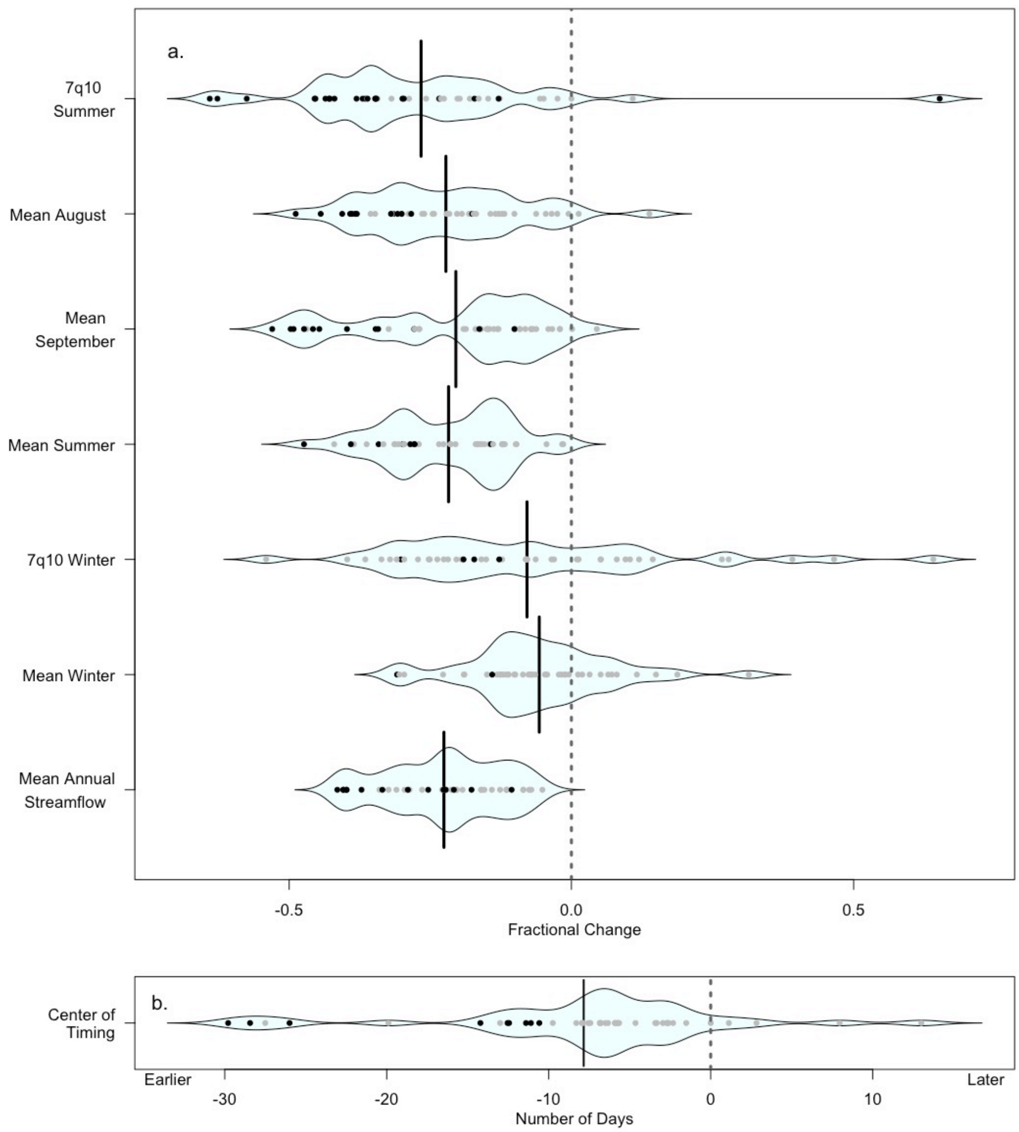

Figure 3. Distribution of changes in a) low flow metrics and *mean annual streamflow*, and b) *center of timing* from 42 gauges in the Pacific Northwest. Beanplots use a mirror image of the kernel density estimate for the blue polygon and circles for the observations. Black circles indicate that the observation at a station was significant at the α=0.10 level. Each polygon has a vertical black line that shows the mean of the distribution. Vertical dotted gray lines depict a zero value, or no change.

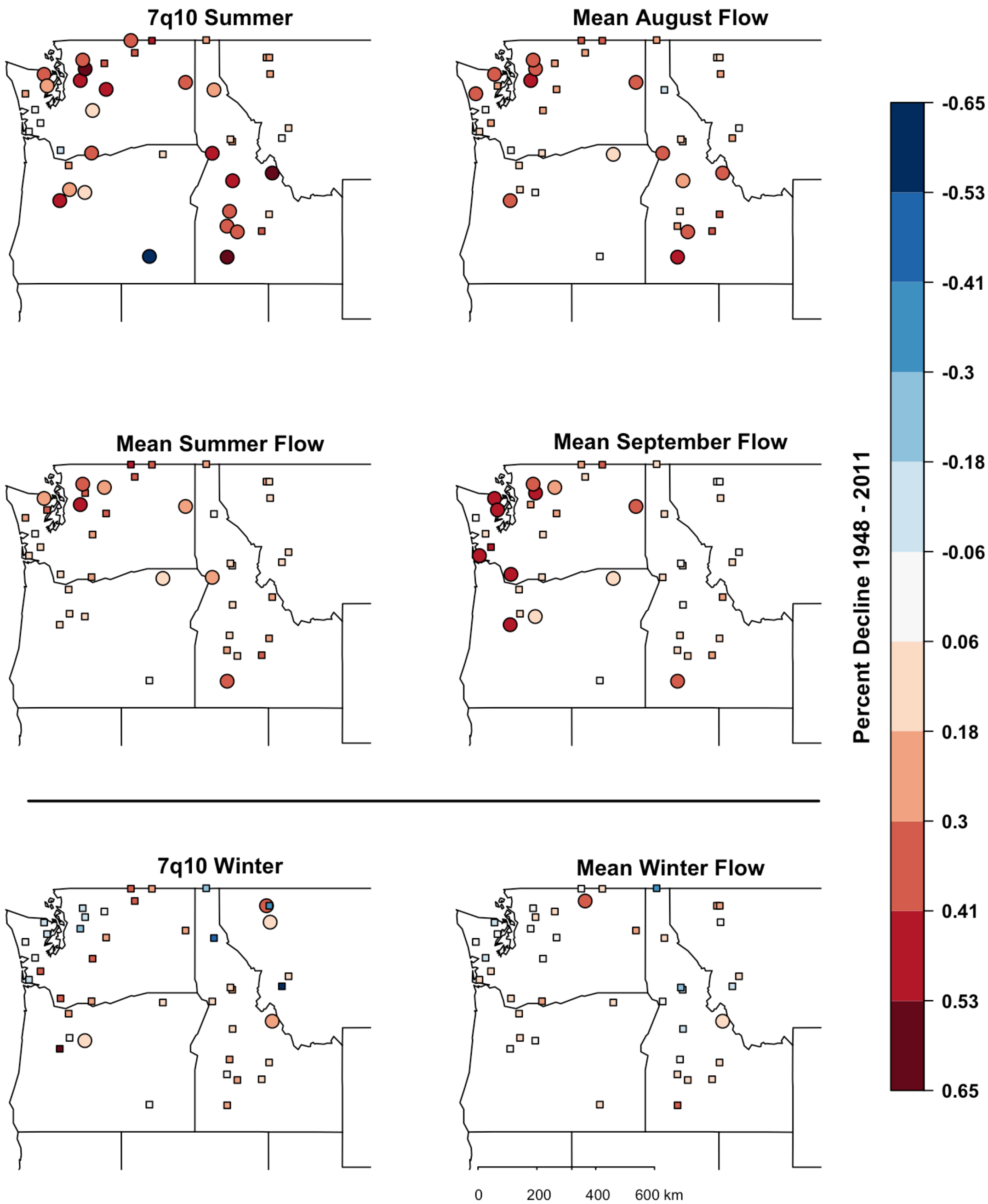

Figure 4. Maps showing mean trends and significance of low flow statistics. Larger circles depict that the trend is significant at the α=0.10 level.

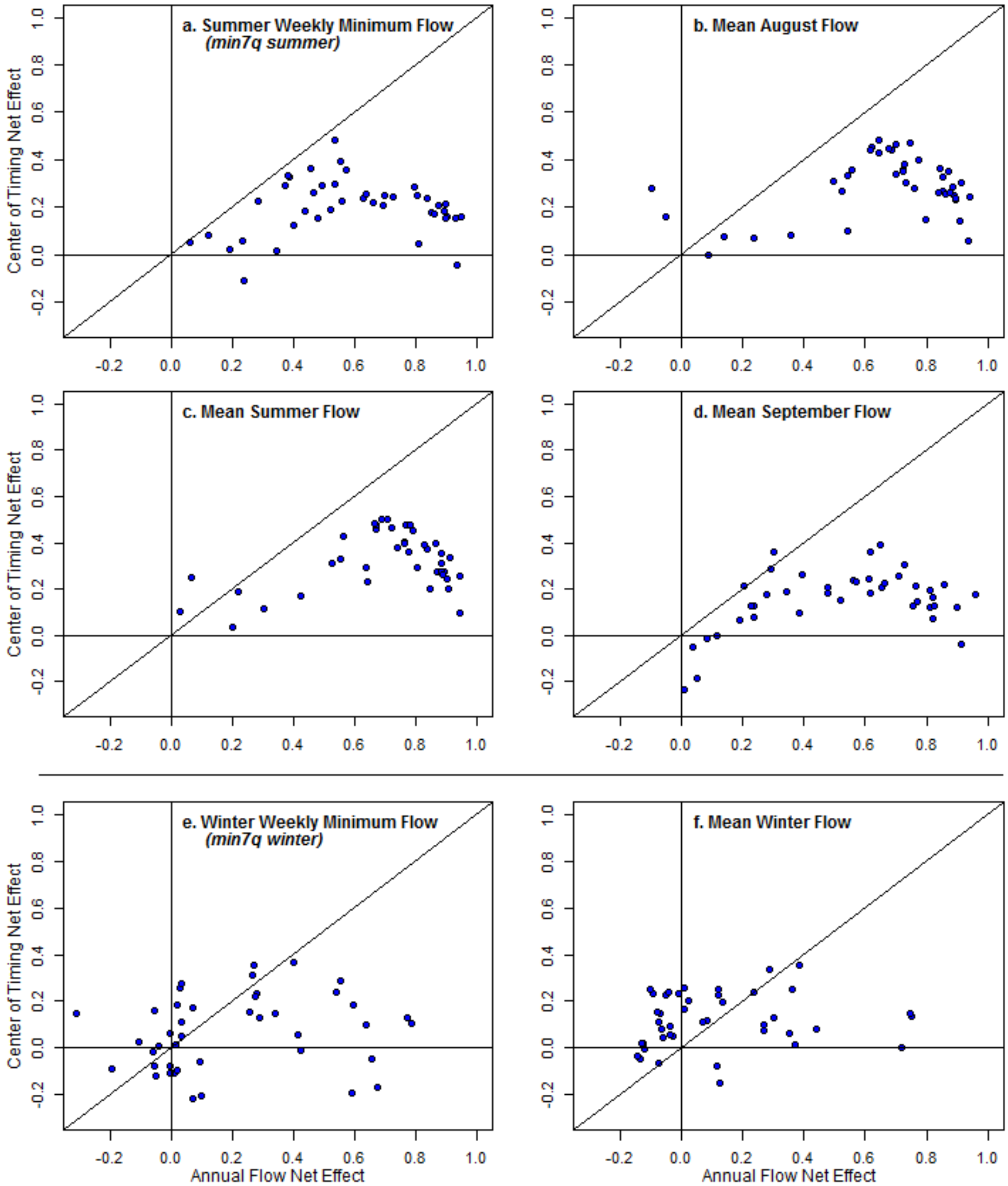

Figure 5. Net effect from *mean annual streamflow* and *center of timing* on low flow metrics at each gauge. Points falling on the 1:1 line would be equally affected by amount and timing of streamflow.

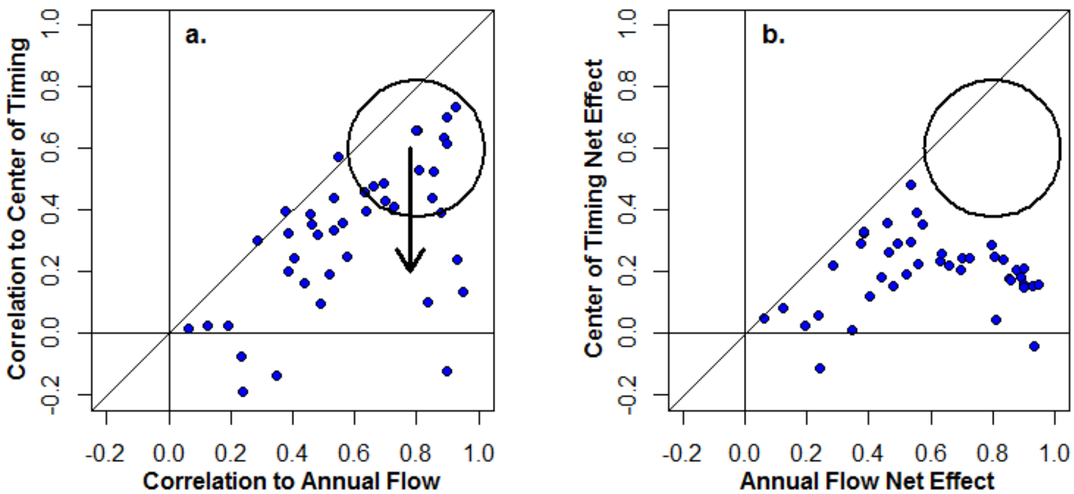

Figure 6. Scatter plots of correlations (a.) and net effects (b.) of *mean annual streamflow* and *center of timing* on *min7q* summer showing the importance of accounting for the correlation between variables.

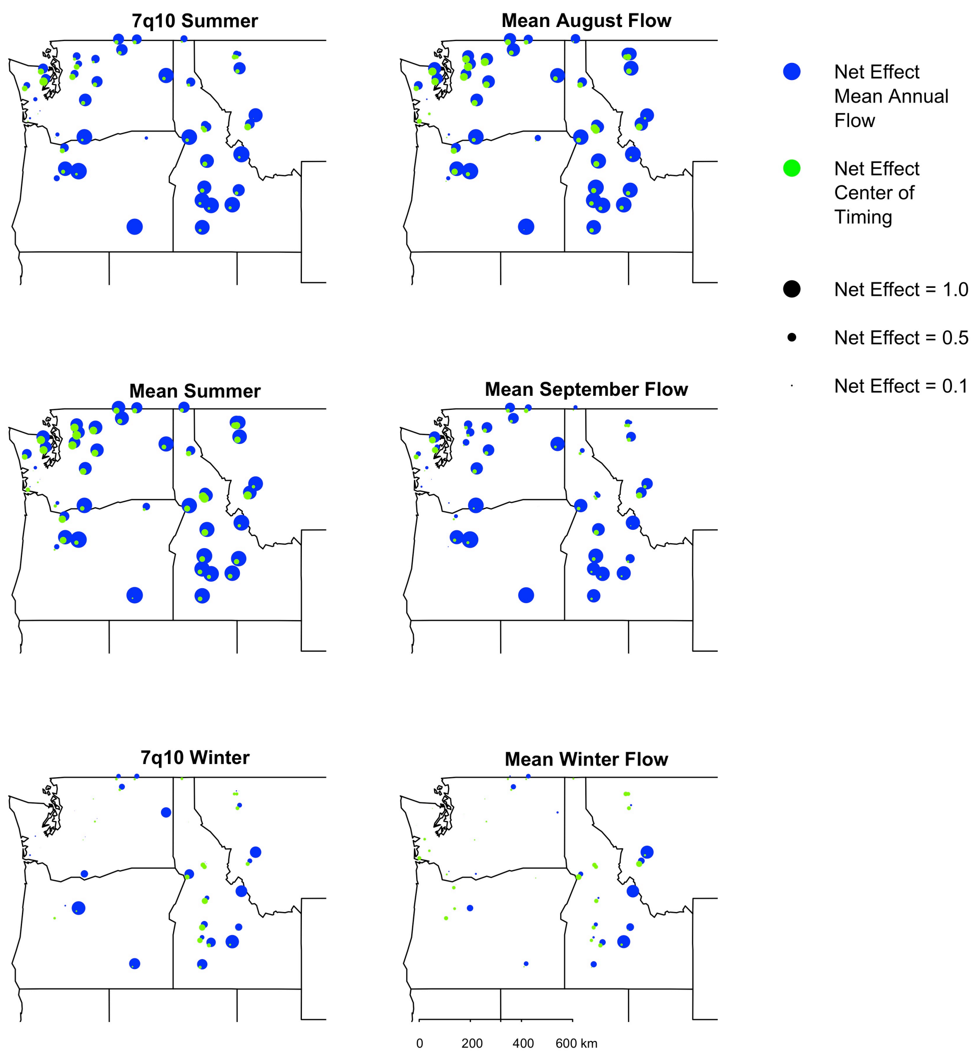

Figure 7. Maps showing the net effect of *mean annual streamflow* (blue dots) and *center of timing* (green dots) on low flow metrics. The size of the dots is proportional to the net effect.